ASSESSING BEST MANAGEMENT PRACTICES AND IMPLEMENTATION STRATEGIES TO IMPROVE WATER QUALITY

By

Subhasis Giri

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Biosystems Engineering-Doctor of Philosophy

2013

ABSTRACT

ASSESSING BEST MANAGEMENT PRACTICES AND IMPLEMENTATION STRATEGIES TO IMPROVE WATER QUALITY

By

Subhasis Giri

Best management practices (BMPs) are widely accepted to control both point and nonpoint source pollution. However, the placement and selection of BMPs plays a vital role in pollution reduction. Therefore, the objectives of this study were (1) to identify pollution generating areas priority areas (high, medium, and low) using four different targeting methods: concentration impact index (CII), load impact index (LII), load per subbasin area index (LPSAI), and load per unit area index (LPUAI), (2) to apply BMPs in the identified priority area to evaluate effectiveness, (3) to assess the spatiotemporal variability of critical source areas (CSAs), and (4) to identify the best BMP and implementation site considering social, economic, and environmental issues using different spatial targeting methods. Ten BMPs were implemented in the identified priority areas in the Saginaw River Watershed by the four targeting methods using the Soil and Water Assessment Tool (SWAT). Analytical hierarchy process (AHP) was used to compare influential criteria with different weights during the BMP selection process. Results suggest that the LPSAI is the best method for sediment targeting whereas the CII is the best method for total nitrogen (TN) and total phosphorus (TP) targeting. Terraces and native grass were the most effective BMPs whereas conservation tillage and no-till were the least effective BMPs both at subbasin and watershed level analysis. In regard to the spatiotemporal variability in the CSAs, a distinct change in high priority areas ranking was observed due to native grass

implementation by the end of second year whereas a minimal change in high priority areas was found in case of contour farming due to the greater pollution reduction capacity of native grass compared to contour farming. Based on environmental, economic, and social issues, strip cropping was preferred in all CSAs based on the subbasin level analysis while strip cropping and residue management were preferred in the CSAs for the watershed outlet analysis.

ACKNOWLEDGEMENTS

First of all, I would like to thank my major professor Dr. Amir Pouyan Nejadhashemi for giving me an opportunity and all his guidance, support, and advice throughout the journey. I would also like to thank my committee members, Dr. Timothy Harrigan, Dr. Steven Safferman, and Dr. Alexandra Sasha Kravchenko for their advice and support in completing this degree.

I would also like to thank my parents for believing in me and their support throughout my life, and my brother, Dipu, for their love and support. To all my friends, who have made my life easier while thousands of mile away from home.

Finally, I would like to thank my lab-mates Sean, Andy, Yaseen, Edwin, Matt, Georgina, Brad, Melissa, Fariborz, and Umesh for their love and support which is an unforgettable experience in my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACF	Autocorrelation function
AHP	Analytical Hierarchy Process
Alpha_BF	Baseflow Recession Constant
AnnAGNPS	Annualized Agriculture Non-Point Source
APEX	Agriculture Policy/Environmental eXtender
AR (1)	Autoregressive model of order one
BASINS	Better Assessment Science Integrating Point and Nonpoint Sources
BMP	Best management practice
CDL	Cropland Data Layer
CF	Contour farming
CH_K_1	Effective hydraulic conductivity
CI	Consistency Ratio
CII	Concentration Impact Index
CN	CN2
CR	Consistency Ratio
CSAs	Critical source areas
CT	Conservation tillage
DEM	Digital elevation model
Esco	Soil Evaporation Compensation Factor
G^2	The likelihood ratio statistic
GIS	Geographic Information Systems

H	High
H + M	High and medium
H+M+L	High, medium, and low
Ha	Hectare
HIT	High Impact Targeting
HRU	Hydrologic response unit
HSPF	Hydrologic Simulation Program FORTRAN
HUC	Hydrologic unit code
Kg	Kilogram
Km^2	Square Kilometer
LH-OAT	Latin Hypercube One Factor-At-a-Time
LID	Low Impact Development
LII	Load Impact Index
LOADEST	Load Estimator
LPSAI	Load per Subbasin Area Index
LPUAI	Load per Unit Area Index
L-THIA	Long Term Hydrologic Impact Analysis
MAUT	Multi-attribute Utility Theory
MAVT	Multi-attribute Value Theory
MCDA	Multi-criteria Decision Analysis
MDEQ	Michigan Department of Environmental Quality
MUSLE	Modified Universal Soil Loss Equation
NASS	National Agricultural Statistics Service

NCDC	National Climatic Data Center
NG	Native grass
NHD	National Hydrography Dataset
NPS	Nonpoint source
NRCS	Natural Resources Conservation Service
NSE	Nash-Sutcliffe efficiency
NT	No tillage
OV_N	Manning's n value for overland flow
PACF	Partial autocorrelation function
PBIAS	Percent bias
R^2	Coefficient of determination
Rchrg_DP	Fraction of Percolation from Root Zone that Recharges Deep Aquifer
RM 0	Residue management (0 kg/ha)
RM 1000	Residue management (1000 kg/ha)
RM 2000	Residue management (2000 kg/ha)
RS	Recharge structure
RSI	Relative Sensitivity Index
RUSLE	Revised Universal Soil Loss
SC	Strip cropping
SCS	Soil Conservation Service
SEDMOD	Spatially Explicit Delivery Model
SMDR	Soil Moisture Distribution and Routing
Spcon	Linear Re-entrainment Parameter for Channel Sediment Routing

SRW	Saginaw River Watershed
STATSGO	State Soil Geographic Database
SWAT	Soil and Water Assessment Tool
T	Terraces
TN	Total nitrogen
TP	Total Phosphorous
USGS	United States Geological Survey
USLE_C	Universal Soil Loss Equation Cover factor
USLE_P	Universal Soil Loss Equation Practice factor

1 INTRODUCTION

Managing global water resources is one of the greatest challenges in the 21st century (Staddon, 2010; Garrido and Dinar, 2008). Increased global populations and extreme events caused by climate change are creating a growing pressure on water resources (Trenberth et al., 2003; Raisanen et al., 2004; Giorgi et al., 2004). Based on United Nations Environment Programme (UNEP), approximately 40% of world population could live in water scarce regions by the year 2025 (UNEP, 2005) which prompts maintaining the sustainability of water resources to avoid adverse conditions in the future. Therefore, managing sustainability of water resources in both quantity and quality, while maintaining a substantial improvement in global food and energy security is a challenging task. (Jordan et al., 2012). In particular, maintaining proper water quality is needed to protect human, animal, and plant health (Giri et al. 2012).

Degradation of water quality occurs due to both point and nonpoint sources (NPS). In general,controlling NPS pollution is more difficult due to the lack of a single identifiable source. Instead more diffuse and complex process create a wide range of complex uncertainty associated with the simulation process (Maciej, 2000; Ouyang et al., 2009; Ding et al., 2010; Laia et al., 2011). In United States, NPS pollution from agriculture is the primary contributor to water quality impairment in rivers and lakes (USEPA, 2005). The primary pollutants from agriculture that degrade water quality are sediment, nutrients, animal wastes, and pesticides. Excessive sediment load degrades wildlife habitat, elevates dredging cost, and reduces storage capacity (Ritter and Shirmohammadi, 2001). Increased nutrients (nitrogen and phosphorus) accelerate eutrophication resulting in the killing of fish and clogging of pipelines (USEPA, 1998;

Carpenter, 2008). Also, eutrophication creates taste and odor problems, which elevate drinking water treatment costs (Dodds et al., 2009).

Improving water quality from NPS pollution requires a strategy, which can prevent entry of pollutants into waterbodies. Best management practices (BMPs) are well-known methods that minimize the pollutant loads in the runoff generated from agricultural activities (Arabi et al., 2007). However, pollutant reduction efficiency of BMPs varies from site to site (Giri et al., 2012), which is due to changes in topography, soil characteristics, geological formations, climate, crops, and cultural practices (Cunningham et al., 2003). It is impractical, expensive, and time consuming to implement BMPs on all fields in a watershed, so the placement of BMPs in Critical Source Areas (CSAs), regions that contribute the most to water quality impairment (White et al., 2009; Giri et al., 2012). Implementing BMPs in CSAs helps to maximize pollution reductions either at the edge of a field or the watershed outlet.

In this study, three knowledge gaps are addressed. These help policy makers and stakeholders to develop more socially acceptable BMP implementation plan based on different scenarios in order to maximize environmental benefit with minimal cost.

1) *Identification of CSAs using multiple targeting techniques and pollutants:* A single method to prioritize the placement of BMPs in pollution generating area (targeting method) is not efficient at identifying CSAs for all pollutants. For example, placement of BMPs, based on the pollutant concentration in the river (targeting method) is more appropriate for designing a stream restoration plan than the placement of BMPs based on

load from the agricultural fields. Similarly, in case of pollutants, one targeting method may or may not be suitable for identifying CSAs for all pollutants (sediment, TN, and TP) or even just one pollutant.

2) *Spatiotemporal variation of CSAs:* CSAs vary with respect to time after BMP implementation. Therefore, knowledge of CSAs variation in space and time is required during the BMP implementation plan in order to achieve maximum environmental benefit throughout the lifespan of the BMP.
3) *Selection of BMPs:* The BMP selection process is generally based on pollutant removal efficiency as a standalone criterion, which does not reflect the practical condition or the maximum environmental benefit. Because the stakeholder input is not considered during the BMP selection process, therefore, the selected BMP may or may not be installed by the stakeholder. Hence, the BMP selection process should include different factors such as environmental, economic, and social concerns to make the selected BMPs more effective and practical.

Based on the above discussion, water quality improvement is greatly depended on producers' acceptance level to new practices, targeting CSAs, and identification of BMPs in order to maximize investment benefits of an implementation plan. The main objectives of this study are to compare the effectiveness of current targeting methods to identify CSAs, design BMP implementation strategies based on the spatial and temporal variation of CSAs, and identify the best BMP type and implementation site while considering social, economic, and environmental.

The specific objectives for this study are:

1) Identify CSAs using multiple targeting techniques and pollutants
2) Assess the sensitivity of BMPs to reduce pollutants both in subbasin level and watershed outlet based on different targeting methods
3) Evaluate the impact of BMP implementation in CSAs at both the field and watershed level
4) Determine the most effective BMPs both for targeted pollutants and non-targeted pollutants
5) Assess the spatial and temporal variability of CSAs
6) Evaluate spatial correlation among targeting methods in categorization of priority areas (high, medium, and low)
7) Determine the most effective BMPs at reducing pollutants by considering both pollutant reduction and BMP cost
8) Identify the best BMPs and implementation sites considering social, economic, and environmental issues

2 LITERATURE REVIEW

2.1 WATER

Water is the basic ingredient of life and it is essential to all living organisms. It is one of the primary solvents and mediums of reactions. Life without water is impossible. It starts with water and relies on water for physical processes such as survival, growth, and development (Chang, 2006). Therefore, water is considered a precious resource. While water is a renewable source; its availability varies according to location (Pimentel et al., 1997). Protection of water leads to protection of life. Managing global water resources is one of the greatest challenges of the 21st century (Staddon, 2010; Garrido and Dinar, 2008). Overall, increased global populations and extreme weather events caused by climatic change is creating a growing pressure on water resources (Trenberth et al., 2003; Raisanen et al., 2004; Giorgi et al., 2004). According to United Nations, up to 40% of the world's population could live in water scarce regions by the year 2025 (UNEP, 2005). Therefore, sustainability of water resources is essential both in quality and quantity.

2.2 FRESH WATER

Fresh water regulates different activities of human beings such as drinking, washing, cooking, growing food, and personal hygiene, and supports all types of aquatic and terrestrial ecosystems (Millennium Assessment, 2005). Approximately 96.5% of all water on the earth is saline ocean water and of the remaining water, 2.5% is fresh water, 0.07% is in saline lakes, and 0.93% is in saline ground water (USGS, 2012). Meanwhile, the quantity of available fresh water is calculated to be 43,750 cubic kilometers per year, which is more than the combined requirement of agriculture, industry, and households (Srebotnjak et al., 2012). However, fresh water is unevenly distributed around the world (UNEP, 2005) and the demand for fresh water is increasing in many parts of the world due to rapid growth of populations and a significant increase in water use for different purpose such as agriculture and industry (Morrison and Gleick, 2004). Fresh water resources are fixed, while the fresh water demand is increasing. For example, additional 64 billion cubic meters of fresh water is required to fulfill the need of increase in nearly 80 million world population in each year (UN-Water, 2013). Therefore, fulfilling the fresh water needs for growing populations and concurrently maintaining fresh water for aquatic life becomes one of the most challenging issues for scientists, technologists, policy makers, and politicians during this 21st century (Postel, 2000).

2.3 FRESH WATER ECOSYSTEMS

An ecosystem is the combination of both living organisms and the nonliving environment interacting with each other as a functional unit (Hassan et al., 2005). Living organisms consist of plants, animals, and microorganisms, whereas the nonliving environment includes water, air, and soil. Ecosystems provide both direct and indirect services such as food, water, fuel, flood regulation, and soil formation (Millennium Assessment, 2005). The fresh water ecosystem is one of the most endangered ecosystems in the world. The decrease in biodiversity in fresh water is greater than seen in terrestrial ecosystems (Sala et al., 2000). Fresh water has been over used; as a result greater than 20% of the fresh water fish populations have become endangered (Dudgeon et al., 2006). The availability of fresh water to meet the demand of the growing human population and maintain the fresh water ecosystem integrity is a growing concern (Alcamo et al., 2008). Overall, the primary factors that affect global fresh water biodiversity are divided into five categories; overexploitation, water pollution, flow modification, destruction or degradation of habitat, and invasion by exotic species (Postel and Richter, 2003; Revenga et al., 2005). Each is explained in more detail below.

- Overexploitation is the excessive removal of water from the ecosystems resulting in decreased fresh water biodiversity (Dudgeon et al., 2006).
- Excessive nutrients, especially nitrogen and phosphorus, promote algal blooms resulting in a decrease in dissolved oxygen content. This reduces fish and other aquatic organism populations (Das and Gazi, 2010). Excessive nitrate in drinking water is harmful to infants as well as livestock (USGS, 2012).
- Flow modification such as dams construction affect streams and rivers flow regimes and subsequently river biota (Dudgeon et al., 2006).
- Habitat degradation is the combination of direct effects such as river excavation or indirect effects such as changes within drainage basins (Dudgeon et al., 2006). An example of habitat degradation is the clogging of river bottom due to excessive river sediment loading as a consequence of forest clearance.
- Introduction of exotic species also have a negative impact on fresh water. For an example, indirect impact of exotic terrestrial plant *Tamaricaceae* affects stream flow in Australia and North America (Dudgeon et al., 2006).

A mutual compatibility between humans and natural ecosystems helps in maintaining a sustainable ecosystem, which is challenging. Part of sustainable ecosystems is acknowledging the societal benefits obtained from a functional ecosystem (Everard and Moggridge, 2012). Human activities are linked to different ecological processes through the act of supplying fresh water (Falkenmark and Folke, 2003). For example, dams and water diversion structures provide fresh water for domestic, commercial, industrial, and agricultural uses (Meybeck, 2004), which changes the hydrology and direction of flow affecting the aquatic organisms and disrupting other ecosystem services that can be obtained from the river like pollutant reduction. Therefore, society is continuously losing ecosystem services provided by the fresh water ecosystem throughout the world (Fitzhugh and Richter, 2004). Identifying ecosystem services such as pollutant reduction may help directly or indirectly with social acceptance of sustaining fresh water ecosystems (Palmer et al., 2005).

2.4 WATER QUALITY

Managing sustainability of water resources while maintaining profitable agriculture and enhancing the environment is a challenging task. (Jordan et al., 2012). A waterbody is declared impaired when it cannot be used for the designated purpose such as drinking, navigation, recreation, fishing, and wildlife (USEPA, 2009). A reference water quality standard is developed to control the water quality of the degraded waterbodies which varies from one waterbody to another depending upon the usage.

Water quality can be improved at two levels: 1) ultimate goal and 2) periodic goal (Enderlein et al., 2012). The ultimate goal allows the water to be used by society without any adverse effect, which would also support the aquatic ecosystem. The periodic goal is designed to reach the ultimate goal.

In order to implement strategies to improve water quality, identification of the cause of water quality degradation and the location is the priliminary step (Srebotnjak et al., 2012). Many physical, biological, and chemical parameters can be used as water quality criteria (UNEP GEM Water, 2006). Therefore, there is no single water quality parameter that defines a healthy freshwater source (Srebotnjak et al., 2012). However, a numeric water quality criterion describes the minimum number of physical, chemical, and biological parameters required to support the water quality of a waterbody (USDA, 2012). Physical and chemical parameters may be used to describe the minimum concentration of a required parameters or maximum concentration of pollutants whereas biological parameters can be used to describe possible community attributes (USDA, 2012).

Water quality standards consists of three components: 1) designated usage, 2) criteria or threshold, and 3) anti-degradation policy (USEPA, 2009). After setting the water quality standard, monitoring of water is required to check the degree in which the water quality is being maintained. Monitoring of water quality data is categorized into six types; physical, chemical, biological integrity, microbial, habitat, and toxicity (USEPA, 2009).

In order to protect water quality in the United State, the total maximum daily load (TMDL) program was introduced under the Clean Water Act section 303 (Riebschleager, 2008). A TMDL is the total amount of pollutant a waterbody can receive while maintaining its water quality standard (USEPA, 2007). The TMDL is the sum of point source load plus nonpoint source load plus a margin of safety.

Extensive studies have been done on water quality, specifically how to maintain water quality by either developing a water quality index, finding the source of pollution, or implementing best management practices (BMPs) (Espejo et al., 2012; Zhoua et al., 2012; Kovacsa et al., 2012; Lee et al., 2012; Santhi et al., 2006). Zhoua et al. (2012) performed a study to assess the effect of landscape pattern on water quality of a river in China. They found that changes in the landscape due to human activities had a major impact on flow and water quality. Espejo et al. (2012) found that small areas in their watershed were contributing higher amounts of phosphorus to the river, which can be minimized by introducing BMPs in these areas.

2.5 Impaired Rivers and Streams, Lakes, Ponds, and Reservoirs

According to the United States Environmental Protection Agency (USEPA), out of 16% of nation's 3.5 million miles of rivers and streams, 44% were declared as impaired and did not meet the water quality standard (USEPA, 2009). Similarly, out of 39% of the nation's 41.7 million acres of lakes, ponds, and reservoirs; 64% did not support the designated usage of water, such as swimming, boating, drinking purposes, and other recreational activities (USEPA, 2009).

2.6 Pollutant Degrade Water Quality

Pollutants, which degrade the water quality, have a significant environmental impact. Therefore, identification of these pollutants is required in order to protect water quality. These pollutants include sediments, nutrients, silt, suspended particles, pathogens, organic materials, metals, toxic organic chemicals, pesticides, and herbicides (USEPA, 1992).

2.6.1 Sediments

Sediment is one of the primary pollutants in degrading water quality (Ondrusek et al., 2012) and is the major component of pollution in the United States (Hangsleben and Suh, 2006). It is generally found in rivers, streams, lakes, and other waterbodies (Malone, 2009). Approximately, US $16 billion can be attributed to sediment damage each year in United States (MARC, 2012). Sediment consists of individual primary particles, aggregates, organic materials, and other chemicals (Haan et al., 1994). It can be generated by either soil erosion or decomposition of plant and animal material (MARC, 2012); however, the primary contributor is erosion (Persyn et al., 2005), in fact 99% of all total suspended solids in waterbodies is from soil erosion (Ritter and Shirmohammadi, 2001). The primary carriers of eroded soil are rainfall, runoff, and wind. The major factors influencing sediment pollution are rainfall, wind, soil erodibility, slope, and crop factor. Out of all these factors, rainfall is most difficult to control.

Different natural factors (such as extreme weather events) and human activities foster formation as well as transformation of soil loss (Wu et al., 2012). Specially, improper agricultural management practices, such as excessive disturbance of soil through plowing and farming in steep areas enhance soil erosion. There are three types of soil erosion: sheet erosion, rill erosion, and gully erosion. Sheet erosion is the detachment of thin layers of soil by raindrop impact and shallow surface flow (NSW-DPI, 2012). This type of erosion is found commonly in the fields without vegetation and have been plowed.Rill erosion is developed due to concentrated flow, where the raindrop impact is insignificant (Govers et al., 2007). This type of erosion is commonly found in loose structured soil and bare or overgrazed soil. Gully erosion is developed by a concentrated flow when the velocity is strong enough to detach large quantities of soil particles.

In a river system, excessive fine sediment influences the physical processes and ecological functioning of riverbeds (Haynes et al., 2009). For example, clogging of the interstitial spaces in gravel alluvial river beds by fine sands delays the hyporheic exchange of water and dissolved constituents, which ultimately affects the oxygenation of fish eggs, nutrient cycling, and pollutant retention (Gartner et al., 2012).

2.6.2 Nutrients

Nutrients are chemical composites, which mainly consist of nitrogen or phosphorus and serve as an essential element for plant and animal nutrition (USGS, 2006), as well as stream biotic activity (Mulholland and Webster, 2010). However, excess amount of nutrients cause detrimental effects to living organisms. Excessive nutrients from NPS source are the primary cause of eutrophication in lakes, streams, and other waterbodies in the United States (Carpenter et al., 1998). NPS pollution are four times greater than the nutrient loading from point sources (Carpenter et al., 1998). The average annual nutrient concentration of streams originating from agricultural watersheds is nine times greater than forested watersheds and four times greater than rangeland watersheds (Brown and Froemke, 2012). The primary sources of NPS nutrients in streams are agricultural fertilizer, livestock manure, and atmospheric deposition (Carpenter et al., 1998; Mallin, 2000; Jones et al., 2001; Driscoll et al. 2003; Dubrovsky et al., 2010). Nitrogen and phosphorus are the two primary nutrients originating from agricultural lands, and they have the greatest effect on water quality (USEPA, 2003). However, these two nutrients are essential for high crop yields; yet the losses of these nutrients downstream can create negative environmental impacts to aquatic life and human beings (Vitousek et al., 2009). According to the United States Environmental Protection Agency (USEPA), streams that exceed NO_3-N concentrations greater than 10 mg/l cannot be used as public water supplies (Jha et al., 2010; Schilling and Wolter, 2009). When phosphorus level in the aquatic environment increased 0.01 mg/l, the productivity of the aquatic plant creates odor and taste problem in water (USEPA, 2003). These excessive nutrients create a negative impact on the local ecosystems. In addition, these nutrients can be transported downstream, which ultimately lead to the degradation of downstream ecosystems communities (Rabalais et al., 2010). Therefore, elevated nutrient load/concentration creates a negative impact on both local and downstream ecosystem due to fluvial linkage of ecosystems (Covino et al., 2012).

Different chemical and biological processes alter the form of nutrients resulting in a nutrient cycle between soil, water, atmosphere, and biological organism. The primary nutrients essential for plant growth are nitrogen, potassium, and phosphorus. A major driving force behind the increasing nitrogen and phosphorus input was fertilizer of industrially fixed N and mined phosphate rocks. Approximately, 11 million tons of nitrogen, 5 million tons of potash, and 4 million tons of phosphate fertilizers are applied to cropland in the United States each year (USDA-ARS, 1997). Apart from fertilizer application, livestock wastes contain high amount of nutrients, hormones, and steroids (Johnson et al., 2006). These enter waterbodies when grazing animals deposit their waste adjacent or directly into streams (Kolodziej and Sedlak, 2007). This increased nutrient application rate, animal waste, and intensive cropping pattern may be the cause of the increased nutrient concentration in the waterbodies (Verma et al., 2012).

Nutrients enter into water resources primarily by three different methods: runoff, runin, and leaching (USDA, 2012). Runoff is the flow of excess water from rainwater and/or melting snow after complete saturation of soil, which ultimately carries the pollutants along the soil surface. Runin transfers nutrients directly into ground water through porous medium in soil or any rock fracture, while leaching carryies nutrients in soil through percolation. The delivery of nutrients downstream is a function of landscape and instream processes. The mobility of land-based nutrients depend on several parameters such as the amount, timing, and composition of fertilizer application, the amount, intensity, and location of precipitation, the location and extent of land disturbances, and stormwater control efficiency (Lebo et al., 2012). Therefore, determining the overall contributions of nutrients to waterbodies relies on the understanding of environmental factors such as hydrology, climate variability, soil, terrain, and land use (Zhu et al., 2012).

2.6.3 Suspended Solids

Solid materials travel with most natural water in a suspension state (Alabaster, 1972). When the water carrying the suspended particles is slow enough, then the suspended particles gradually settle down to the bottom of the waterbodies (RAMP, 1996). A suspended solid is the material that can be trapped by a filter. It consists of different material such as silt, decaying plant and animal matter, industrial wastes, and sewage (LRRB, 2010). The different potential sources of suspended solids are agriculture, dredging, flooding, forest fires, logging activities, mining, recreational boating and navigation, roads, and urban development. Suspended solids are composed of both organic and inorganic fractions. The organic fraction contains algae, zooplankton, bacteria, and detritus, whereas the inorganic fraction consists of silts and clays. Suspended solids have a negative impact on water treatment cost, aesthetic value, fishery resources, and ecology (Bilotta and Brazier, 2008; Bilotta et al., 2012). For example, increase in water turbidity due to suspended solids reduces light penetration into waterbodies, which ultimately decrease photosynthesis creating an adverse effect on fish and other aquatic species

(Devlin and McVay, 2001). In addition, deposition of suspended solids prevents the exchange of dissolved oxygen and carbon dioxide between flowing water and respiring eggs leading to reduce survival and development of salmon eggs (Bilotta and Brazier, 2008).

2.6.4 Pathogens

Impairment of surface water by a pathogen places the waterbody into 303(d) list of USEPA (Hathaway and Hunt, 2012). The elevated pathogen concentration is the primary reason for a surface water impairment. Pathogen concentrations are generally estimated using indicator organisms. In agricultural watersheds, the environmental benchmark for water quality analysis is waterborne pathogen standard (Edge et al., 2012). Bacterial pathogen primarily, *Escherichia coli* (*E. coli*) and fecal coliform are the main cause of waterbodies impairment in the United States (USEPA, 2008). When a stream segment exceeds the indicator organism, *E. coli* 394 cfu/100mL or the geometric sample mean 126 cfu/100mL in 25% of the total samples, the stream segment is considered as impaired (Riebschleager, 2008). The *E. coli (*O157:H7) can cause hemorrhagic colitis (HC) and hemolytic uremic syndrome (HUS) in humans. Other enteropathogenic *E. coli* causes diarrhea in children (Ibekwe et al., 2011). Apart from *E. coli*, Zoonotic waterborne protozoa, specifically *Cryptosporidium* and *Giardia* spp can cause diarrhea (Carey et al., 2004; Fayer, 2004). Also, *Cryptosporidium* oocysts and *Giardia* cysts can persist in adverse conditions and contribute to health risks (Hogan et al., 2012). Therefore, pathogen contaminated waterbodies is a vital public health concern in the multiuse ecosystems.

The potential sources of pathogens are from either point sources or nonpoint sources such as: confined animal feeding operations, waste water treatment plants, combined sewer overflows, slaughterhouses, meat processing facilities, tanning, textile, pulp and paper factories, and fish and shellfish processing facilities (USEPA, 2001c). With a growing numbers of livestock, increasingly intensive cattle, hog, and poultry farming operations, a variety of pathogens can be observed from livestock fecal wastes (Olson et al., 1997; Hutchison et al., 2004; Lee and Newell, 2006; Opporto et al., 2007). The nonpoint pathogen sources consist of urban litter, excrement from barnyards, pastures, contaminated refuse, domestic pet and wildlife excrement, feedlots and uncontrolled manure storage areas in rural or agricultural areas, failing sewer lines in urban and suburban areas, small confined animal operations, onsite wastewater systems, and rangelands (Paul, 2003). Human population, housing density, and land development have strong positive correlation with bacterial densities (Young and Thackston, 1999). Additionally, specific human enteric diseases are linked to high cattle density found from epidemiological studies (Michel et al., 1999; Valcour et al., 2002).

The fate and transport of pathogens depends on the different factors such as temperature and rainfall intensity (Jokinen et al., 2012). For example, precipitation can carry pathogens from land to waterbodies or mobilize pathogens within the flow zone by increasing the water flow to the waterbodies (Wilkes et al., 2011). Therefore, in order to understand the fate and transport of pathogens, it is essential to understand the interaction of pathogens with land use, hydrology, and temperature (Auld et al., 2004; Thomas et al., 2006; Wilkes et al., 2009). This includes the occurrence and densities of pathogens in waterbodies and the ability to specify pathogens associated point and non-point sources (Ice, 2004; USEPA, 2005; Benham et al., 2006; Rao et al., 2009).

2.6.5 Organic Material

Organic material is composed of both living and non-living carbon based materials (ASWP, 2012) and can occur naturally or may be from municipal and industrial effluent runoff (Malcolm, 1985). Natural organic material consists of complex organic materials, which exists in the environment (Teixeiraa and Nunesb, 2011). The quality and concentration of organic matter depends on several factors such as climate, location, and environmental (Kotti et al., 2005). Eatherall et al. (2000) observed that the higher concentrations of dissolved organic matter in the watershed is due to the sewage point source and the diffuse nonpoint sources during low and high flows, respectively.

The water quality, food webs, and structural complexity of forested headwater streams are influenced by coarse particulate organic matter and associated elements (Benstead *et al*. 2009). The amount of coarse particulate organic matter that is transported from the headwater of a stream primarily depends on rainfall, plant phenological patterns, stream flow, channel geomorphology, rates of litter decomposition and biotic processing (Scalley et al., 2012). Like particulate organic matter, dissolved organic matter also plays a significant role in the biogeochemical cycles of carbon and nitrogen (White et al., 2010). Dissolved organic matter helps in carrying different elements from one place to another. For example, mercury binds with organic matter facilitating its transport from forested ecosystems to water ecosystems (Akerblom et al., 2008; Brigham et al., 2009).

2.6.6 Metals and Toxic Organic Chemicals

Elevated concentrations of metals such cadmium, lead, cobalt, copper, mercury, chromium, nickel, selenium, zinc, and iron in stream sediment and water is a serious and widespread environmental problem. These metals originated from various sources such as mining, industrial development, and increase in urban area (Buyuksonmez et al., 2012). Several researchers (Milner and Kochian, 2008; Das et al., 2011; Leung et al., 2008; Johri et al., 2010) have looked at the health risks caused by metals. Metal contamination in the aquatic environment becomes a serious concern due to their toxicity levels. For example, metals can deposit on microorganisms, aquatic flora and fauna, and pass through the food chain to the human body causing health hazards (Varol and Sen, 2012; Sin et al., 2001).

In general, metals are heavier than other particles and insoluble in water, they deposit on the bottom of rivers with sediment (Tsakovski et al., 2012). Therefore, sediments play a major role in the storage and transportation of metals in waterbodies (Lee et al., 2012). Apart from the above factors, the fate and transport of heavy metals rely on several processes related to redistribution, mobility, and transformation.

2.6.7 Pesticides

The term pesticide is defined as mixture of substances, which are made for preventing, killing, and mitigating any types of pest (USEPA, 1993). Pesticides can be subdivided to herbicides, insecticides, fungicides, miticides, and nematicides (USEPA, 2003). Pesticide from agricultural fields is a common nonpoint source of contamination in waterbodies and is regarded as one of the greatest stressors to stream ecosystems (Rasmussena et al., 2011). The use of pesticides to protect crops from insects, fungi, and weeds is a general agricultural practice. However, pesticides can contaminate both surface and ground water (Juniori and Silva, 2011). Agricultural pesticides are primarily applied during growing period, early spring through fall. Apart from agricultural pesticides, pesticides are heavily used in urban areas, especially in residential lawns, gardens, parks, and golf courses (Glozier et al., 2012). The sources of pesticides are liquid and solid wastes from pesticide manufacturing, residual post-applied plant pesticides, washing equipment used with pesticides, and pesticides packing and distribution (Grynkiewicz et al., 2003) whereas the other sources of pesticides consist of agricultural and horticultural activities, landfills, destruction of unwanted vegetation, and forest protection activities (Babu et al., 2011).

Pesticides are a concern to both the public and water quality managers due to their negative impacts on both aquatic life and human health (Kreuger, 1996). Pesticides enter waterbodies through diffuse pathways such as runoff, aerial drift, leaching, volatilization, and food chain movement (USEPA, 2003). Both pesticides in solution and pesticides attached to soil particle can be transported during runoff. Organic carbon and clay content of soil helps in partitioning pesticide between solution and solid phase (Katrijn et al., 2007).

Some pesticides do not degrade quickly and may persist and accumulate in waterbodies. Pesticide contamination occurs due to different factors such as improper application, erosion, cropping systems, inadequate equipment maintenance, inappropriate selection, leaching, artificial drainage, and volatilization (UNEP, 1998). The threat pesticides present to water quality depends on both the application method and location (USEPA, 2003). Peak concentration and duration of exposure are two factors, which determine the degree of the negative impact the pesticides will have on flora and fauna in surface water (Kreuger, 1998). Up to five percent of applied pesticides can be lost through leaching, but generally, it is less than one percent (Carter, 2000). Surface water is more susceptible to pesticide contamination than ground water due to easy entry of pesticides into surface water . According to Gilliom et al. (2007) pesticides were found more than 90% of the time in streams in developed watersheds (dominated by agriculture, urban and mix land use) but only slightly greater than 50% of the time in shallow ground water. Pesticides are characterized as highly soluble and have a low adsorption capacity to soil, which enables them to reach waterbodies easily (Glozier et al., 2012). In addition, conversion of natural areas into urban areas increases the impervious surface that reduces infiltration and helps in easy transportation of pesticides.

Studies on herbicides showed that less than two percentage of the total herbicide applied ended up in the nearby waterbodies shortly after application (Capel et al., 2001). The loss of herbicides into a watershed depends on weather conditions, soil type, land use, intrinsic properties of the compound (Kreuger, 1998; Capel et al., 2001; Katrijn et al., 2007).

The possible effects of pesticides on the environment and human health raised public concern, which ultimately resulted into laws regulating pesticide concentration in different parts of the world (Glozier et al., 2012). For example in Canada, two types of environmental thresholds are suggested, (1) ecological threshold and (2) achievable threshold (Environment Canada, 2010).

In the United States, both Federal and State agencies are actively working to reduce pesticide transport into waterbodies in order to prevent the negative impacts of pesticides to stream ecology and human health (Lerch et al., 2011). Many studies have been conducted on pesticides in order to understand their fate and transport (Hoffman et al. 2000; Kolpin et al. 2006; Weston et al. 2009). A detailed understanding of watershed- scale pesticides mobility is possible through understanding the complex biogeochemistry and interactions pesticides have with hydrologic processes and land use (Zanardo et al., 2012). Lerch et al. (2011) stated that the (1) chemistry of the contaminant, (2) hydrology and soils of the watershed, (3) land (i.e. herbicide use and crop management), and (4) climate (particularly precipitation) are the primary factors controlling watershed susceptibility to pesticide transport.

2.6.8 Animal Waste

The size, production, and amount of livestock manure has increased with the increasing number of animal feeding operations (Jenkins et al., 2009). In fact, 32% of all land in the United States is used as rangeland where cattle are free to access the waterbodies within it (USDA, 2005), and as the animals graze, they deposit feces on the land, which then enter the waterbodies through runoff (Kolodziej and Sedlak, 2007). The chance of spreading waterborne pathogens and diseases through waterbodies has potentially increased. Animal waste consists of fecal and urinary waste both from livestock and poultry, which includes processed water from milking parlor, feed, bedding, and litter (USEPA, 2003). These wastes contains high concentration of pollutants such as nutrients, steroid estrogens metals, salts, organic solids, bacteria, viruses, and other microorganisms (Hanselman et al., 2003; Johnson et al., 2006; Mallin and Cahoon, 2003; USDA, 1992). The presence of so many contaminants in the animal waste can create adverse effects in both surface and ground water (USDA, 1992). These nutrients, steroids, metals, and microorganisms can enter into the waterbodies through runoff or leachate from agricultural lands (Kjaer et al., 2007; Matthiessen et al., 2006).

Poultry litter consists of a mixture of feces, bedding material, and feathers. These poultry litters are applied to agricultural lands to provide nutrients such as nitrogen, phosphorus, and potassium (Moore et al., 1995). Additionally, these poultry litters contain pathogenic bacteria, such as Salmonella, Campylobacter, and fecal coliform, and appreciable concentration of the sex hormones (Jeffrey et al., 1998; Jenkins et al., 2006). Application of poultry litter increases the potential risk of contaminating surface and ground water with these pollutants.

2.7 SOURCES OF WATER POLLUTION

Water pollution is of great concern in both developed and developing countries. Water pollution control is required to improve water quality. In order to do that, we need to identify the different sources of water pollution. Water pollution occurs due to both point and nonpoint sources. Point sources are easy to control as they come from a single identifiable source, whereas nonpoint sources are difficult to control due to the associated complex diffuse processes (Chiwa et al., 2012; Giri et al., 2010; Carpenter et al., 1998).

2.7.1 Point Source

The point source is the confined, single, exact point where pollution originates and discharges into waterbodies (USEPA, 2012). A point source could be a pipe, channel, conduit, rolling stock, concentrated animal feeding operation, municipal sewage treatment plants, or industrial facility. Point source pollution generation is not controlled by natural factors; it is controlled by anthropogenic processes such as industrial activities. Therefore, point source pollution can be measured and controlled periodically at a single place (Carpenter et al., 1998). In order to control the point sources in the United States, the Environmental Protection agency (EPA) introduced the National Pollutant Discharge System (NPDES), which is under Clear Water Act of 1972 (USEPA, 2012). It is a permit-based system that regulates the discharge of point source pollution.

2.7.2 Nonpoint Source (NPS)

Being the largest threat to water resources, NPS pollution has drawn attention from both scientific communities as well as government agencies (Wanga et al., 2012). NPS pollution is a spatially diverse load carried by surface and subsurface runoff to receiving waterbodies (Laia et al., 2011). NPS pollution results from agricultural activities, precipitation, atmospheric deposition, street runoff, infiltration, and drainage (Shi et al., 2012). NPS pollution is more complex and harder to identify and control, due to complex uncertainties associated with the simulation process (Ding et al., 2010; Laia et al., 2011; Maciej, 2000; Ouyang et al., 2009). Factors affecting NPS pollution are soil, topography, climate, hydrology, and land use types (Ou and Wang, 2008). Runoff is the primary mechanism that transports pollutants from one place to another. For example, when runoff or snowmelt washes over the surface it carries pollutants such as sediments, nutrients, organic matter, bacteria, oil, and metals to the receiving waterbodies.

In the United States, NPS pollution from agricultural activities is recognized as a primary source of water pollution (USEPA, 2003). The increasing use of chemicals in agriculture to meet the food demand of a constantly growing population degrades water quality. In order to maintain the balance between crop productivity and the negative impact of NPS pollutant on water quality, we need to understand the fate of NPS pollutants (Wali et al., 2011). In the United States, in order to control the NPS pollution, the agricultural NPS policies, the Coastal Nonpoint Pollution Control Program, and National Estuary Program under section 320 of the Clean Water Act were developed (USEPA, 2012; Shortle et al., 2012).

2.8 Agricultural Pollutants and their Economic and Environmental Risks

The primary pollutants originating from agriculture are sediment, nutrients, animal wastes, and pesticides. Increased amounts of these pollutants degrade water quality, which ultimately increases the cost of water use. The following are the detail description of each pollutant and its economic impact on water quality.

2.8.1 Sediment Damage

Increase in sediment content affects waterbodies in several ways. Excessive sediment decreases water storage capabilities, degrade wildlife habitat, and increases dredging cost (Ritter and Shirmohammadi, 2001). In the United States (US), the excessive sedimentation causes approximately, $13.4 billion per year as an external cost (Tegtmeier and Duffy, 2004). Sediment loads result in temperature changes and deplete oxygen levels, which is harmful to aquatic organisms (Malone, 2009). Increases in sediment decreases the aesthetic value of water, increases clarity problems, and hampers recreational activities (USDA, 1997). In addition, higher sediment load reduces fish growth rates, reduce availability of food for fish (which changes migration pattern), and also can be toxic at higher concentration (Newcombe and MacDonald, 1991). Excessive sediment raises the streambed, which ultimately increases the probability and severity of flooding. Suspended sediment increases the purification cost of drinking water and increases the water treatment cost of municipal and industrial use (USDA, 2012). In addition, suspended sediment decreases the amount of sunlight available to the aquatic plants and clogs the gills of fish (USEPA, 2003).

2.8.2 Nutrient Damage

Increase in nitrogen and phosphorus in the fresh water and coastal ecosystems accelerates eutrophication, which results in fish death and clogged pipelines (Carpenter, 2008; USEPA, 1998). Additionally, recreational activities such as swimming, fishing, and boating are affected due to excessive plant growth and odor and taste problem of the water (USEPA, 1999). Lowering of oxygen level creates hypoxic zones, which do not support life. Also, studies have shown that movement of nitrogen from land into surface water creates serious environmental hazard such as death and abnormalities in amphibians (Rouse et al., 1999) and dead zones like in the Gulf of Mexico (Ebionews, 2010). Nitrate is a potential threat to human health especially to infants, which can prevent supply of sufficient oxygen to the blood stream called blue baby syndrome (USDA, 2012). Increased phosphorus content contributes to odor and taste problems and also increases the purification cost of drinking water (Malone, 2009). According to USEPA, a total of $200 million is required to maintain the federal nitrate standard in drinking water due to nitrate contamination of drinking water resources (USDA, 2012).

2.8.3 Pesticide Damage

All pesticides have harmful effect on humans, animals, and aquatic life (Lorenz, 2009). Increased pesticide content kills fish, frogs, turtles, and other wildlife (Helfrich et al., 2009; Gormley et al. 2005). In addition, increased pesticide amounts in waterbodies promote the growth of algae, which results in interference of swimming, fishing, and boating (Helfrich et al., 2009). Pesticides can cause health hazards for humans by consumption of contaminated fish (UNEP, 1998; USDA, 2012).

2.8.4 Animal Waste Damage

Several contaminates present in animal waste can have negative effects both to surface and ground water. Additionally, specific elements of animal waste can adversely affect terrestrial plants, grazing animals, and air quality (USDA, 1992). Endocrine glands of aquatic organism can be interrupted by estrogen from animal wastes at concentrations higher than 10 mg/L (Young et al., 2004). Increases in animal waste application on agricultural lands increases the probability of eutrophication in surface water as well as disruption of the endocrine gland in aquatic organisms (Yonkos et al., 2010; Mallin and Cahoon , 2003; Kellog et al., 2000). Presence of estradiol in poultry litter has potential to affect ecological as well as public health (Jenkins et al., 2009). Additionally, estrogen in poultry litter can have a negative effect (premature udder growth and lactation) in heifer (Shore et al., 1995). Testosterone present in animal waste (Lintelmann et al., 2003) can create negative impacts on aquatic ecology (Jenkins et al., 2009). Phosphorus present in animal manure can enter waterbodies and causes eutrophication (Soupir et al., 2006; Sharpley et al., 1993), which ultimately leads to low oxygen levels, reduced aquatic species diversity, turbidity, and poor taste and odor in waterbodies (Hansen et al., 2002).

2.10 MECHANISM TO CONTROL AGRICULTURAL NON-POINT SOURCE POLLUTION

The non-point source pollution from agricultural activities can be controlled by different management activities such as BMPs systems, accepted agricultural practices, management measures, management practice systems, resources management systems, and total management systems (USEPA, 2012). This study discusses how BMPs can be effectively used to control agricultural NPS.

2.11 Best Management Practices

BMPs are the practices and procedures that minimize the amount of pollutants in runoff from agricultural activities while providing a viable economic option to the farmers (UNEP, 1998). BMPs reduce NPS pollution by three mechanisms: 1) reducing pollution mass through erosion control practices and concentration through nutrient and pesticide managements, 2) reducing pollutant delivery to waterbodies through filter strip or different types of vegetative barrier, and 3) remediation through chemical and biochemical processes (Cunningham et al., 2003). In general, BMPs are categorized primarily into structural and non-structural (Kaplowitz and Lupi, 2009). A structural BMP requires a construction or more permanent land use change to capture runoff (e.g., filter strip or artificial wetland) (Sommerlot et al., 2013). A non-structural BMP does not require construction but modifications of agricultural practices (UNEP, 1998). Meanwhile, some researchers have classified BMPs into three categories: structural (such as manure storage facilities, stream fencing and stabilization, and alternative watering systems), vegetative (such as cover crops, filter strips, riparian buffers, and reforestation), and management (such as loafing lot systems, and rotational grazing) (Cunningham et al., 2003).

Some of the common BMPs described in USDA NRCS conservation practice technical documents are provided below. Table 2-1 describes the BMP type, definition and specification, and purpose and condition of BMPs application.

Table 2-1. Common BMPs in the United States described in the NRCS technical guide.

BMP	Definition	Purpose	Condition of application	Specification
Conservation Crop Rotation (NRCS Code 328)	Crops grown in a planned sequence on the same field (USDA-NRCS, 2010)	-Reduce sheet and rill and wind erosion -Improve soil quality - Conserve water -Reduce energy use by supplying nitrogen through nitrogen fixation	-Applied in all cropland where one third of the crop sequence is produced by annual crops	-Fallow land should not cover more than 25% of the planned crop sequence during uncropped period - A planned two crop sequence should contain a warm and cool season crop
Terraces (NRCS Code 600)	Earthen embankment, which consists of ridges and channel across the field slope (USDA-	-Reduce erosion, conserve moisture by retaining runoff	-Area having excessive slope, excess runoff - Soil and topography are suitable for terrace construction	-Capacity to control 10-year 24-hour storm -The ridge should have a minimum width of 3 ft. -Maximum allowable slope should be 2 horizontal to 1 vertical -Length of the terrace

Table 2-1 (cont'd)

	NRCS, 2010)			should not exceed 3500 ft. in order to avoid the potential failure risk
Strip Cropping (NRCS Code 585)	Systematic arrangement of equal width of row crops, forages, and small grains (USDA-NRCS, 2010)	-Reduce soil erosion by water and wind -Protect growing crops from wind-borne soil particle -Reduce amount of sediments and water-borne contaminants in the runoff	-Applied in all croplands and other suitable areas for growing crops	-Strips of the crops should be placed at an angle perpendicular to the water and wind erosion forces -At least 50% of the cover consists of erosion resistant crops or sediment trapping cover -Strip boundary should be parallel to each other and as close as possible to the contour
Contour Farming	Consists of ridges and	-Reduce sheet and rill erosion	-Applicable on sloping land	-Minimum ridge height of two inches should be

Table 2-1 (cont'd)

(NRCS Code 330)	furrows formed by different farming operations such as tillage and planting. It helps in changing the direction of runoff from down slope to around the hill (USDA-NRCS, 2010)	-Increase infiltration -Reduce sediment, suspended solid, and contaminants in the runoff	suitable for annual crops	maintained during the rotation period for row spacing greater than 10 inches -Minimum ridge height of one inch should be maintained for close grown crops having row spacing 10 inches or less -Row grade should not exceed 0.2%
Conservation Cover (NRCS Code 327)	Establishing and maintaining a permanent vegetative cover (USDA-	-Reduce sedimentation and soil erosion -Improve soil, water , and air quality -Helps in	-Applicable on lands require a permanent vegetative cover	-Perennial crop vegetation should provide full ground coverage in the pathway during mowing and harvesting -Combination of

Table 2-1 (cont'd)

	NRCS, 2010)	wildlife habitat and pollinator habitat		grasses, forbs, legumes, and shrubs should be planted in order to promote biodiversity
Constructed Wetland (NRCS Code 656)	Artificial ecosystem consisting of hydrophytic vegetation (USDA-NRCS, 2010)	-Improves storm water quality -Improves water from waste water treatment plant, agricultural processing, livestock, and aquaculture facilities	-For agricultural waste water management system where constructed wetland is a component	-Construction of an auxiliary spillway or inlet bypass to control peak flow of 25-year, 24-hour storm -Provide an suitable inlet control structures to avoid entering debris into wetland -Minimum of two rows of functionally parallel cells should be considered in the wetland system design
Filter Strip (NRCS Code 393)	Growing herbaceous vegetation in a strip to remove	-Reduce sediment, suspended solids, and other contaminants	-Applicable to environmental sensitive areas require reduction of	-Minimum width of the filter strip should be 20 feet - Slope of one percent or greater is preferable

Table 2-1 (cont'd)

	contaminants from overland flow (USDA-NRCS, 2010)	-Decrease dissolved contaminants in irrigation water	sediment, suspended solids, and dissolved contaminants	for the area up-stream of filter strip -Maximum of four inches plant spacing is preferable in the filter strip
Residue and Tillage Management (NRCS Code 329)	Distribution of amount and orientation of crop and other plant residue on soil surface throughout the year, also minimizing soil disturbance (USDA-NRCS, 2010)	-Reduce soil erosion, especially rill and sheet erosion - Increase the organic matter of the soil -Reduce energy use and CO_2 losses from soil -Increase moisture content of the soil which increases the plant available water	- Applicable to all cropland	-Soil tillage intensity rating value should be within 20 -Crops having row spacing less than 15 inches should have a minimum 10 inches crop stubble height -One to three inches deep soil disturbance is preferable to release less CO_2

Table 2-1 (cont'd)

Grassed Waterway (NRCS Code 412)	Establishment of suitable vegetation along the graded channel which prevents erosion (USDA-NRCS, 2010)	-Protect erosion and flooding in the terraces and diversions -Improve water quality and reduce soil erosion	-Areas need erosion control from concentrated flow	-Can control the peak runoff from 10-year 24-hour rainfall -Bottom width of the grass waterway should be less than 100 feet -Slide slope should be less than 0.5 -Freeboard should be provided above the designed depth to avoid damage
Sediment Basin (NRCS Code 350)	Construction of a basin by earthen embankment, or excavation, or combination of both (USDA-NRCS, 2010)	-Capture sediment in the runoff and provide longer period of time which allows to settle in the basin	-Urban land, construction sites, agricultural lands	-Basin can at least store 3600 ft^3/acre of drainage area - Length to width ratio of the basin should be 2 to1 or greater -Construction of porous baffles in the entire basin is recommended to control the turbulence in the basin

Table 2-1 (cont'd)

Riparian Forest Buffer (NRCS Code 391)	Areas dominated by shrubs and trees located closer to the waterbodies (USDA-NRCS, 2010)	-Improve aquatic life habitat by maintaining the water temperature -Decrease amount of sediments, nutrients, and pesticides in the runoff -Increase carbon storage -Reduce pesticide drift into the waterbodies - Help in stabilizing stream bank or shoreline	-Applied in an area closer to streams, ponds, and wetlands	-Minimum width of the riparian forest buffer should be 35 ft. -Sheet flow is preferred through the riparian buffer -Native and non-invasive trees and shrub species are in the riparian buffer

In the United States, different agencies such as United States Department of Agriculture (USDA), Natural Resources Conservation Service (NRCS), Environmental Protection Agency (EPA), and other state natural resources and agricultural agencies work with landowners to implement agricultural BMPs in their fields to reduce NPS pollutants. For examples, USDA offers different conservation programs to promote BMPs implementation such as Conservation Reservation Program (CRP), the Environmental Quality Incentive Program (EQIP), and the Conservation Stewardship Program (CSP) (Sommerlot et al., 2012).

The pollution reduction efficiency of a BMP is site specific (Giri et al., 2012a). BMP efficiency varies due to topography, soil characteristics, geological formations, climate, crops, and cultural practices (Cunningham et al., 2003). Implementation of BMPs is difficult due to conflicting environmental, economic, and institutional interests (Arabi et al., 2007). Certain pollutants cannot be controlled appropriately by a single method for all situations (USEPA, 1999). Therefore, selection, design, and implementation of BMPs are required to evaluate potential impact.

Meanwhile, a broad range of BMPs is available to the farmers, each having their own strength and limitations. The wide array of BMPs and influential criteria makes selecting a BMP a daunting task. Apart from selection, placement of BMPs also plays an important role in pollutant reduction efficiency, as pollutant contribution is disproportionate between areas in a watershed (Tripathi et al. 2003). In addition, implementation of BMPs randomly throughout a watershed is time consuming, expensive, and resource intensive. Also, in general monitoring water quality is expensive, time consuming, and ineffective for larger area. However, developments of powerful watershed/water quality computer models are providing reliable information regarding BMP effectiveness both at field and watershed levels.

2.12 COMPUTER MODELS

BMP effectiveness in a watershed can be evaluated through computer modeling, since computer modeling can accurately capture site-specific characteristics (Tuppad et al., 2010) by using various input data. Several watershed models such as Soil and Water Assessment Tool (SWAT), Hydrologic Simulation Program FORTRAN (HSPF), Annualized Agriculture Non-Point Source (AnnAGNPS), Agriculture Policy/Environmental eXtender (APEX), Spreadsheet Tool for Estimating Pollutant Load (STEPL), GIS Pollutant Load Application (PLOAD), Long Term Hydrologic Impact Analysis (L-THIA), and High Impact Targeting (HIT) are available. The following sections represent each model, their components, methods, and finally the application of the model.

2.12.1 Soil and Water Assessment Tool

SWAT is specifically used to predict the impact of land use management practices on water, sediments, and agrochemicals in a complex watershed with different soil, land use, and management scenarios (Parajuli et al., 2009; Boscha et al., 2011; Zhang et al., 2011; Gassman et al., 2007; Gassman et al., 2010). SWAT is a physically based and spatially distributed watershed-scale model developed by USDA-ARS (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007). SWAT uses readily available input data and can simulate flow, sediment, nutrient, and pesticide movement in a watershed. The major components of this model include weather, hydrology, soil characteristics, plant growth, nutrients, pesticides, and land management practices (Gassman et al., 2007). Surface runoff is calculated either by the Soil Conservation Service (SCS) curve number or by the Green and Ampt infiltration method. Sediment yield for hydrologic response units is calculated by the Modified Universal Soil Loss Equation (MUSLE), and Manning's equation is used for flow calculation (Neitsch et al., 2005).

2.12.2 Hydrologic Simulation Program –FORTRAN

The HSPF is useful to evaluate the impact of land use change and point and NPS pollution management scenarios. HSPF model is one of the most widely used water quality model developed by EPA to simulate hydrology and water quality (Bicknell et al., 1997). This model is a comprehensive and continuous watershed-scale model, which simulates several water quality parameters (Bicknell et al., 2000). Pollutant loads are estimated by taking into consideration both in-stream processes and overland flow. The hydrological response units are considered during overland flow (Bhaduri et al., 2000). The HSPF model components consist of sediment, phosphorus, nitrogen, dissolved oxygen, pesticides, zooplankton, temperature, and pH. This model uses many theoretically and empirically developed relations in order to simulate physical, chemical, and biological processes. This model is incorporated into EPA-Better Assessment Science Integrating Point and Non-point (BASIN) and is used for total maximum daily load analysis.

2.12.3 Annualized Agriculture Non-Point Source Model

AnnAGNPS was developed by the USDA to simulate the complex problems related to NPS pollution. It estimates NPS pollution on a daily time step through continuous and event-based simulations (Bosch et al., 2001). This model simulates runoff, sediment, and nutrients from a watershed dominated by agriculture lands using a cell-by-cell basis (Finn et al., 2002). These cells are formed by dividing the watershed into uniform square areas (Polyakov et al., 2007). The model requires 22 input parameters, which come from base data elevation, land cover, and soil (Finn et al., 2002). The model components include hydrology, sediments, nutrients, pesticides, irrigation, precipitation, and snowmelt (Bosch et al., 2001). The lateral subsurface flow is calculated by Darcy's equation. Flow in tile drain is estimated by Hooghoudt's equation. Sediment load is calculated by the Revised Universal Soil Loss (RUSLE) equation and sediment transport in channel is estimated by the revised Einstein equation (Bosch et al., 2001).

2.12.4 Agriculture Policy/Environmental eXtender

APEX is used to determine land management strategies, erosion, soil quality, and plant competition for small watersheds or whole farm managements (Williams et al., 2008). APEX can be used to model field- scale management practices such as furrow diking, buffer strips, terraces, waterways, tillage, grazing, pesticides, crop rotation, and manure management, (Williams and Izaurralde, 2005). The model components comprise of hydrology, sediments, nutrient cycling, pesticides, crop growth, tillage, and weather simulation (Williams et al., 2008). In APEX, surface runoff is calculated by SCS curve number. Peak runoff is estimated by TR-55 and soil erosion is calculated by different methods such as Universal Soil Loss Equation (USLE), Revised Universal Soil Loss Equation (RUSLE), and MUSLE (Williams et al., 2008).

2.12.5 Spreadsheet Tool for Estimating Pollutant Load

STEPL is a watershed-scale model used to estimate pollutant load in the stream. This model calculates the impact of BMPs and low impact development (LIDs) on sediments and nutrients load from various land uses (Tetra Tech, 2006). The outputs are surface runoff, nutrients load, and five-day biological oxygen demand. The model components consist of runoff, ground water, all types of erosion, and pollutant transport (Tetra Tech, 2006). The annual sediment load is estimated by universal soil loss equation and sediment reduction is calculated by predefined BMP efficiencies (Nejadhashemi et al., 2011).

2.12.6 GIS Pollutant Load Application

PLOAD is designed to calculate the impact of BMPs on pollutant loads on an annual basis (USEPA, 2001). The input data for this model are land use, watershed physiographical characteristics, BMP site, pollutant loading rate, impervious terrain factor, point source location, and loads (USEPA, 2001). This model is generally recommended when a high level of uncertainty with BMP effectiveness is acceptable. Several studies have used PLOAD model to evaluate water quality due to NPS pollution (Nejadhashemi et al., 2011; Endreny and Wood, 2003).

2.12.7 Long Term Hydrologic Impact Analysis

L-THIA was developed as a spreadsheet tool but it was incorporated into geographic information systems (GIS) by Perdue University (Bhaduri et al., 1997). The input data for this model are climate data, soil, and land use. The model outputs include runoff and NPS pollution and are presented in the form of tables and graphs (Bhaduri et al., 2000). This is a lumped parameter model where curve number method is used to calculate the annual runoff (Bhaduri et al., 2000). Several studies have used L-THIA to predict NPS pollution in different watersheds (Bhaduri et al., 2000; Muthukrishnan, 2002; Yang et al., 2006; Nejadhashemi et al., 2011).

2.12.8 High Impact Targeting

HIT is the combination of Revised Universal Soil Loss Equation (RUSLE) and Spatially Explicit Delivery Model (SEDMOD), which estimates annual sediment loading for waterbodies (IWR, 2012). The HIT model identifies critical areas for sediment loading both at the field level and the watershed- scale. The input data required is to identify the critical erosive areas are land cover, soil clay content, digital elevation model, land use/ tillage, soil erodibility, rainfall, and support practices (IWR, 2012).

2.13 TARGETING APPROACH

Effective control of agricultural NPS pollution requires BMP implementation in the areas of watersheds that produce more pollution. These areas, called CSAs, produce a disproportionate amount of pollution in the watershed (White et al., 2009). Prioritizing BMP implementation based on CSAs is called a targeting approach, which can resulted in greater pollution reduction (Giri et al., 2012). This prioritization is based on their pollution load generation. The CSAs of NPS pollution can be further divided based on land resources and water quality prospective (Maas et al., 1985). Based on the land resources, CSAs are the areas where soil erosion rates exceed the soil tolerance value (maximum annual soil loss without hampering current crop production level). From the water quality prospective, CSAs are the areas where the greatest improvement in water quality can be achieved with minimum BMP implementation cost (Tripathi et al., 2003). The identification of CSAs and the selection of appropriate BMPs are performed by watershed and water quality models and tools such as SWAT and GIS.

3. INTRODUCTION TO METHODOLOGY AND RESULTS

This thesis consists of three research papers out of which two are already published and the third one is submitted. In the first paper, the CSAs were identified by using different targeting methods and BMPs were implemented using in order to evaluate the effectiveness of BMPs using these targeting methods. In the second paper, the additional benefit of BMP implementation was considered which is reduction of non-targeting pollutant while reduction of targeting pollutants. Also, the effect of multiyear BMP implementation plan in high priority area was examined in order to determine the order of BMP implementation in the watershed in order to achieve maximum BMP efficiency. Additionally, a correlation between two targeting methods was identified to reduce the number of targeting methods to simplify. In the third paper, BMPs and placement location were identified by considering environmental, economic, and social factors simultaneously using the targeting methods.

The title of the first paper is "Evaluation of targeting methods for implementation of best management practices in the Saginaw River Watershed". The objectives were to identify priority areas (high, medium, and low) using four different targeting methods: concentration impact index(CII), load impact index (LII), load per subbasin area index (LPSAI), and load per unit area index (LPUAI); and to evaluate the effectiveness of BMPs in the priority areas. SWAT was used to simulate ten BMPs in the identified priority areas. Results suggested that the LPSAI targeting method is able to identify the highest priority areas for sediment, whereas the CII targeting method was able to identify the highest priority areas for TN and TP. Additionally, out of the ten BMPs, terraces and native grass were the most effective whereas conservation tillage and no-till were least effective both for subbasin and watershed outlet analysis.

The second paper is titled "Analysis of best management practice effectiveness and spatiotemporal variability based on different targeting strategies". The objectives of this study were to assess the spatiotemporal variability of critical source areas (CSAs) and to evaluate the spatial correlation among the targeting methods in the categorization of priority areas based on different pollutants. The study area was same as the previous study and SWAT was used to simulate BMPs in the high priority areas of all four targeting methods. For spatiotemporal analysis of priority areas, native grass and contour farming were implemented for two consecutive years. Kappa, weighted kappa coefficient, and agreement plus linear-by-linear association model were used to determine the correlation among the targeting method in categorizing priority areas. Results suggest that a distinct change in high priority areas of native grass was observed by the end of second year whereas a minimal change in high priority area was found in case of contour farming due to greater pollution reduction capacity of native grass compared to contour farming. A strong agreement was found between LPSAI and LPUAI targeting methods in categorization of priority areas for sediment and TN targeting as these methods are both based on pollutant load targeting.

The title of the third paper is "Application of analytical hierarchy process for effective selection of agricultural best management practices". The objective of this study was to identify the best BMP and implementation site using the analytical hierarchy process (AHP) while considering social, economic, and environmental issues under different spatial targeting methods. Five BMPS, strip cropping, residue management, conservation tillage, native grass, and no till, were implemented in the agricultural lands of Saginaw River Watershed using SAWT based on the high priority areas of three targeting methods (CII, LPSAI, and LPUAI). Based on environmental factors, native grass was selected most over the CSAs for subbasin level analysis while strip cropping, residue management, and native grass were selected in the CSAs for watershed outlet analysis. However, native grass was replaced by strip cropping in CSAs of both subbasin level and watershed scale analysis, when BMP selection was based on environmental and economic factors. When the BMP selection was based on environmental, economic, and social issues, strip cropping was preferred in all the CSAs based at the subbasin level analysis while strip cropping and residue management were selected in the CSAs for the watershed outlet analysis.

4. EVALUATION OF TARGETING METHODS FOR IMPLEMENTATION OF BEST MANAGEMENT PRACTICES IN THE SAGINAW RIVER WATERSHED

4.1 ABSTRACT

Increasing concerns regarding water quality in the Great Lakes region are mainly due to changes in urban and agricultural landscapes. Both point and nonpoint sources contribute pollution to Great Lakes surface waters. BMPs are a common tool used to reduce both point and nonpoint-source pollution and improve water quality. Meanwhile, identification of critical source areas of pollution and placement of BMPs plays an important role in pollution reduction. The goal of this study is to evaluate the performance of different targeting methods in 1) identifying priority areas (high, medium, and low) based on various factors such as pollutant concentration, load, and yield, 2) comparing pollutant (sediment, total nitrogen-TN, and total phosphorus-TP) reduction in priority areas defined by all targeting methods, and 3) determining the BMP relative sensitivity index among all targeting methods. Ten BMPs were modeled in the Saginaw River Watershed using the Soil and Water Assessment Tool (SWAT) model following identification of priority areas. Each targeting method selected distinct high priority areas based on the methodology of implementation. The concentration based targeting method was most effective at the reduction of TN and TP, likely because it selected the greatest area of high priority for BMP implementation. The subbasin load targeting method was most effective at reducing sediment because it tended to select large, highly agricultural subbasins for BMP implementation. When implementing BMPs, native grass and terraces were generally the most effective, while conservation tillage and residue management had limited effectiveness. The BMP relative sensitivity index revealed that most combinations of targeting methods and priority areas resulted

in a proportional decrease in pollutant load from the subbasin level and watershed outlet. However, the concentration and yield methods were more effective at subbasin reduction while the stream load method was more effective at reducing pollutants at the watershed outlet. The results of this study indicate that emphasis should be placed on selection of the proper targeting method and BMP to meet the needs and goals of a BMP implementation project, because different targeting methods produce varying results.

4.2 INTRODUCTION

Maintaining proper water quality conditions is important to protect human, animal, and plant health and is an ongoing concern in water resources (Pejman et al., 2009). Overall, the quality of water bodies depends on natural processes such as precipitation rate, infiltration, and weathering processes. Meanwhile, human activities such as urbanization and agricultural practices disturb natural processes and ultimately affect water quality (Nouri et al., 2008). Operations such as improper application of fertilizer, pesticides, animal wastes, irrigation water, and frequent plowing can elevate the concentration of sediments, nutrients, and fecal bacteria in receiving waters. Increased nutrient concentration leads to eutrophication in water bodies, which is harmful to aquatic organisms (TNRCC, 1999). Activities such as nutrient enrichment cause adverse effects on water quality and lead to increases in toxic substances, reduction of available aquatic habitat, and decreases in overall values of human uses (Wang et al., 2007). Therefore, it is important to restore and protect water quality through mitigation of negative impacts of human disturbances.

In 2009, the USEPA National Water Quality Inventory Report determined that 44% of rivers and streams and 64% of lakes and reservoirs in the United States are impaired; these water bodies did not meet water quality standards for designated uses such as fishing and swimming. Water quality impairment in rivers and lakes can be attributed to point and non-point sources NPS of pollution. NPS pollution is particularly difficult to control due to its diffusive nature. Agricultural activities are a prominent source of NPS pollution and, therefore, are a major contributor to the degradation of water quality (USEPA 2009).

The management of NPS pollution requires a strategic combination of practices to prevent their entry into receiving water bodies. BMPs are widely accepted methods that minimize the impact of agricultural activities on both surface water and groundwater (Arabi et al. 2007). However, pollutant reduction efficiencies of BMPs fluctuate due to varying design methods, implementation, and maintenance frequency. Consequently, a thorough understanding of BMP mechanisms in pollution mitigation and uncertainty in BMP effectiveness are needed during the BMP selection process. Apart from BMP selection, placement in the watershed also plays a vital role in the pollution reduction as the contribution of pollutants is disproportionate in the watershed (Maringanti et al. 2009). This means that potential BMP effectiveness is site specific. Therefore, an effective BMP implementation strategy for one site may or may not be useful in reducing and/or controlling pollution for other sites in a watershed (Tuppad and Srinivasan, 2008).

Measuring pollution loads from all fields in a watershed and evaluation of BMP effectiveness through actual implementation at the field level is time consuming, expensive, resource intensive, and impractical. However, watershed/water quality models are efficient and provide accurate information needed for evaluating pollution loads and BMP implementation strategies at the field and watershed levels. Using watershed/water quality models allows for the identification of CSAs, which are locations that contribute significantly high pollution load per unit area. Using CSAs to prioritize placement of BMPs is called the targeting approach, which provides greater reduction of pollutants. Targeting CSAs in the watershed is a well-known procedure for implementing BMPs to control NSP and to improve environmental quality (Qiu 2009; Gitau et al. 2004; Srinivasan et al. 2005; Tripathi et al. 2003; Yang et al. 2005). However, the comparison of different targeting techniques in identifying CSAs and the overall impacts of these techniques to reduce NPS pollution at both the field and watershed levels are yet to be determined.

Among existing watershed/water quality models, SWAT has been widely used to evaluate the water quality impacts of different land use changes at watershed scale (Arnold et al. 1998; Gassman et al. 2007, Arabi et al. 2007). The SWAT model is capable of simulating various agricultural management practices such as tillage operations, fertilizer and pesticide applications, vegetative filter strips, and crop rotations which makes it an ideal model for evaluation of agricultural watersheds. For this reason, several studies have used SWAT to develop BMPs implementation strategies in conjunction with various targeting methods (Jha et al. 2010; Maringanti et al. 2009; Parajuli et al. 2008; Schilling and Wolter 2009; Tuppad et al. 2010; White et al. 2009). Srinivasan et al. (2005) used SWAT to identify critical source runoff areas for phosphorus transport and compared the results with the Soil Moisture Distribution and Routing (SMDR) physically based model. Overall, it was determined that SWAT performed better than

SMDR. Jha et al. (2010) studied the impacts of land use restoration to 1990 conditions and land use conversion in the CSAs (defined as highly erodible land areas, floodplain areas, and upper subbasin areas) to native grass in order to assess the effect of nitrate load reduction strategies in an Iowa agricultural watershed. Nitrate load reduction was determined to be 7% for the land use restoration and 47%, 16%, and 8% for the land use conversions in the highly erodible lands, upper subbasin areas, and floodplain areas, respectively. Tuppad et al. (2010) implemented various BMPs (reduced tillage, edge of field vegetative filter strips, and contoured terraced) on 10%, 26%, 52%, and 100% of total targeted cropland and compared the pollutant reduction efficiency at the outlet of the watershed using targeting and random placement. The results demonstrated that the targeting method is more effective than the random placement method. In both the Jha et al. (2010) and Tuppad et al. (2010) studies, CSAs were identified based on a total load per unit area at the subbasin basis. White et al. (2009) used SWAT to identify CSAs and quantify sediment and total phosphorus loads generated from five watersheds in Oklahoma. The identification of CSAs was based on the threshold unit area load at each hydrologic response unit (HRU). The HRUs were ranked based on sediment and phosphorus yields and the highest ranking fractions were defined as CSAs. They found that only 5% of agricultural land produced approximately 22% of sediment and phosphorus load. Schilling and Wolter (2009) used SWAT to evaluate nitrate load reduction in Des Moines River in Iowa using four targeting methods. All targeting methods were based on CSAs that have the potential to generate greater than 15 kg/ha nitrate annually. Four different configurations were identified: all subbasins with the above criteria, only CSA subbasins within the Boon River basin, targeting CSA subbasins closer to the Des Moines Water Works, and targeting CSAs subbasins away from the Des Moines Water Works. Results showed that 95% of total nitrate originated from nonpoint sources and the greatest nitrate reduction was found when fertilizer application was reduced in subbasins closer to the watershed outlet. However, in all of the targeting strategies the fertilizer application rate was reduced assuming that the difference of fertilizer application rate compared to the base scenario would be compensated by different BMPs. Diebel et al. (2008) introduced four allocation approaches (aggregated/targeted, aggregated/random, dispersed/targeted, and dispersed/random) for implementing BMPs at both field and watershed scales. In the aggregated/targeted allocation approach fields were selected according to the descending order of phosphorus load contribution to the watershed, whereas in the aggregated/random approach fields producing highest phosphorus load were selected randomly until the desired application area was reached. In the dispersed/random approach, fields were selected randomly without having any criteria while in dispersed/targeted approach fields were selected based on the descending order of phosphorus load production without consideration of watershed membership. The allocation approaches were evaluated by two methods: modeled pollutant reduction index and water quality change index. The modeled pollutant reduction index was the proportion of phosphorus load reduced after BMP application, while the water quality change index was the proportion of the watershed observing significant reduction of stream phosphorus concentration. For both methods, the targeted approach performed better than the random approach.

As it was discussed above, some studies exist that relate the effectiveness of targeting methods and BMP implementation strategies to environmental health and water quality improvement. However, these methods have not been comprehensively evaluated and compared for multiple pollutants. The objectives of this research are to (1) identify CSAs using multiple targeting techniques and pollutants, (2) assess the sensitivity of BMPs to different targeting methods using SWAT, and (3) evaluate the impact of BMP application in CSAs at subbasin and watershed scales modeled using SWAT. The results of this study will aid policymakers and stakeholders in making informed decisions regarding BMP placement while maximizing the environmental benefits at a lower cost than current approaches.

4.3 Materials and Methods

4.3.1 Study Area

The Saginaw River Watershed (SRW) (hydrologic unit code-HUC 040802) located in east-central Michigan was selected for this study. The SRW consists of six subwatersheds: Tittabawassee (HUC 04080201), Pine (HUC 04080202), Shiawassee (HUC 04080203), Flint (HUC 04080204), Cass (HUC 04080205), and Saginaw (HUC 04080206) (Figure 4-1). The Saginaw River flows north towards Lake Huron. The total watershed area covers 22,260 km^2, of which 42% is forest, 23% is agriculture, 17% is pasture, 11% is wetlands, and the remaining is urban. Dominant agricultural crops in the watershed are corn and soybean. Expansive wetland areas provide habitat to large populations of wildlife species. Average watershed elevation is 242 m above mean sea level, while the minimum elevation is 177 m and the maximum elevation is 457 m.

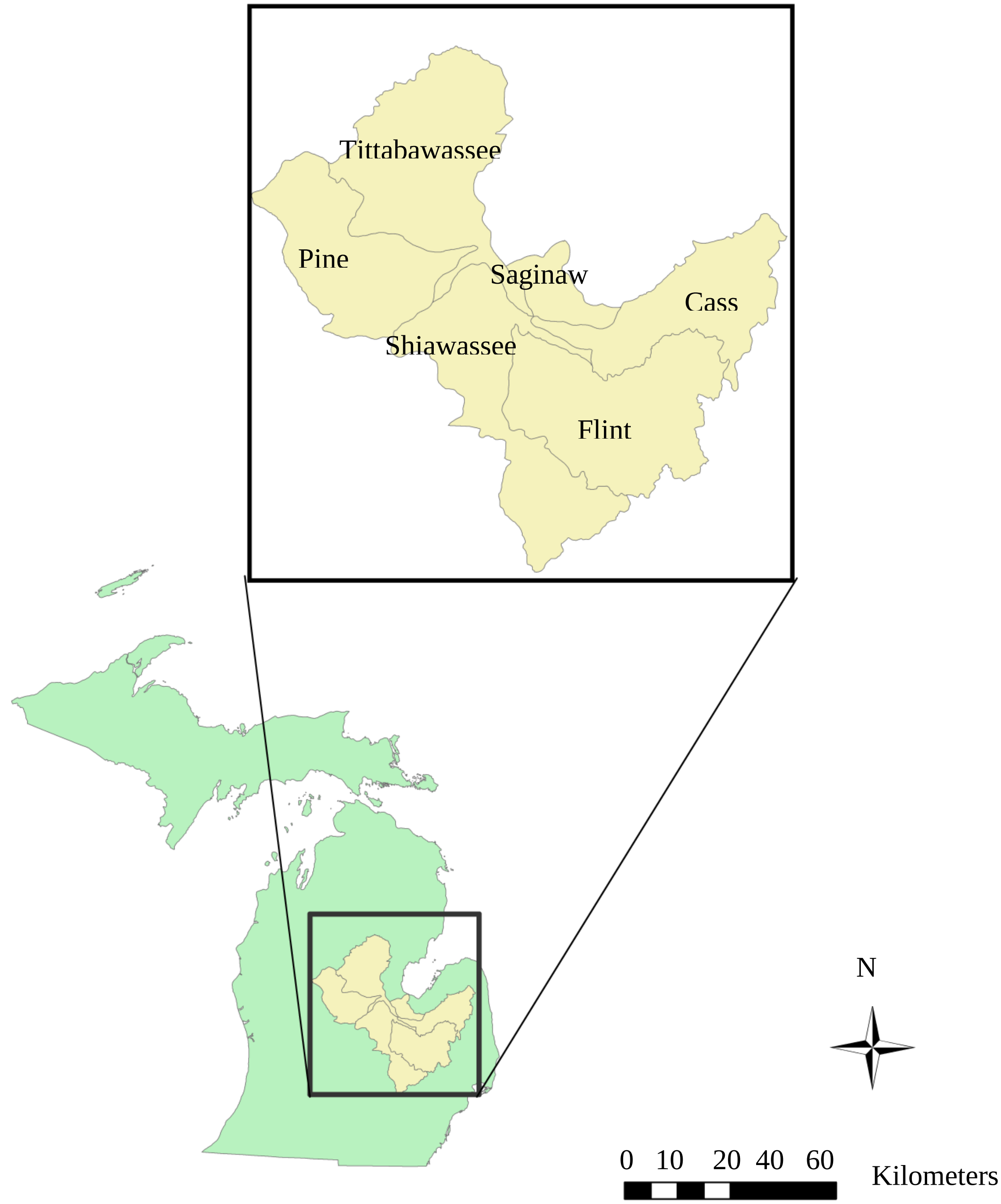

Figure 4-1. Saginaw River Watershed. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis.

4.3.2 Model Description

Watershed/water quality models are useful tools to assess the effectiveness of BMPs on the watershed scale (Woznicki et al. 2011). SWAT was selected to evaluate CSAs for sediment, TN, and TP. SWAT is a physically based, spatially distributed watershed scale model developed by the USDA-ARS (Arnold et al. 1998; Neitsch et al. 2005; Gassman et al. 2007). In SWAT, a watershed is divided into subbasins and further divided into hydrologic response units (HRUs) based on homogeneous land use, soil, slope, and management practices. The major components of the model consist of weather, hydrology, soil characteristics, plant growth, nutrients, pesticides, and land management practices (Gassman et al. 2007). Runoff volume in SWAT is calculated either by the SCS curve number or Green and Ampt infiltration method (Neitsch et al. 2005).

Soil erosion comprises of three processes (detachment, transport, and deposition/degradation) and is caused by two forces: raindrop impact and surface runoff. SWAT uses the Modified Universal Soil Loss Equation (MUSLE) to calculate erosion and sediment yield for each hydrologic response unit (HRU) within the watershed. In MUSLE, the average annual gross erosion is calculated as a function of runoff (where runoff is the function antecedent moisture condition and rainfall energy). Sediment yield in MUSLE is also function of peak runoff rate, HRU area, soil erodibility, land cover, topography, and percent coarse fragments of soil (Neitsch et al., 2005). Sediment transport in the channel depends on deposition and degradation. When sediment concentration in the reach is exceeded the maximum sediment carrying concentration of the reach, deposition occurs, while when the reverse is true degradation occurs. The maximum amount of sediment that can be transported from a reach segment is a function of peak channel velocity (Neitsch et al. 2005).

Nitrogen transport from overland areas into the stream is estimated in different ways in SWAT. The nitrogen in the main channel is transported by surface runoff and lateral subsurface flow. SWAT calculates nitrogen in the soil profile and the shallow aquifer. Two forms of nitrogen (organic and inorganic) in the soil are computed by SWAT. The organic forms of nitrogen consist of fresh organic nitrogen (crop residue and microbial mass), active organic nitrogen, and stable organic nitrogen. The active and stable organic nitrogen are related to soil humus. The inorganic form of nitrogen comprises of NH_4^+ and NO_3^-. In SWAT, the organic nitrogen associated with sediment is calculated as a function of concentration of organic nitrogen in the top 10 mm of soil, sediment yield on a given day, and nitrogen enrichment ratio. The nitrate in runoff, lateral flow, and percolation is calculated as the product of runoff volume and nitrate concentration in the soil layer.

SWAT tracks both mineral and organic forms of phosphorus. Organic phosphorus consists of fresh organic phosphorus and active and stable organic phosphorus. Fresh organic phosphorus is related to crop residue and microbial biomass whereas active and stable organic phosphorus connected to soil humus. Organic and mineral phosphorus attached to sediment are estimated as a function of concentration of phosphorus attached to sediment in top 10 mm of soil, sediment yield on a given day, and phosphorus enrichment ratio. The amount of soluble phosphorus is calculated as a function of solution phosphorous concentration, runoff volume, and a partitioning factor. The movement of phosphorus in soil is primarily driven by diffusion, which is based on concentration gradient. Nutrient routing (nitrogen and phosphorus) in SWAT is calculated through the use of the nitrogen and phosphorus cycle.

4.3.3 Data Sources

The SWAT model requires different types of physiographic data such as topography, land use, soil, and stream network. Topography data was obtained from the Better Assessment Science Integrating point and nonpoint Sources (BASINS) program in the form of a digital elevation model (DEM). For land use representation the 2008 Cropland Data Layer (CDL) was obtained from the USDA National Agricultural Statistics Service (NASS, 2008). Watershed soil characteristics were defined using the State Soil Geographic Database (STATSGO). The STATSGO dataset was developed by the National Cooperative Soil Survey at a scale of 1:250,000 and was linked to tabular data containing soil chemical and physical properties (Muttiah and Wurbs, 2002). Stream network was defined using the United States Geological Survey (USGS) National Hydrography Dataset (NHD). The NHD dataset was used to improve hydrologic segmentation and sub-watershed boundary delineation (Winchell et al. 2007).

Daily streamflow data from USGS gauging station 04157000 was used for streamflow calibration and validation. Water quality calibration and validation was performed using data from Michigan Department of Environmental Quality (MDEQ) station 090177. The USGS Load Estimator (LOADEST) was used to convert the daily observed water quality (sediment, TN, and TP) data to monthly loads. Twenty years (1990-2009) of observed daily precipitation and temperature data was obtained from the National Climatic Data Center (NCDC). In this study 19 precipitation stations and 11 temperature stations were represented within the SRW. The remaining required meteorological data (wind speed, relative humidity, and solar radiation) were estimated using the SWAT weather generator program.

The SRW land use is 23% agricultural, with corn and soybean being the predominant crops. To more accurately assess the fate and transport of sediment and nutrients in the watershed, management operations were developed based on common agricultural practices in the region, including tillage and fertilizer applications. Regarding crop rotations, the continuous corn rotation is six years in length, where corn is planted for five years and soybeans are planted in the final year. The continuous soybean rotation is three years in length and contains two years of soybean planting and a final year of corn planting. A detailed description of tillage operations and fertilizer applications are provided in tables 4-1 and 4-2.

Table 4-1. Continuous corn conventional tillage management operations.

Date	Practice	SWAT Practice	Application Rate	Year
1-May	Soil Finish	Field Cultivator > 15 ft		1-5
4-May	Nitrogen Application (Urea)	Urea	194 kg/ha	1-5
4-May	Soil Finish	Field Cultivator > 15 ft		1-5
5-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	59 kg/ha	1-5
5-May	Plant Corn Seed	Plant/Begin Growing Season		1-5
5-May	Bicep II Magnum (PRE)	Atrazine	1.39 kg/ha	1-5
5-May	Bicep II Magnum (PRE)	Metolachlor	1 kg/ha	1-5
1-Nov	Combine Harvest Corn Grain	Harvest and kill		1-5
15-Nov	Fall Chisel	Coulter-Chisel Plow		1-5
14-May	Soil Finish	Field Cultivator > 15 ft		6
14-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	45 kg/ha	6
14-May	Soil Finish	Field Cultivator > 15 ft		6
15-May	Plant Soybean Seed	Plant/Begin Growing Season		6
7-June	Spay Roundup Weathermax	Glyphosate Amine	0.87 kg/ha	6
1-Oct	Combine Harvest Soybean Grain	Harvest and kill		6
30-Oct	Fall Chisel	Coulter-Chisel Plow		6

Table 4-2. Continuous soybean conventional tillage management operations.

Date	Practice	SWAT Practice	Application Rate	Year
14-May	Soil Finish	Field Cultivator >15 ft		1-2
14-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	45 kg/ha	1-2
14-May	Soil Finish	Field Cultivator >15 ft		1-2
15-May	Plant Soybean Seed	Plant/Begin Growing Season		1-2
7-June	Spray Roundup Weathermax	Glyphosate Amine	0.87 kg/ha	1-2
1-Oct	Combine Harvest Soybean Grain	Harvest and kill		1-2
30-Oct	Fall Chisel	Coulter-Chisel Plow		1-2
1-May	Soil Finish	Field Cultivator >15 ft		3
4-May	Nitrogen Application (Urea)	Urea	194 kg/ha	3
4-May	Soil Finish	Field Cultivator > 15 ft		3
5-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	59 kg/ha	3
5-May	Plant Corn Seed	Plant/Begin Growing Season		3
5-May	Bicep II Magnum (PRE)	Atrazine	1.39 kg/ha	3
5-May	Bicep II Magnum (PRE)	Metolachlor	1kg/ha	3
1-Nov	Combine Harvest Corn Grain	Harvest and kill		3
15-Nov	Fall Chisel	Coulter-Chisel Plow		3

4.3.4 Sensitivity Analysis and Calibration Process

Sensitivity analysis is conducted to determine the most influential parameters on model output to be used in model calibration by providing a rank of parameters sensitive to model outputs. The SWAT model uses Latin Hypercube One factor-at-a-time (LH-OAT) sampling to perform the sensitivity analysis (van Griensven et al. 2006). A sensitivity analysis was performed in this study to evaluate the model parameters sensitive to streamflow, sediment, TN, and TP.

Calibration is an iterative process of adjusting model input parameters that compares simulated and observed data of interest. It plays an important role in watershed modeling through reducing uncertainty in model prediction. This process consists of sensitivity analysis followed by manual and automatic calibration In automatic calibration, model selects the parameter for the calibration process whereas in manual calibration, user select the parameter for calibration process. The most sensitive parameters are used to perform model calibration. In order to determine model reliability, validation is performed for the time period following the calibration period without implementation of BMPs. (Woznicki et al. 2011).

Calibration and validation were performed on monthly a time step for streamflow, sediment, TN, and TP. A warm up period of two years was used to initialize model parameters. Ideal calibration and validation consists of three to five years of data (Moriasi et al. 2007). In this study, the calibration period was from 2002-2003 and the validation period was from 2004-2005. When a calibrated model is used to simulate multiple processes such as streamflow, sediment, and nutrients, two or more model evaluation statistics are required to assure model reliability in addressing different processes (Balascio et al. 1998). Three statistical methods were used to evaluate the prediction of calibrated model: Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), coefficient of determination (R^2), and percent bias (PBIAS). On a monthly time step, the model performance is classified as satisfactory if the NSE value greater than 0.50 and the PBIAS value for streamflow remains between ±25, sediment between ±55, and TN and TP between ±70 (Moriasi et al. 2007). Values of R^2 greater than 0.5 are considered acceptable for a monthly time step (Santhi et al. 2001).

NSE describes the fitting of observed and simulated data in 1:1 line (Moriasi et al. 2007). The range of NSE varies between negative infinity to 1, where 1 is the optimal value. The calculation of NSE is presented in equation 4-1:

$$NSE = 1 \quad \frac{\sum_{i=1}^{n}\left(Y_i^{obs} \quad Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} \quad Y^{obs,mean}\right)^2} \tag{4-1}$$

Where, Y_i^{obs} is the ith observed value of the constituent, Y_i^{sim} is the ith simulated value of the constituent, and $Y^{obs,mean}$ is the mean observed data of the constituent. The NSE value is calculated as the sum of squared values of the difference between observed and predicted values, resulting in strong overestimation for the larger values while neglecting smaller values. This leads to an overestimation of model performance during peak flows and underestimation during low flow periods (Krause et al. 2005).

The coefficient of determination describes the degree of collinearity between observed and predicted data (Moriasi et al. 2007). The range of R^2 varies from 0 to 1 with 1 being the optimal value. R^2 is calculated using equation 4-2.

$$R^2 = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} \quad Y^{obs,mean}\right)\left(Y_i^{sim} \quad Y^{sim,mean}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} \quad Y^{obs,mean}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} \quad Y^{sim,mean}\right)^2}} \tag{4-2}$$

PBIAS depicts the tendency of the simulated data to be larger or smaller compared to the observed data (Moriasi et al. 2007). A positive value of PBIAS indicates model underestimation and a negative value reflects overestimation, while zero is the optimal value (Moriasi et al. 2007). PBIAS is calculated using equation 4-3.

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} \quad Y_i^{sim}\right) \; 100}{\sum_{i=1}^{n} Y_i^{obs}} \tag{3}$$

4.3.5 Best Management Practices in SWAT

In order to assess the impact of BMP effectiveness on pollution reduction, ten BMPs were modeld using SWAT on agricultural lands in the SRW. Each BMP was evaluated compared to a base scenario in which no BMPs are implemented. The ten BMPs selected were: contour farming (CF), terraces (T), recharge structures (RS), conservation tillage (CT), no tillage (NT), native grass (NG), residue management (0 kg/ha) (RM 0), residue management (1000 kg/ha) (RM 1000), residue management (2000 kg/ha) (RM 2000), and strip cropping (SC). Implementation procedures for BMPs were collected from various published literatures and implemented in SWAT.

4.3.5.1 Contour Farming

Contour farming consists of ridges and furrows constructed by tillage, planting, and other operations, which creates numerous small dams (USDA-NRCS, 2005). This BMP slows down runoff, increases infiltration, and thereby reduces the soil erosion. To implement this practice in SWAT, curve number (CN2) was reduced by three and the Universal Soil Loss Equation Practice factor (USLE_P) was adjusted to 0.6, 0.5, and 0.55 for slopes of 0-2%, 2-5%, and 5-10%, respectively (Arabi et al.2007; Tuppad and Srinivasan, 2008).

4.3.5.2 Terraces

Terraces are earth embankments or a combination of ridge and channel constructed across the slope (USDS_NRCS, 2005). This BMP reduces long slopes and serves as a small dam, guiding water to an outlet. Terraces reduce surface runoff by holding water in small depressions and decreases peak runoff by reducing the hillside slope (Arabi et al. 2007). Incorporation in SWAT is accomplished by reducing CN2 by five and adjusting USLE_P to 0.12, 0.1, and 0.11 for slopes of 0-2%, 2-5%, and 5-10%, respectively (Arabi et al.2007; Tuppad et al. 2010).

4.3.5.3 Recharge Structures

Recharge structures are small dams in the channel designed to capture a portion of flowing water (Tuppad and Srinivasan, 2008). This BMP increases infiltration and percolation of water while reducing stream energy, resulting in less sediment carrying capacity. To simulate recharge structures in SWAT the effective hydraulic conductivity (CH_K1) value is replaced by 25 mm/hr (Tuppad and Srinivasan, 2008).

4.3.5.4 Conservation Tillage

Conservation tillage involves reducing tillage operations and soil disturbances when compared to conventional tillage (Tuppad and Srinivasan, 2008). Crop residue on the surface is left in place, which acts as ground cover and prevents soil erosion. Detailed operations of continuous soybean conservation tillage schedules are provided in Table 4-3.

Table 4-3. Continuous soybean conservation tillage operations.

Date	Practice	SWAT Practice	Application Rate	Year
14-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	45 kg/ha	1-2
14-May	Soil Finish	Field Cultivator > 15 ft		1-2
15-May	No Till Planting	Generic no Till Mixing		1-2
15-May	Plant Soybean Seed	Plant/Begin Growing Season		1-2
7-Jun	Spay Roundup Weathermax	Glyphosate Amine	0.87 kg/ha	1-2
1-Oct	Combine Harvest Soybean Grain	Harvest and kill		1-2
4-May	Nitrogen Application(Urea)	Urea	194 kg/ha	3
4-May	Soil Finish	Field Cultivator > 15 ft		3
5-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	59 kg/ha	3
5-May	No Till Planting	Generic no Till Mixing		3
5-May	Plant Corn Seed	Plant/Begin Growing Season		3
5-May	Bicep II Magnum (PRE)	Atrazine	1.39 kg/ha	3
5-May	Bicep II Magnum (PRE)	Metolachlor	1 kg/ha	3
1-Nov	Combine Harvest Corn Grain	Harvest and kill		3

4.3.5.5 No Tillage

No tillage operations leave crop residue on the field and the soil is kept undisturbed from the time of harvest until planting (USDA, 2010). Minimum soil disturbances are achieved during nutrient application and planting of crops. The objective of no tillage farming is to increase soil moisture while reducing soil erosion. Detailed operations of continuous soybean no tillage schedules are provided in Table 4-4.

Table 4-4. Continuous soybean no tillage operations.

Date	Practice	SWAT Practice	Application Rate	Year
14-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	45 kg/ha	1-2
15-May	No Till Planting	Generic no Till Mixing		1-2
15-May	Plant Soybean Seed	Plant/Begin Growing Season		1-2
7-Jun	Spay Roundup Weathermax	Glyphosate Amine	0.87 kg/ha	1-2
1-Oct	Combine Harvest Soybean Grain	Harvest and kill		1-2
4-May	Nitrogen Application (Urea)	Urea	194 kg/ha	3
5-May	Phosphorus Application (P_2O_5)	Elemental Phosphorus	59 kg/ha	3
5-May	No Till Planting	Generic no Till Mixing		3
5-May	Plant Corn Seed	Plant/Begin Growing Season		3
5-May	Bicep II Magnum (PRE)	Atrazine	1.39 kg/ha	3
5-May	Bicep II Magnum (PRE)	Metolachlor	1 kg/ha	3
1-Nov	Combine Harvest Corn Grain	Harvest and kill		3

4.3.5.6 Native Grass

Native grass planting involves replacing agricultural row crops with native grasses such as Indian switchgrass and big bluestem (Nejadhashemi and Mankin, 2007). Sediment and nutrient transport in runoff are reduced by the dense vegetative cover combined with the elimination of tillage practices and fertilizer applications. Native grass was implemented in SWAT by converting all agricultural row cropland to range grass (Woznicki et al. 2011).

4.3.5.7 Residue Management - 0 kg/ha

Residue management involves controlling the amount and distribution of crop residue on the soil surface (USDA, 1996). This management practice reduces sheet and rill erosion by providing soil cover. Representation of residue management within SWAT is accomplished by applying no till operations on agricultural land while adjusting CN2, USLE_P, Universal Soil Loss Equation Cover factor (USLE_C), and Manning's n value for overland flow (OV_N) (Arabi et al. 2007). These values vary depending on the amount of residue left on the field in kg/ha (0, 1000, and 2000), and are presented in Table 4-5.

Table 4-5. SWAT Inputs for Residue Management.

Residue (kg/ha)	CN2	USLE_P	USLE_C0	OV_N
0	-2	1	0.2	0.14
1000	-2	0.39	0.2	0.2
2000	-2	0.29	0.2	0.3

4.3.5.8 Strip Cropping

Strip cropping involves growing planned rotations of row crops in a systematic arrangement of equal width strips across a field (USDA-NRCS, 2011). This BMP serves as a vegetative barrier and reduces soil erosion due to wind and water. Strip cropping is represented in SWAT by reducing the CN2 by three and adjusting USLE_P to 0.3, 0.25, and 0.27 for slopes of 0-2 %, 2-5%, and 5-10%, respectively (Arabi et al. 2007).

4.3.6 Spatial Targeting Methods

Establishing BMPs throughout the watershed is impractical and expensive. Therefore, identifying CSAs of pollutants in the watershed should be the primary step before BMP implementation. Four targeting techniques, namely, Concentration Impact Index (CII), Load Impact Index (LII), Load per Subbasin Area Index (LPSAI), and Load per Unit Area Index (LPUAI) were analyzed to prioritize BMP placement within the watershed. Each targeting method was applied for sediment, TN, and TP, creating three sub-targeting methods (sediment-based, TN-based, and TP-based) for a total of 12 targeting scenarios. Then, subwatersheds were categorized into high, medium, and low priority areas based on the natural breaks method of classification. Based on natural statistical groupings in the dataset, different classes are formed in natural breaks classification. Data having similar values are put together into groups while trying to maximize the difference between the groups using geographical information system. Therefore, a relatively substantial difference is found between the data values of any two groups. In addition, although each targeting strategy is always based on one pollutant (e.g. sediment), the impacts of BMPs implementation on other contaminants (e.g. TN and TP) were also analyzed.

4.3.6.1 Concentration Impact Index

The CII method identifies high priority areas based on the pollutant concentration level in the subwatershed reaches (Tuppad and Srinivasan, 2008). This method considers pollutants from the adjacent subwatershed as well as the upstream. It is effective in addressing localized pollution in low and high flows, especially concerning aquatic health.

4.3.6.2 Load Impact Index

The LII method identifies high priority areas based on the total pollutant load from the reach (Tuppad and Srinivasan, 2008). This method considers pollutant load from both the subwatershed and the upstream subwatersheds. LII represents the cumulative pollutant load up to a point of interest, such as a water treatment plant.

4.3.6.3 Load per Subbasin Area Index

The LPSAI index method identifies high priority areas based on the pollution load for each subbasin. Subbasin area was multiplied by load per unit area to calculate total pollutant load per subbasin. This method is also effective in identifying local concerns by identifying the subbasins with the largest amount of pollutant discharge. This can lead to aquatic health concerns since large amounts of pollution load may enter small streams.

4.3.6.3 Load per Unit Area Index (LPUAI)

The LPUAI method identifies the high priority areas based on average pollutant load per unit area from each subbasin (Tuppad and Srinivasan, 2008). As this method portrays load within individual subwatershed, it is applicable to identify local concerns within the subbasin.

4.3.7 BMP Relative Sensitivity Index

Relative sensitivity index (RSI) was calculated for each targeting method using equation 4-4.

$$RSI = \frac{S_{base} \quad S_{BMP}}{R_{base} \quad R_{BMP}} \times \frac{R_{base}}{S_{base}} \qquad (4\text{-}4)$$

where, S_{base} is the total subbasin load for the no BMP scenario, S_{BMP} is the total subbasin loads after BMPs application to CSAs (high, medium, or low priorities), R_{base} is the reach load at the outlet of the watershed for the no BMP scenario, and R_{BMP} is the reach load at the outlet after application of BMPs to the targeted areas (high, medium, or low priorities). The RSI may vary from $-\infty$ to $+\infty$. Positive relative sensitivity index indicates that the BMP implementation strategy was effective in pollution reduction both at the outlet and subbasin level while negative relative sensitivity index indicates that BMPs implementation strategy was unsuccessful in pollution mitigation. Meanwhile, RSI = 0 represents no impact due to BMPs implementation and RSI = 1 demonstrates an equal pollution reduction rate at subbasins and the outlet. If 0 < RSI <1 then the BMP implementation strategy is more effective at pollution reduction at the watershed outlet than at the subbasin level, while for RSI > 1 the reverse is true. In this study, the relative sensitivity index was calculated for sediment, TN, and TP under each targeting method.

4.4 RESULTS AND DISCUSSIONS

4.4.1 Sensitivity Analysis

Sensitivity analysis was performed for flow, sediment, TN, and TP of the SRW. The ten most sensitive parameters for flow, sediment, TN, and TP are presented in Table 4-6. In general, CN2 and Alpha_Bf (baseflow recession constant) are highly sensitive for all constituents. Parameters such as Spcon (linear re-entrainment parameter for channel sediment routing) and Spexp (exponential re-entrainment parameter for channel sediment routing) are highly sensitive for sediment but are not sensitive for the other constituents. For flow, Cn2, Alpha_Bf, Rchrg_Dp (fraction of percolation from root zone that recharges deep aquifer), Esco (soil evaporation compensation factor), and Timp (snow pack temperature lag factor) were the most sensitive whereas for sediment Spcon, Ch_N2 (Manning's n value for main channel), Cn2, Spexp, and Usle_P were the most sensitive. Sensitive parameters for TN and TP were similar: Cn2, Alpha_Bf, and Timp. Sensitivity analysis results were taken into consideration when performing model calibration.

Table 4-6. Sensitivity analysis results for flow, sediment, TN, and TP.

Rank	Flow	Sediment	TN	TP
1	Cn2	Spcon	Cn2	Cn2
2	Alpha_Bf	Ch_N2	Alpha_Bf	Alpha_Bf
3	Rchrg_Dp	Cn2	Canmx	Ch_K2
4	Esco	Spexp	Timp	Timp
5	Timp	Usle_P	Sol_Awc	USLE_P
6	Gwqmn	Alpha_Bf	Nperco	Sol_Awc
7	Sol_Awc	Ch_K2	Blai	Canmx
8	Canmx	Timp	Ch_K2	Surlag
9	Sol_Z	Esco	Rchrg_Dp	Blai
10	Ch_K2	Surlag	USLE_P	Smtmp

4.4.2 Model Calibration

Calibration of the model was performed for flow, sediment, TN, and TP on a monthly basis in the SRW. The calibration, validation, and overall combined calibration/validation results are presented in Table 4-7. According to guidelines developed by Moriasi et al. (2007) the flow, sediment, and TP calibrations were considered 'good', while the TN calibration was considered 'satisfactory' for this study. The flow calibration/validation hydrograph is presented in Figure 4-2. Peaks and baseflow are generally well represented by the calibrated model, although the model under-predicts for one peak in the validation period.

Table 4-7. SRW calibration and validation results.

Constituent	Statistic	Calibration	Validation	Overall
Flow	NSE	0.77	0.71	0.74
	R^2	0.78	0.71	0.74
	PBAIS (%)	7.33	0.73	3.47
Sediment	NSE	0.55	0.74	0.72
	R^2	0.69	0.79	0.77
	PBAIS (%)	-47.81	-30.68	-36.66
TP	NSE	0.57	0.78	0.76
	R^2	0.65	0.80	0.78
	PBAIS (%)	-15.22	-18.12	-16.99
TN	NSE	0.76	0.41	0.53
	R^2	0.82	0.81	0.719
	PBAIS (%)	24.32	50.53	39.36

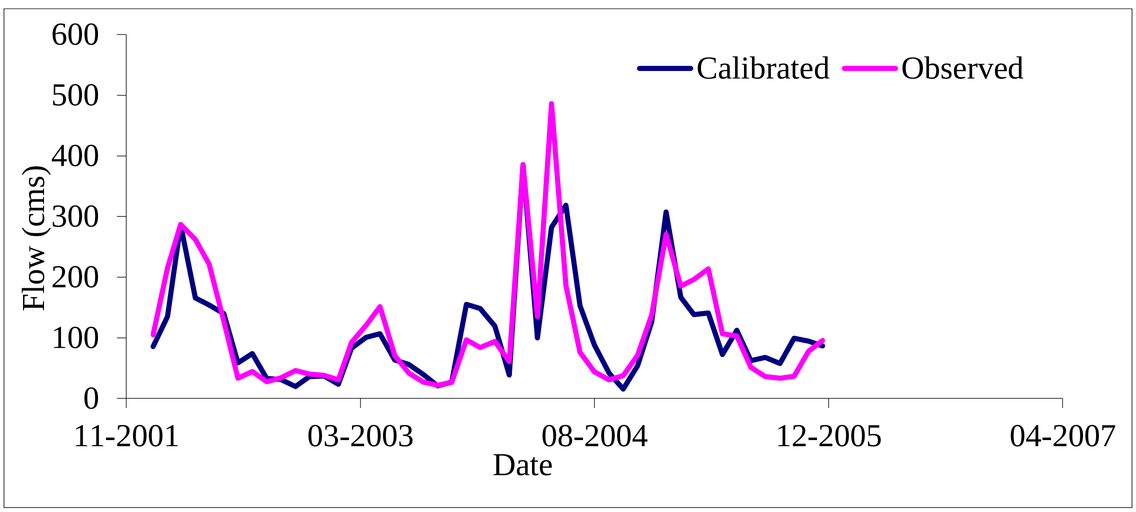

Figure 4-2. Flow calibration and validation hydrograph.

4.4.3 Spatial Targeting Methods

Four spatial targeting methods (CII, LII, LPSAI, and LPUAI) were compared in the SRW to prioritize the subbasins into three classes (high, medium, and low priority area) according to the pollution of interest (sediment, TN, and TP). A detailed description of the results of each method is presented below.

4.4.3.1 CII

The location prioritization in the CII method is based on the pollution concentration in the reach (Figure 3). The watershed was divided into high, medium, and low priority areas and the sediment concentration range for high, medium, and low priority area was 0.0 to 86.4 mg/l, 86.4 to 259.0 mg/l, and 259.0 to 515.0 mg/l, respectively. For the sediment targeting scenario (Figure 4-3a), the high priority areas were located on the upstream sections of the watershed and the main source of pollution was from agricultural land. The TN concentration range was 0.0 to 1.7 mg/l, 1.7 to 4.8 mg/l, 4.8 to 10.8 mg/l for high, medium, and low priority area whereas the TP concentration range was 0.0 to 0.3 mg/l, 0.3 to 0.8 mg/l, and 0.8 to 1.5 mg/l for high, medium, and low priority areas, respectively. Both TN and TP high priority area were located upstream, center, and also near the outlet of the watershed (Figure 4-3b) and (Figure 4-3c), respectively. Similar to the sediment high priority areas, the main source of pollution in high priority areas of TN and TP was due to the agricultural lands. A greater number of subbasins were identified as high priority area according to TN and TP targeting. Additionally, a greater number of subbasins were categorized into medium priority areas for TN targeting, followed by sediment and TP targeting methods, respectively. In all three cases, most subbasins were selected as low priority.

(a)

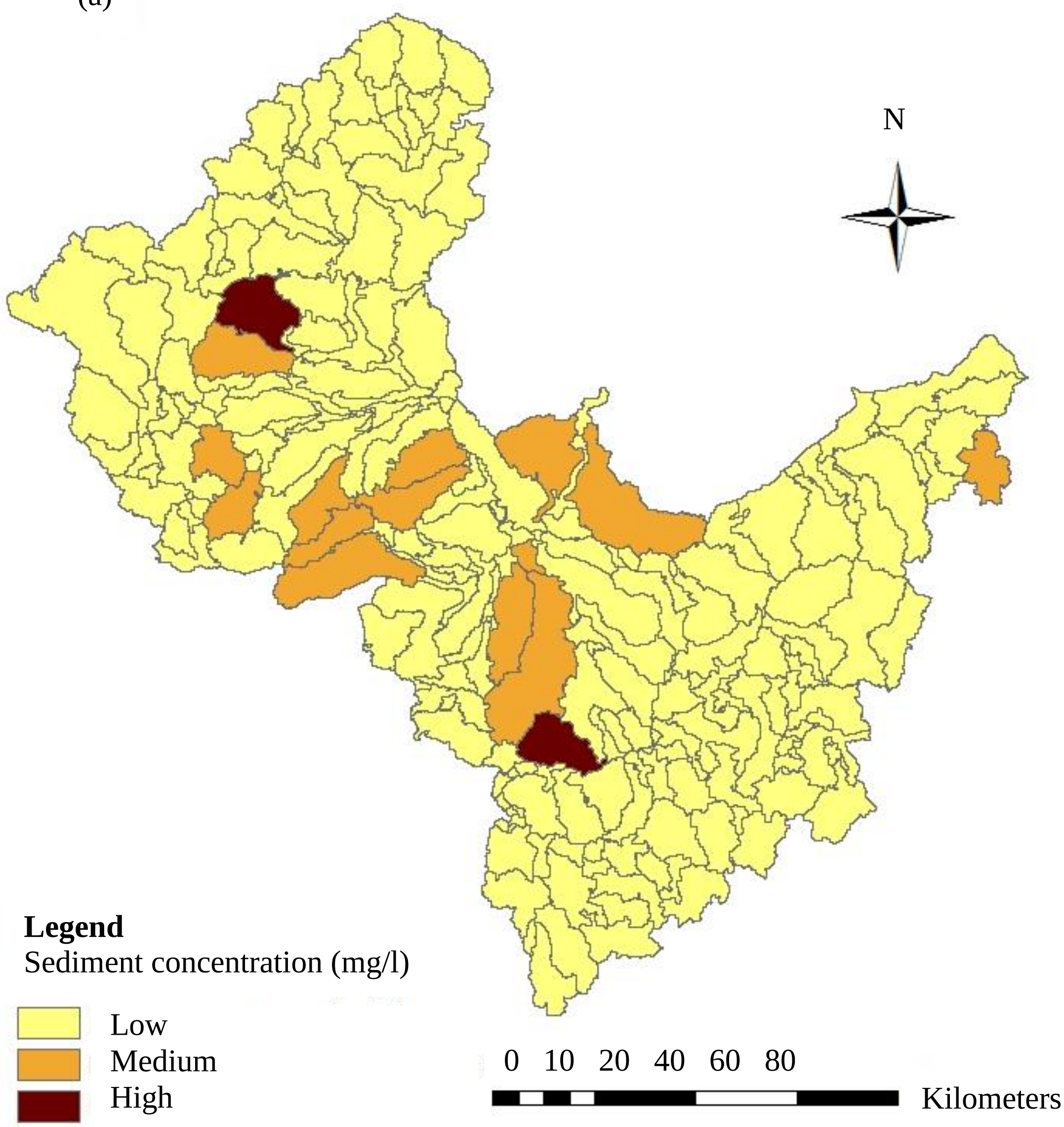

Figure 4-3. (a) CII targeting method priority areas based on sediment concentration.

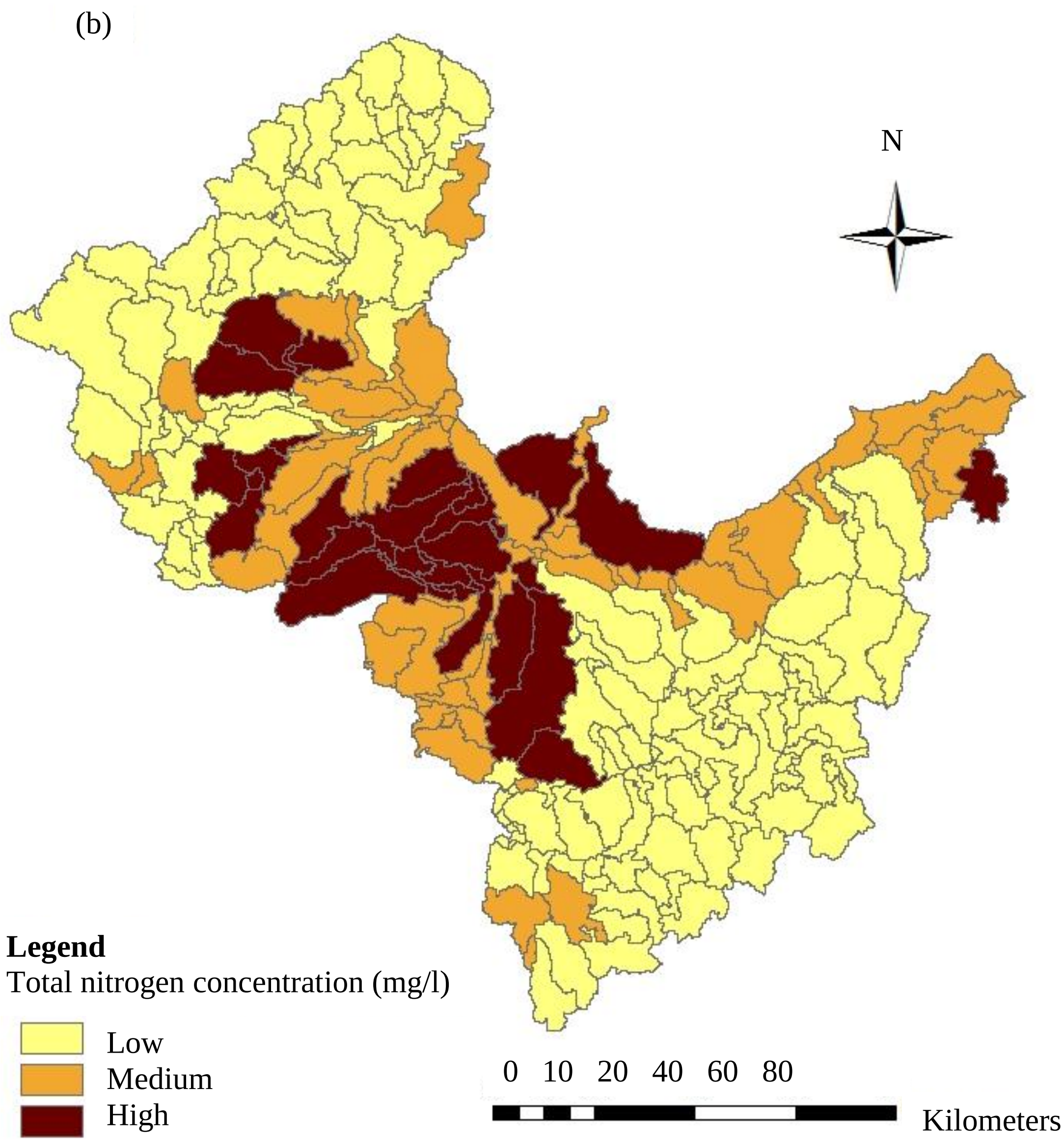

Figure 4-3. (b) CII targeting method priority areas based on TN concentration.

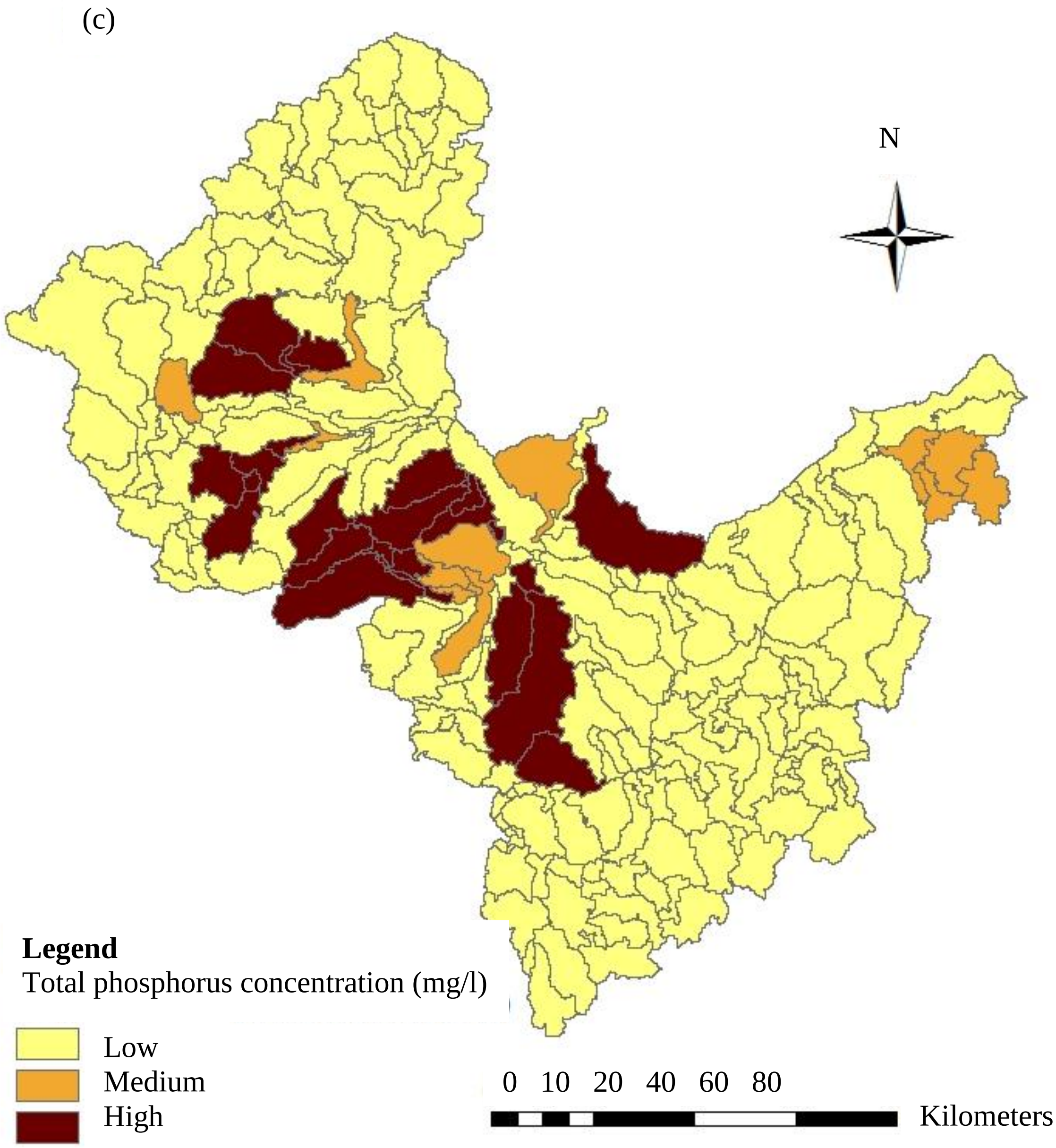

Figure 4-3. (c) CII targeting method priority areas based on TP concentration.

4.4.3.2 LII

Priority areas in this method were determined according to the pollutant load for each reach (Figure 4-4). The sediment load range for high, medium, and low priority areas was 0 to 18300 tons, 18300 to 98500 tons, 98500 to 206000 tons, respectively for the sediment targeting scenario. For the TN targeting scenario, the load ranges for high, medium, and low priority area were 0 to 1000000 kg, 1000000 to 4190000 kg, and 4190000 to 8050000 kg, respectively whereas for the TP targeting scenario, the load ranges were 0 to 46900 kg, 46900 to 223100 kg, and 223100 to 585700 kg for high, medium, and low priority areas, respectively. An approximate equal number of subbasins were categorized as high priority for all pollutants. High priority areas were generally located near the outlet of the SRW, while medium priority subbasins were also located within the general proximity of the watershed outlet. The large concentration of high and medium priority areas near the outlet is likely due to the targeting methodology because pollutant load from both the subwatershed and the entire upstream watershed are accumulated near the outlet. Low priority areas are predominant for all three pollutants using the LII targeting method, which is likely due to a large number of small tributaries in the SRW. Tributaries generally have smaller flows when compared to the main channel, which leads to smaller load carrying capacity and therefore low priority under this targeting method.

The LII targeting maps are very similar when performing a comparison between sediment, and TP, which is likely due to the strong correlation between sediment and phosphorus transport as phosphorus attaches to sediment. Conversely, there are a considerably smaller number of medium priority areas for TN, indicating that most nitrogen is generated near the outlet of the watershed. While this method has the advantage of considering pollution from both the subbasin and upstream, it seems that the resulting priority areas are skewed toward being placed near the watershed outlet.

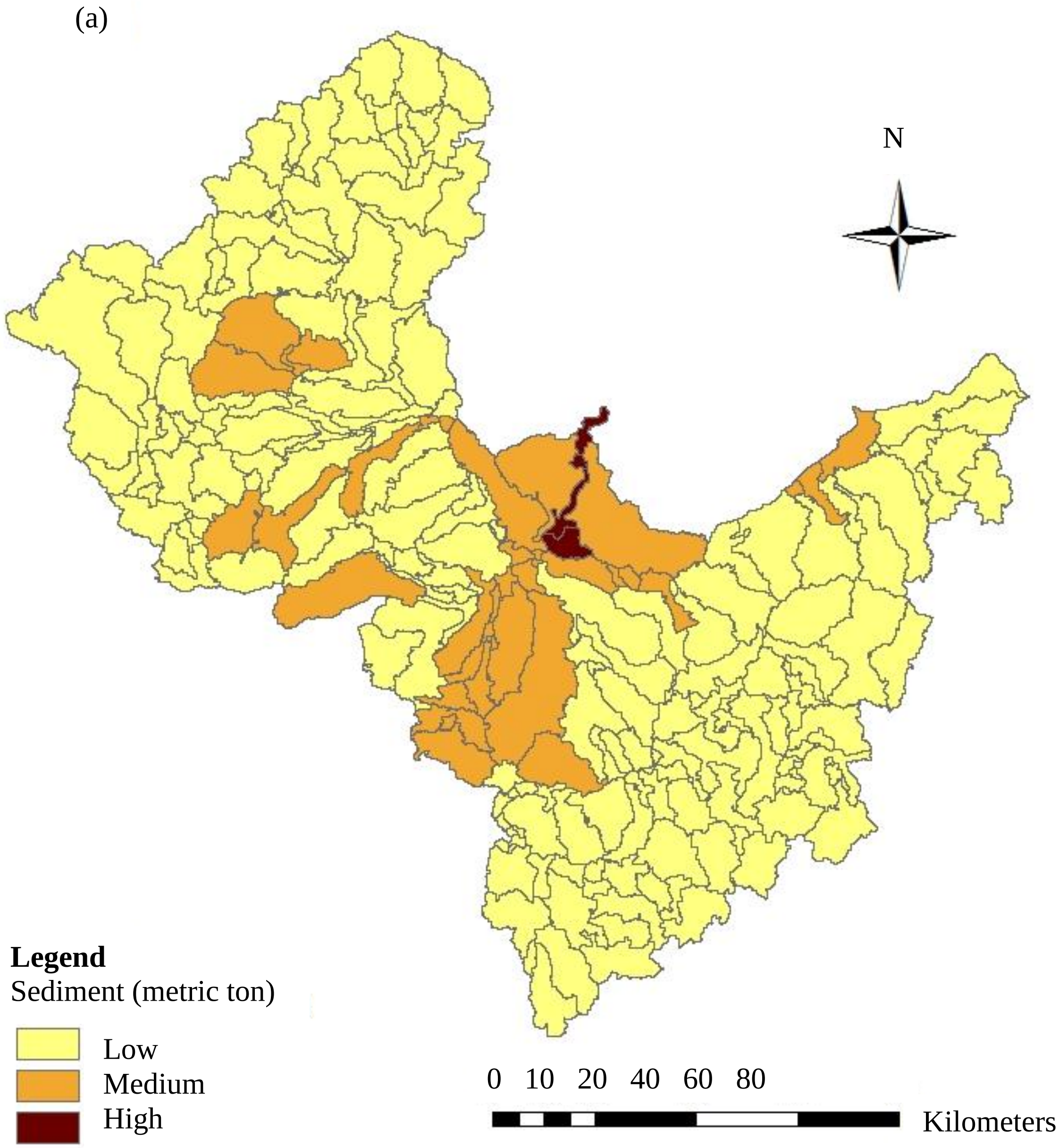

Figure 4-4. (a) LII targeting method priority areas for sediment.

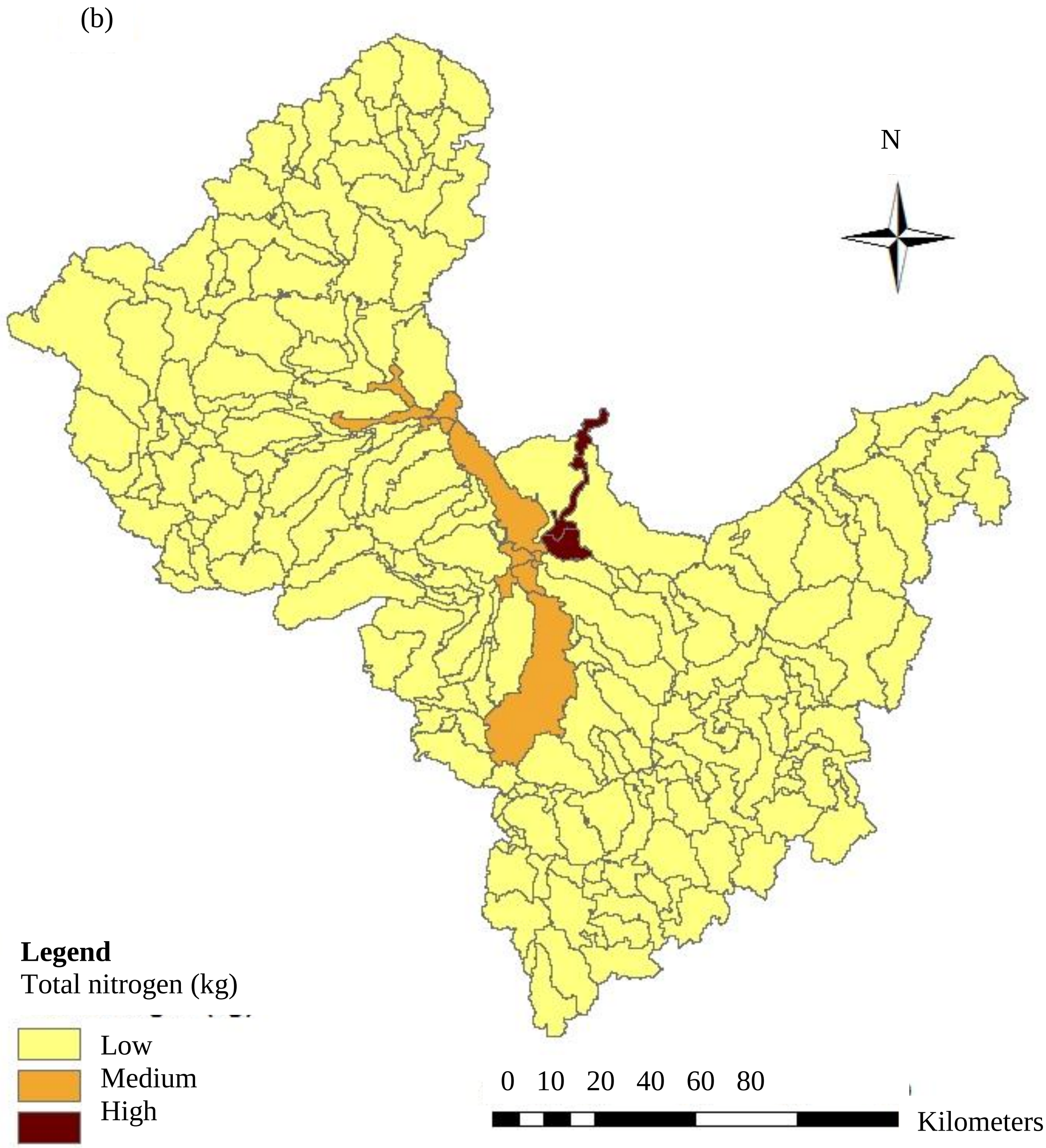

Figure 4-4. (b) LII targeting method priority areas for TN.

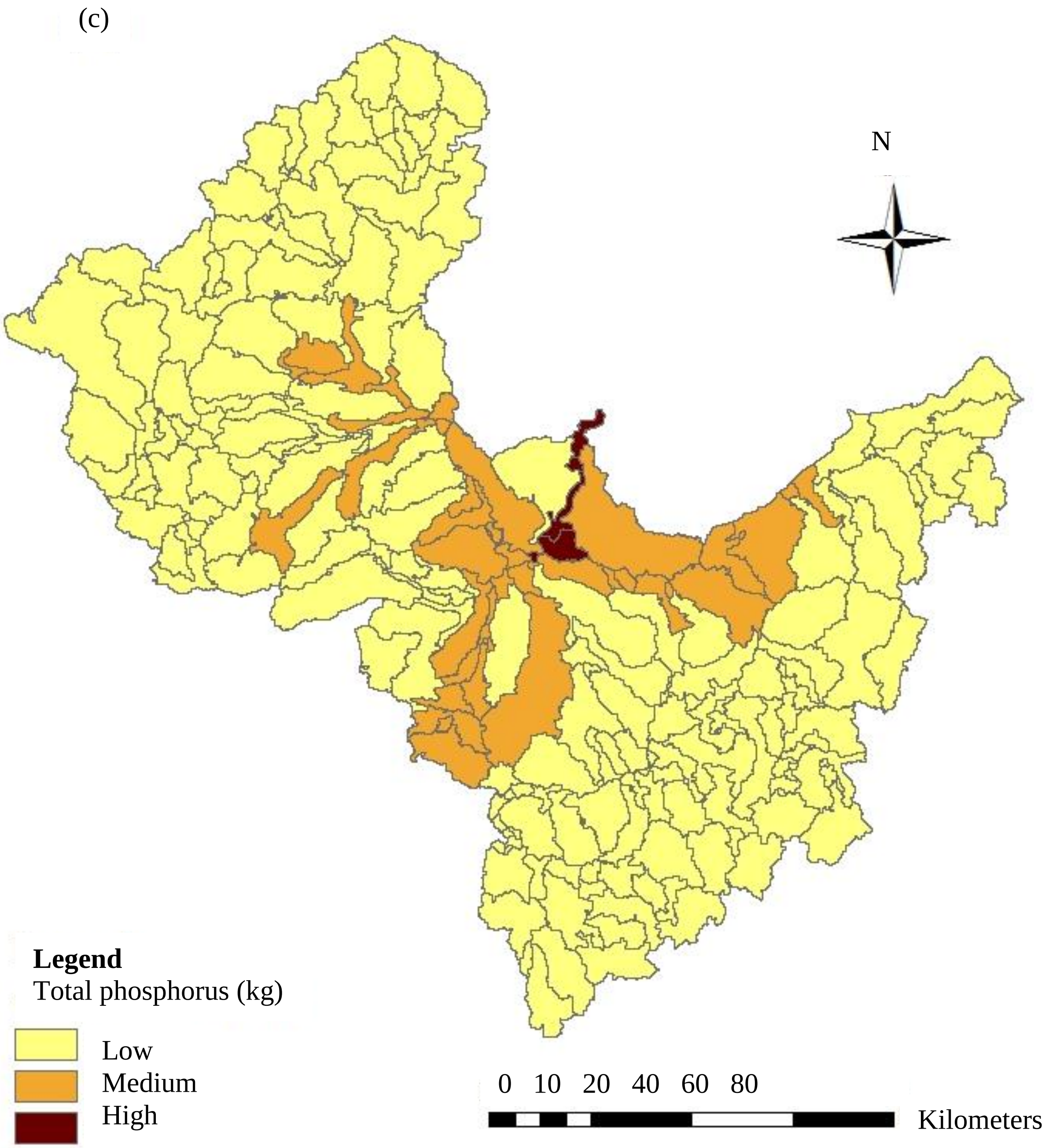

Figure 4-4. (c) LII targeting method priority areas for TP.

4.4.3.3 LPSAI

In this method the priority areas were identified based on the pollutant load from each subbasin (yield multiplied by area), which primarily identifies the origin of a pollutant from its local source (Figure 4-5). Based on the sediment targeting scenario, the sediment load varied from 0.0 to 8210 tons, 8210 to 25624 tons, and 25624 to 86539 tons for low, medium, and high priority areas, respectively. In the TN targeting scenario, the TN load varied from 0 to 69200 kg, 69200 to 257000 kg, and 257000 to 1000000 kg for low, medium, and high priority areas, respectively, whereas based on TP targeting scenario, the TP load varied from 0 to 8170 kg, 8170 to 26291 kg, 26291 to 108680 kg for low, medium, and high priority areas, respectively. The LPSAI method generally identifies high and medium priority areas as subbasins that generate a relatively large amount of pollution and are large in area because of the inherent areal dependence. Therefore, most high and medium priority areas defined using this method are subbasins that predominantly contain agricultural row crops and are large in size. Priority area identification using the LPSAI method can be considered subjective, because it is highly dependent on watershed delineation and DEM resolution for creation of subbasins in the model. One way to limit the subjectivity is to ensure that all subbasins are of similar size when performing watershed delineation.

Targeting maps using the LPSAI method are very similar for each pollutant. High and medium priority areas are generally scattered across the watershed for all three pollutants. The subbasins that fell under high priority areas were almost the same for all targeting pollutants. A greater number of subbasins were identified as medium priority for the TN targeting method, whereas a similar number of subbasins were categorized as medium priority for both sediment and TP.

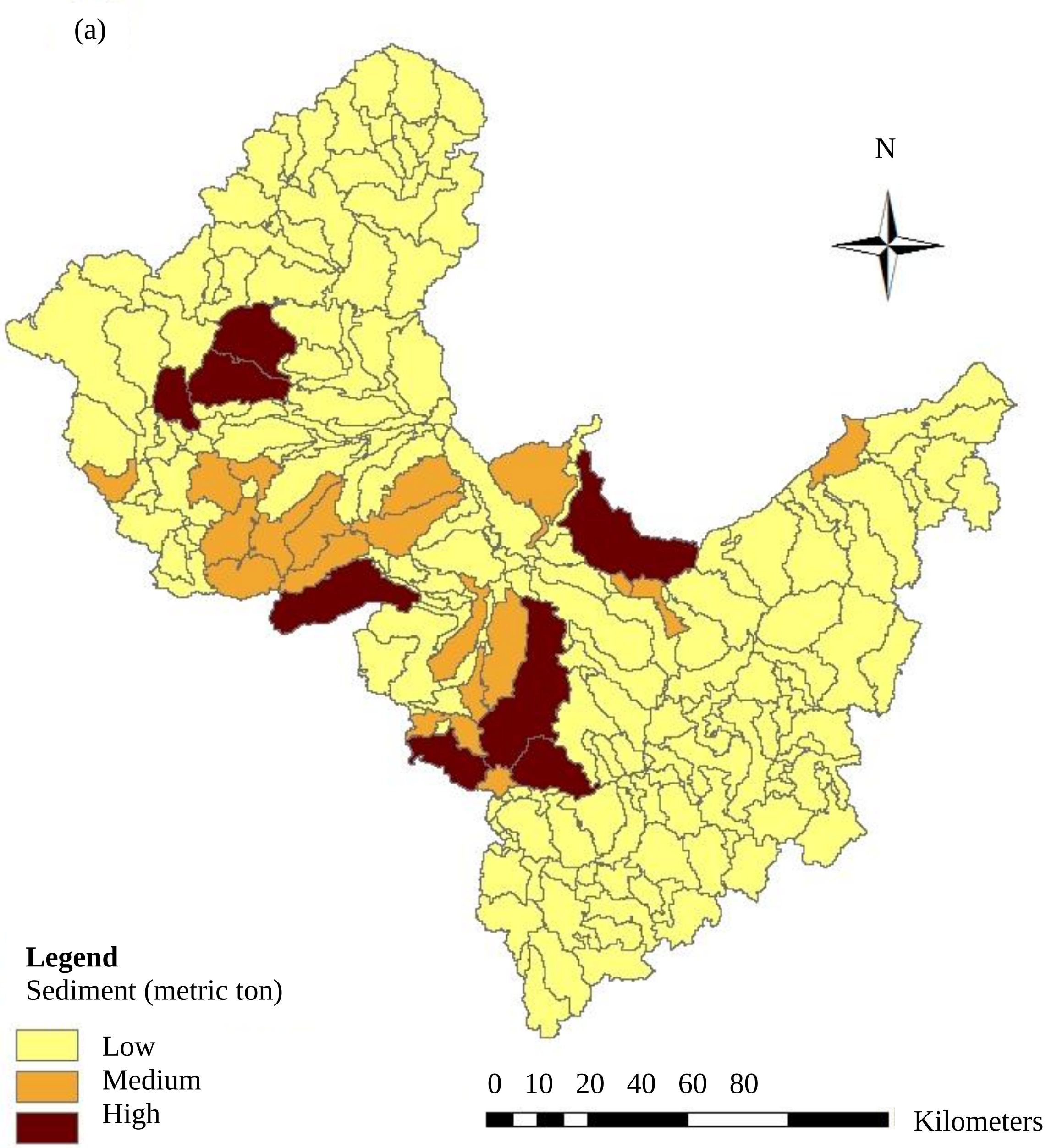

Figure 4-5. (a) LPSAI targeting method priority areas for sediment.

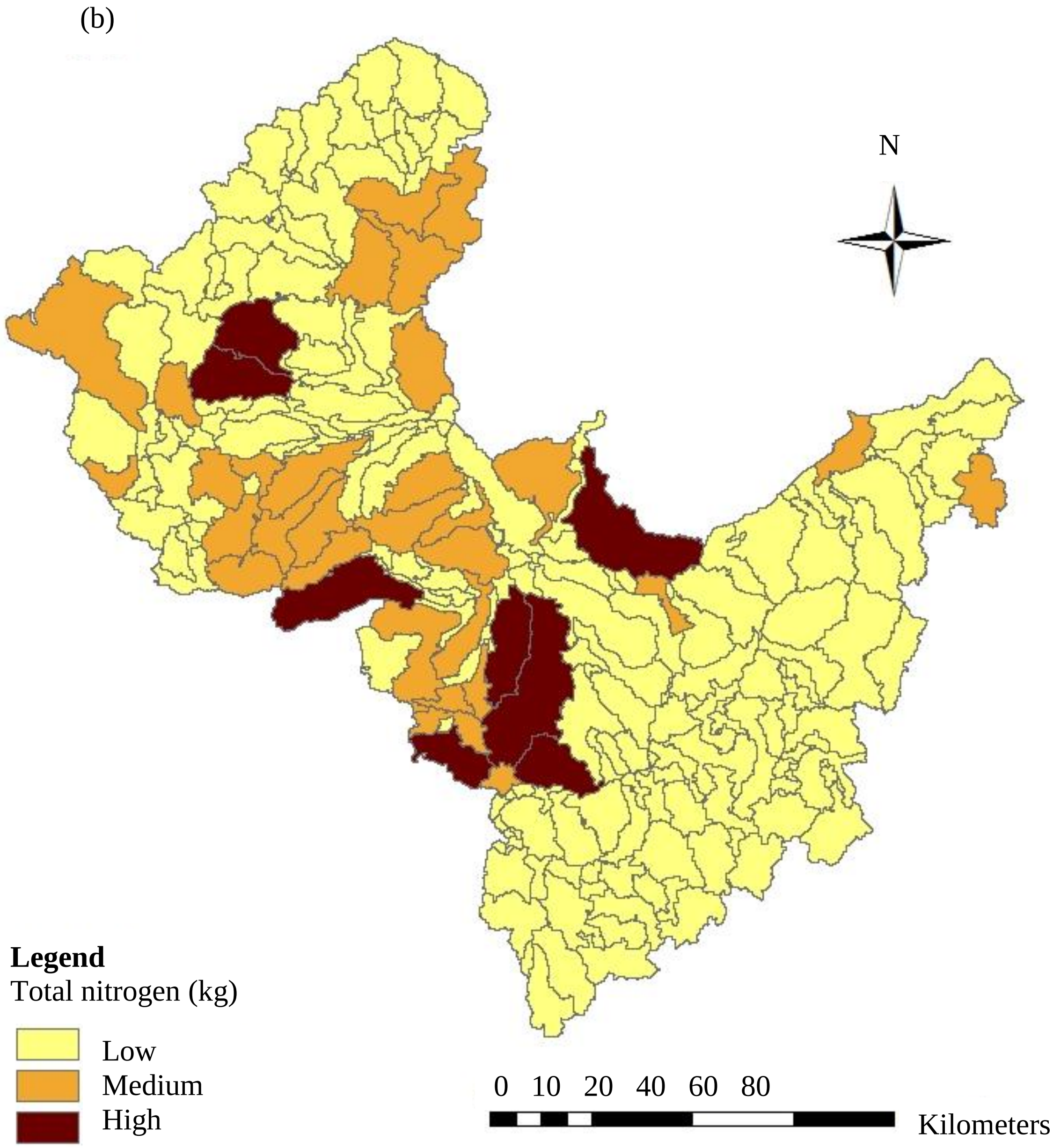

Figure 4-5. (b) LPSAI targeting method priority areas for TN.

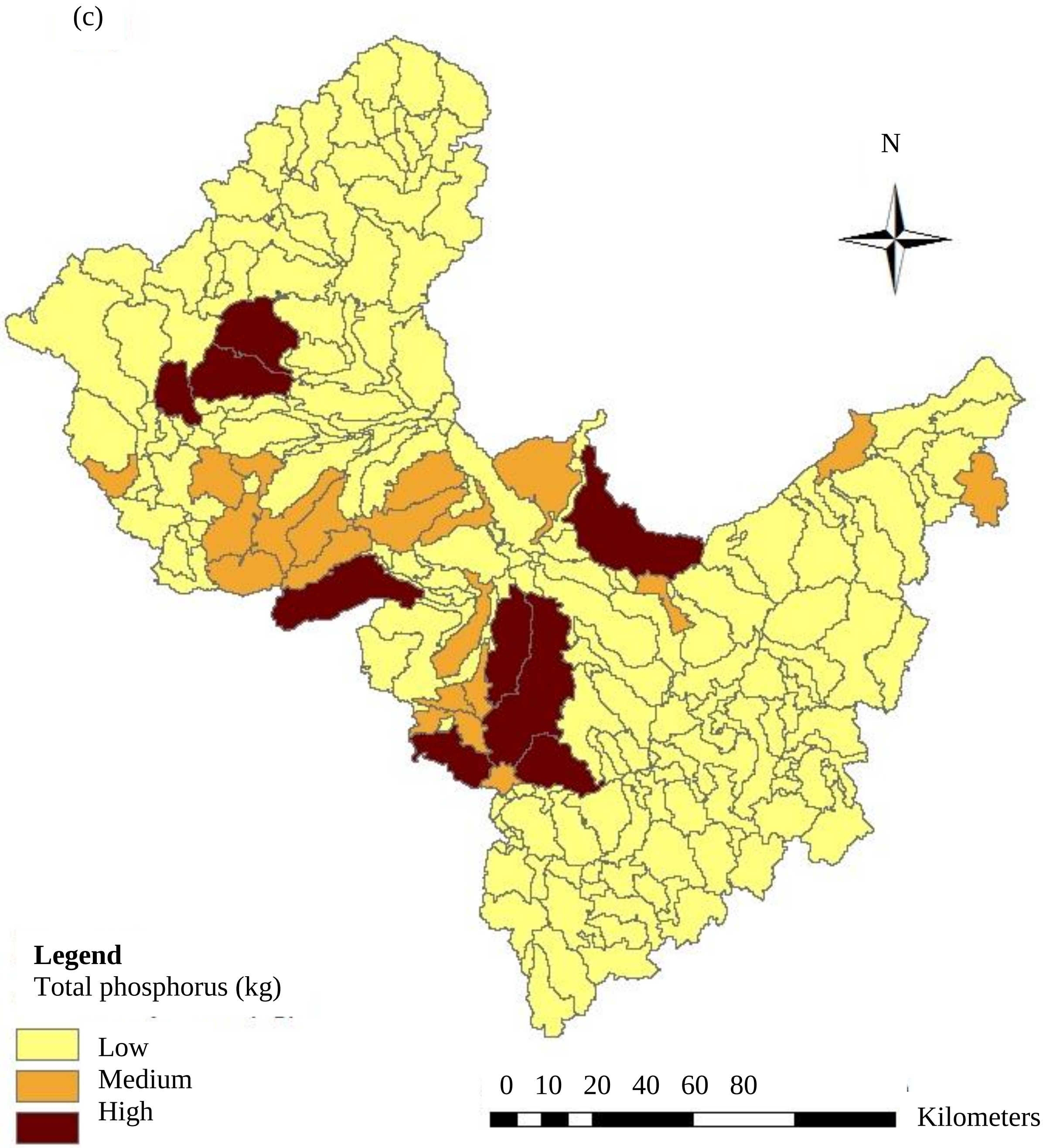

Figure 4-5. (c) LPSAI targeting method priority areas for TP.

4.4.3.4 LPUAI

This targeting method is based on pollutant load per area, which normalizes each subbasin for comparison (Figure 4-6). Based on sediment targeting scenario, the sediment yield varied from 0.0 to 0.8 (tons/ha), 0.8 to 2.8 tons/ha, and 2.8 to 6.9 tons/ha for low, medium, and high priority areas, respectively. According to the TN targeting scenario, the TN yield varied from 0.0 to 8.9 kg/ha, 8.9 to 25.5 kg/ha, 25.5 to 73.4 kg/ha for low, medium, and high priority areas, respectively, while based on the TP targeting scenario the TP yield varied from 0.0 to 1.1 kg/ha, 1.1 to 3.4 kg/ha, and 3.4 to 10.4 kg/ha for low, medium, and high priority areas, respectively. High and medium priority areas identified with this method are strongly correlated with agricultural land in the SRW. Subbasins that are predominantly agricultural were identified as high and medium priority with this method. Compared to the LPSAI method, there are less high and medium priority subbasins because some large subbasins were eliminated due to the areal normalization.

Targeting maps were similar for all pollutants in this method. More subbasins were categorized into high priority area for the sediment targeting method, followed by TN and TP. An equal number of subbasins were identified as medium priority area for sediment, TN, and TP. Similar to the other targeting methods, a majority of the SRW subbasins were characterized as low priority.

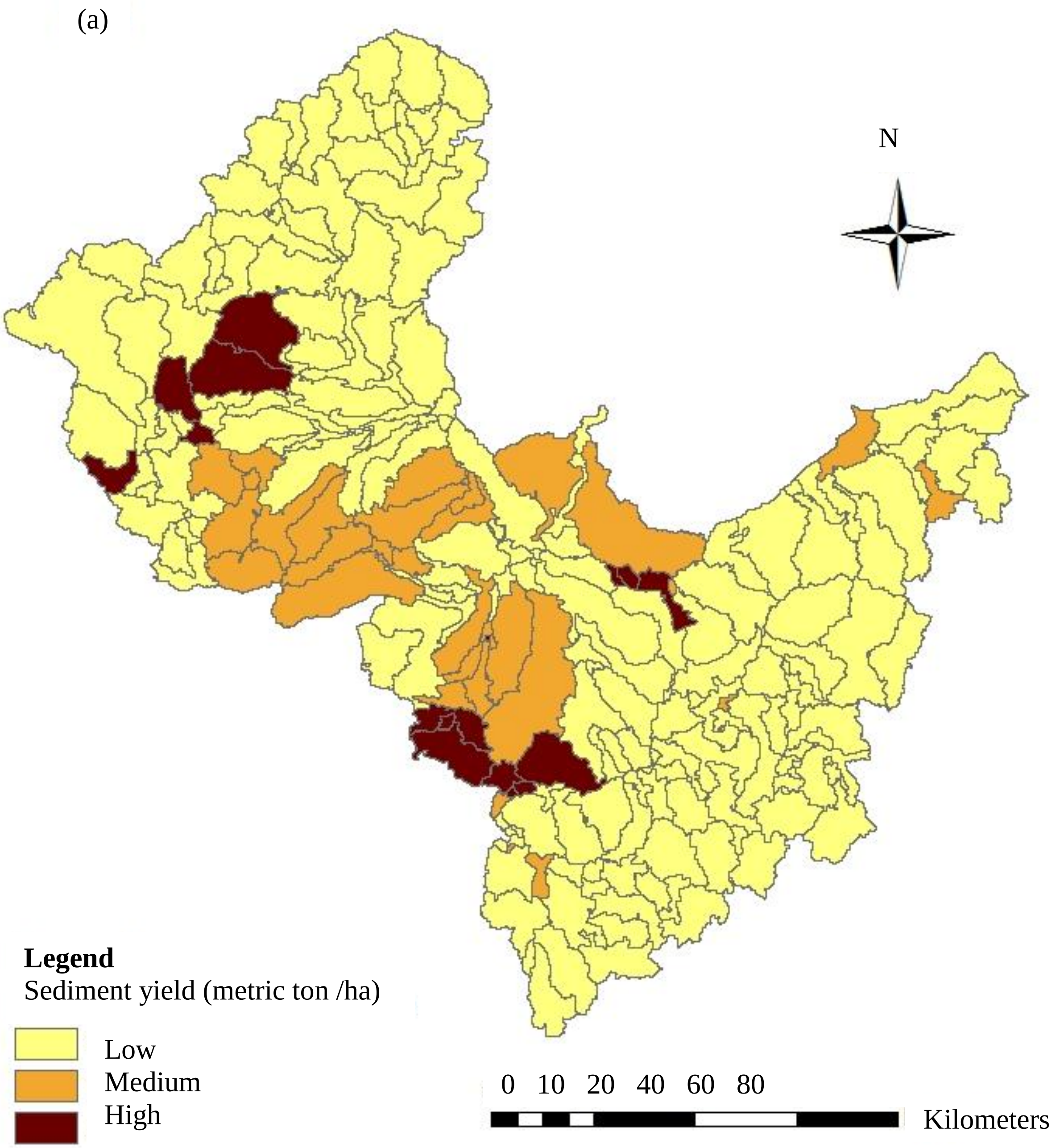

Figure 4-6. (a) LPUAI targeting method priority areas for sediment.

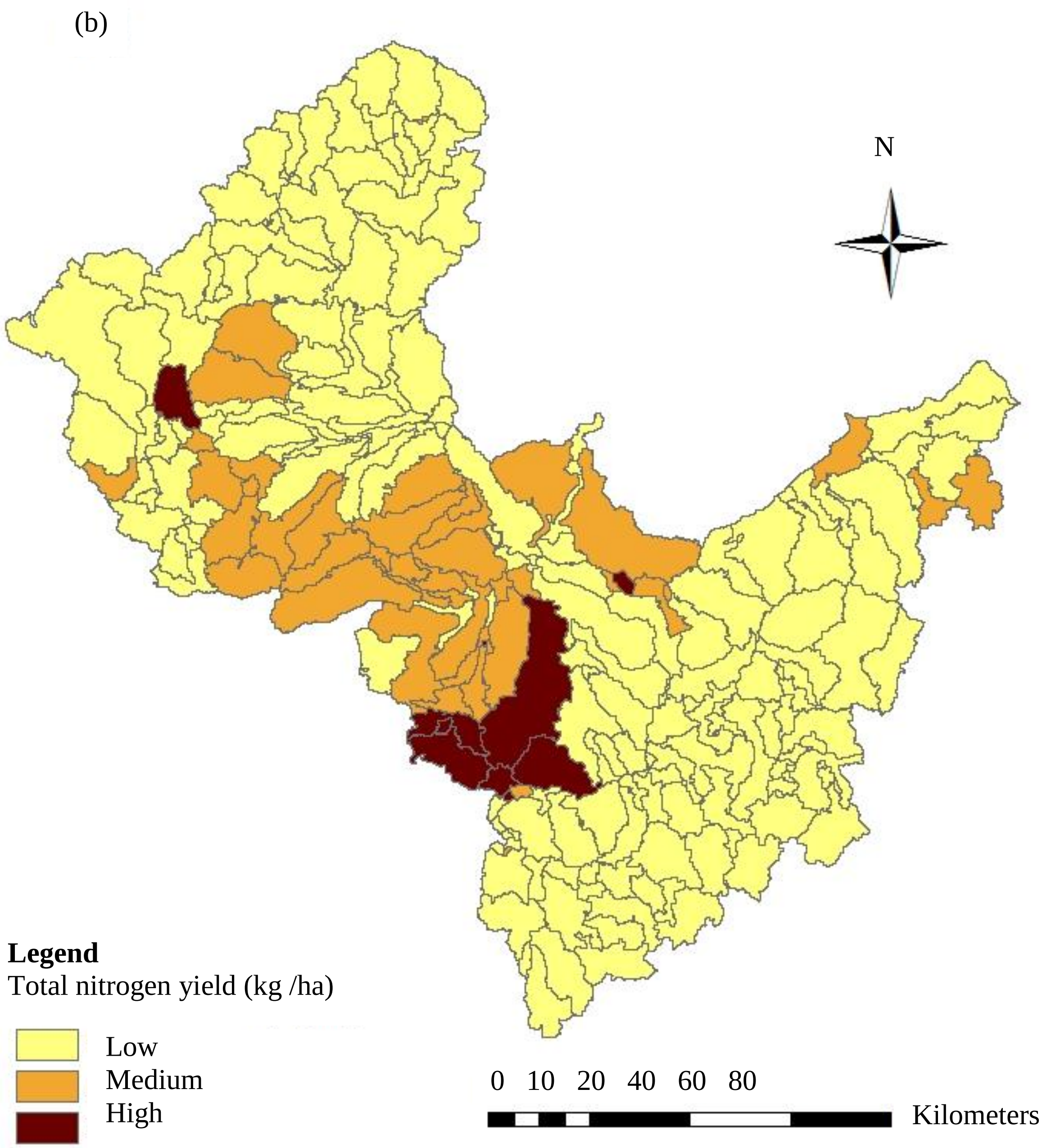

Figure 4-6. (b) LPUAI targeting method priority areas for TN.

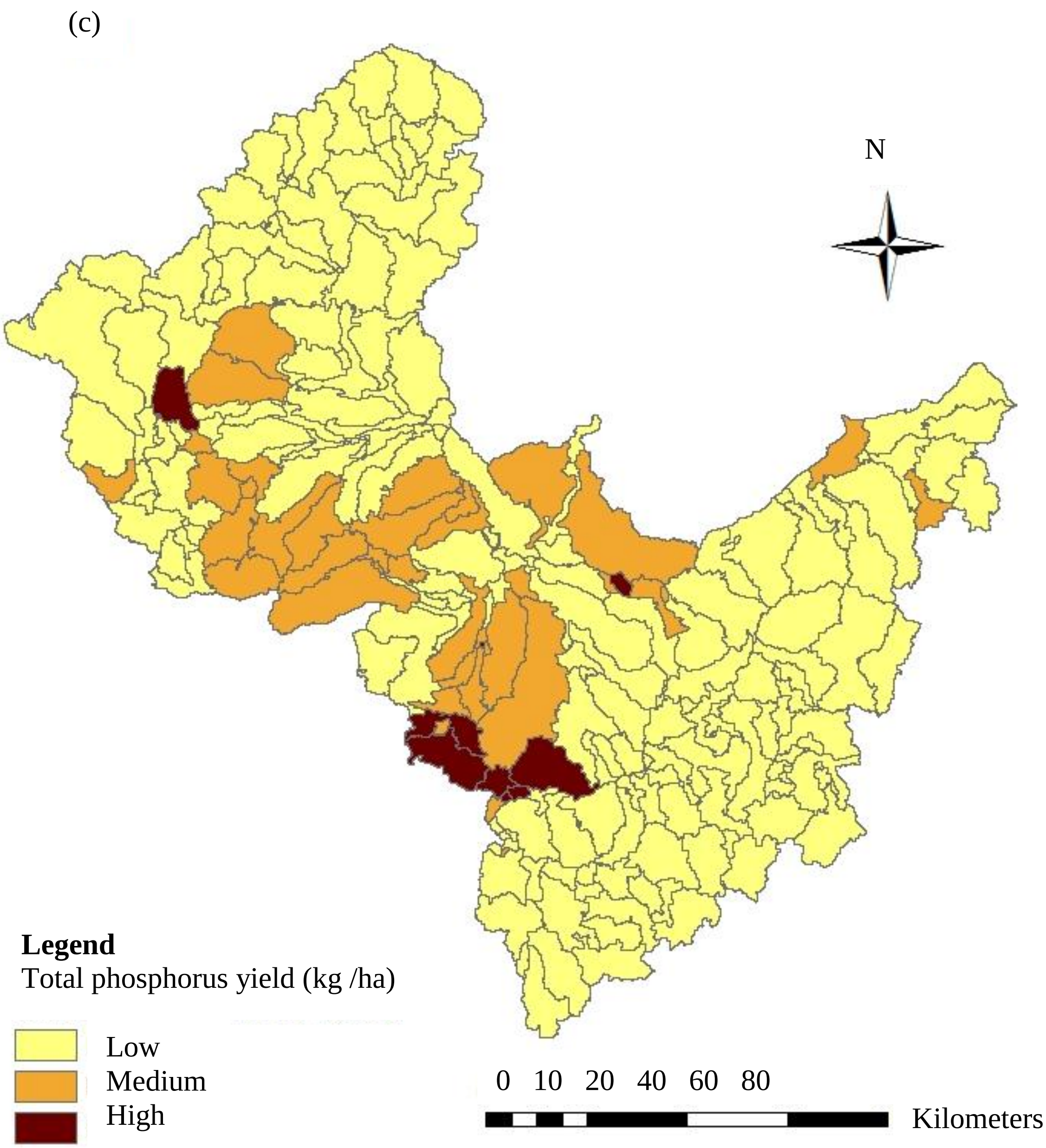

Figure 4-6. (c) LPUAI targeting method priority areas for TP.

4.4.4 Comparison of Agricultural Lands in Sub-targeting Scenarios for Sediment, TN, and TP

The goal of this section is to quantify the capability of each targeting method to identify agricultural lands as source of NPS. In addition, comparing the distribution of priority areas for the entire SRW and its agricultural lands provides insight into what watershed characteristics influence each method of identifying CSAs.

4.4.4.1 Sediment Targeting Scenario

A different proportion of high, medium, and low priority areas is obtained for the sediment targeting scenario in each of the four targeting methods as presented in Figure 4-7.

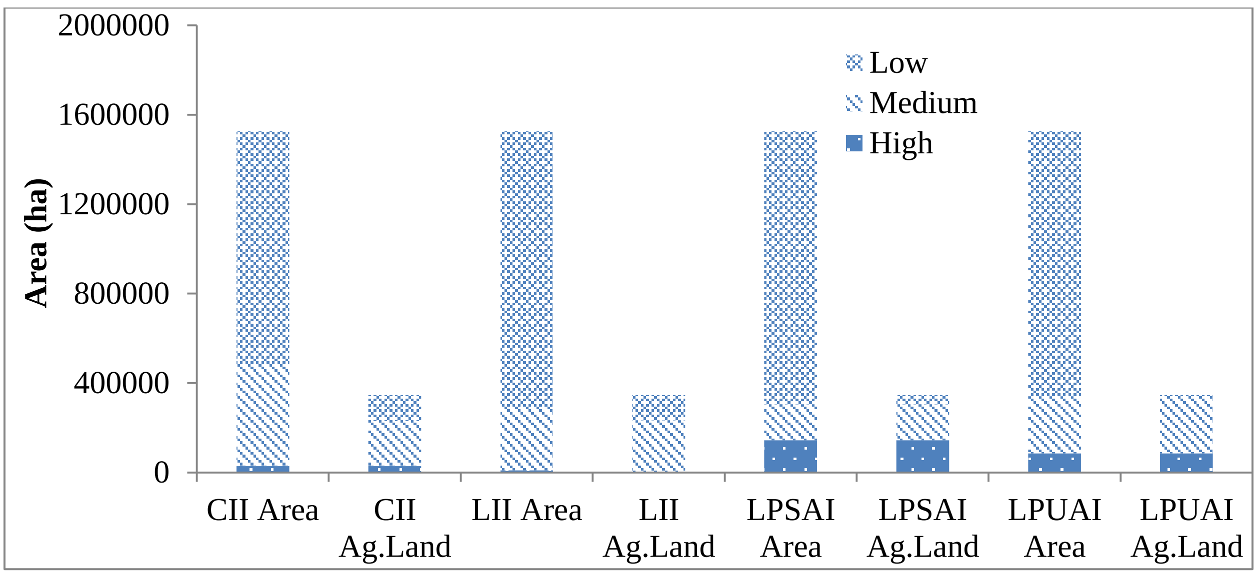

Figure 4-7. Distribution of high, medium, and low priority areas for sediment targeting scenario.

For the whole watershed, the LPSAI method identified the largest high priority area (143349 ha), while the LII method identified the smallest (9543 ha). The CII method identified the largest area (448083 ha) under medium priority, while the LPSAI method had the smallest amount of medium priority area (160973 ha). The CII method had the smallest low priority area (1050596 ha), while the other three targeting methods had approximately equal areas of low priority.

A similar trend was observed for agricultural lands as was observed for the whole SRW. The LPSAI method had the greatest amount of agricultural lands (143318 ha) identified as high priority, while the LII method did not identify any agricultural land as high priority. Therefore, no BMPs were implemented for the LII high priority area in this study. The LPUAI method had the highest amount of medium priority area (249368 ha) on agricultural land, while LPSAI had the least (160939 ha). For low priority areas on agricultural land, the CII and LII targeting methods had the most while LPUAI had the least (11077 ha).

The targeting methods based primarily on field generated pollutants (LPSAI and LPUAI) had most high and medium priority areas attributed to agricultural lands. This is likely because agricultural practices have a large impact on sediment generation. In addition, the LPSAI method has a higher total high priority area because it does not normalize for subbasin area, unlike the LPUAI method. Conversely, the targeting methods based primarily on the reach (CII and LII) identified some high and medium priority areas not located in agricultural subbasins. In the case of LII, this is likely because the high priority areas were located at the outlet (where accumulation of upstream sediment occurs). For the CII method, tributaries may have high sediment concentrations because of relatively low flows, creating medium and high priority areas in these locations, regardless of land use.

4.4.4.2 TN Targeting Scenario

Proportions of high, medium, and low priority areas under the TN scenario are different for each sub-targeting method for both the entire SRW and agricultural land in the SRW. Figure 4-8 presents the proportions of priority areas for each sub-targeting method.

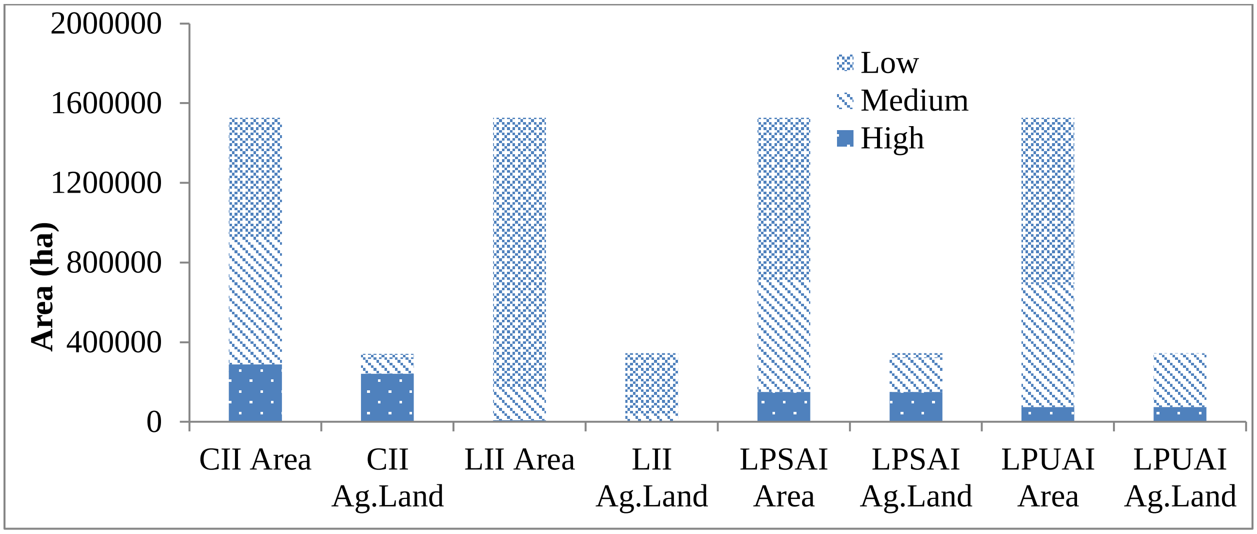

Figure 4-8. Distribution of high, medium, and low priority areas for TN targeting scenario.

Based on the TN targeting scenario for high priority areas in the whole watershed the CII method had the largest area (289,157 ha), while the LII method had the smallest (9,543 ha). For medium priority areas, the CII, LPSAI, and LPUAI methods had approximately equal areas, whereas the LII targeting method had the least amount of area (157,566 ha). Meanwhile, the LII method had the largest (1,359,231 ha) area of low priority, while CII had the smallest area (612,177 ha) of low priority.

For agricultural lands, the CII method had the greatest amount of high priority areas (242,318 ha), while LII had none. The LPUAI method had the most agricultural land (2694656 ha) under medium priority and LII had the least (33,865 ha) of all targeting methods. Under low priority, LII had the greatest area (311,558 ha) while LPUAI had the smallest area (24,227 ha).

Similar to sediment targeting, the field based methods' (LPSAI and LPUAI) high and medium priority areas were generally all classified as agriculture. Meanwhile, the reach methods (CII and LII) identified high and medium priority areas that were both agricultural and non-agricultural lands. In addition, for CII, LPSAI, and LPUAI methods, 50% or less of the land was classified as low priority, indicating that to target TN for medium and high priority areas would still be resource and cost intensive. Once again, the LII method was mostly low priority, because medium and high priority areas were located only near the outlet of the SRW.

4.4.4.3 TP Targeting Scenario

Similar to sediment and TN, quantity of priority areas are different using each of the four sub-targeting methods. Proportions of high, medium, and low priority areas for the entire SRW and agricultural lands of the SRW are presented in Figure 4-9.

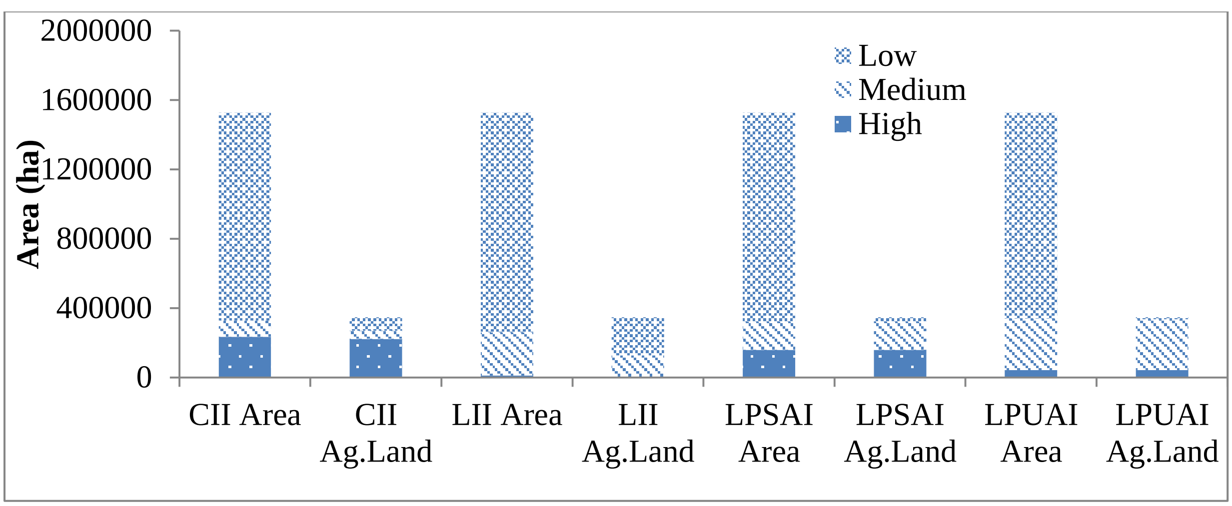

Figure 4-9. Distribution of high, medium, and low priority areas for TP targeting scenario.

When considering the entire SRW, CII has the greatest area (232,636 ha) of high priority, while LII has the smallest area (9,853 ha) for TP. In the case of medium priority areas, LPUAI had the greatest area (296,666 ha), while CII had the least (95,150 ha) of all targeting methods. The low priority area was greatest (1,267,596 ha) for the LII method, while the other targeting methods had approximately equal areas of low priority.

The area of agricultural lands attributed to high, medium, and low priorities for the four targeting methods varies based on technique. The CII method had the largest (221,198 ha) amount of high priority, while LII had no high priority for agricultural lands. The greatest amount of area (291,776 ha) to fall under medium priority was LPUAI and the least (46,558 ha) was CII. In the case of low priority the LII targeting method was had the greatest (219,175 ha), while LPUAI had the least area (11,521 ha).

The TP targeting depicts similar trends to both sediment and TN. For the field based methods (LPSAI and LPUAI), the high and medium priority areas are completely characterized as agricultural lands. For the LII scenario, there is no high priority area classified as agriculture because the high priority areas are located near the SRW outlet. The CII method reveals that agricultural land is a prominent contributor to high and medium priority areas.

4.4.5 BMP Pollutant Reduction

The effectiveness of BMPs was determined in terms of percent reduction compared to the no BMP scenario. The results are presented according to the reduction of pollutants (sediment, TN, and TP) at the watershed outlet and subbasin by four targeting methods. In addition, BMP effectiveness was compared to the effectiveness of the BMP after it is normalized by its application area. The total BMPs application area of each targeting scenario was divided by the amount of pollution reduction from the base scenario of each BMP in each targeting method in order to normalize reduction by area. Normalization allows for an accurate comparison of the targeting methods, because each method identifies different priority areas.

4.4.5.1 Sediment Reduction

4.4.5.1.1 Sediment reduction without normalizing BMPs application area

Sediment reduction at the watershed outlet for each BMP without areal normalization is presented in Figure 4-10 (a, b, and c). Sediment reduction varies between the BMP applied, the priority area the BMP was applied on, and the method of priority area identification. Overall, the greatest percentage of sediment reduction for all priority areas was native grass, while the lowest percent reduction was residue management (0 kg/ha) for all targeting methods and priority areas. Comparing BMPs, native grass likely has the highest reduction efficiency because it is the most intensive, while residue management (0 kg/ha) is much less. Overall, the BMPs applied under LPSAI for high priority are the most effective in sediment reduction at the outlet because the priority areas were identified based on the pollutant load from each subbasin and this method identified the greatest amount of high priority area. For medium priority, the case is similar with LII, where the BMPs are most effective because they are applied on more area. Comparing, medium priority generally had the greatest reduction because the greatest proportion of area (agricultural land) was selected as medium priority.

Similar sediment reduction trends as the watershed outlet were observed at the subbasin level (Figure 4-10 d, e, and f). Native grass and terraces were generally the most effective, regardless of priority and targeting method, likely because of the intensive nature of the BMP implementation. Recharge structures were the only BMP to have a prominent decrease in percent sediment reduction at the subbasin when compared to the watershed outlet across all targeting methods and priorities. This is likely because recharge structures are implemented in the channel rather than on the field. Once again it is observed that overall reduction is greatest when the area of application is large. Therefore, LPSAI has the overall greatest percent sediment reduction for high priority, while LII and CII have the greatest for medium and low priority, respectively.

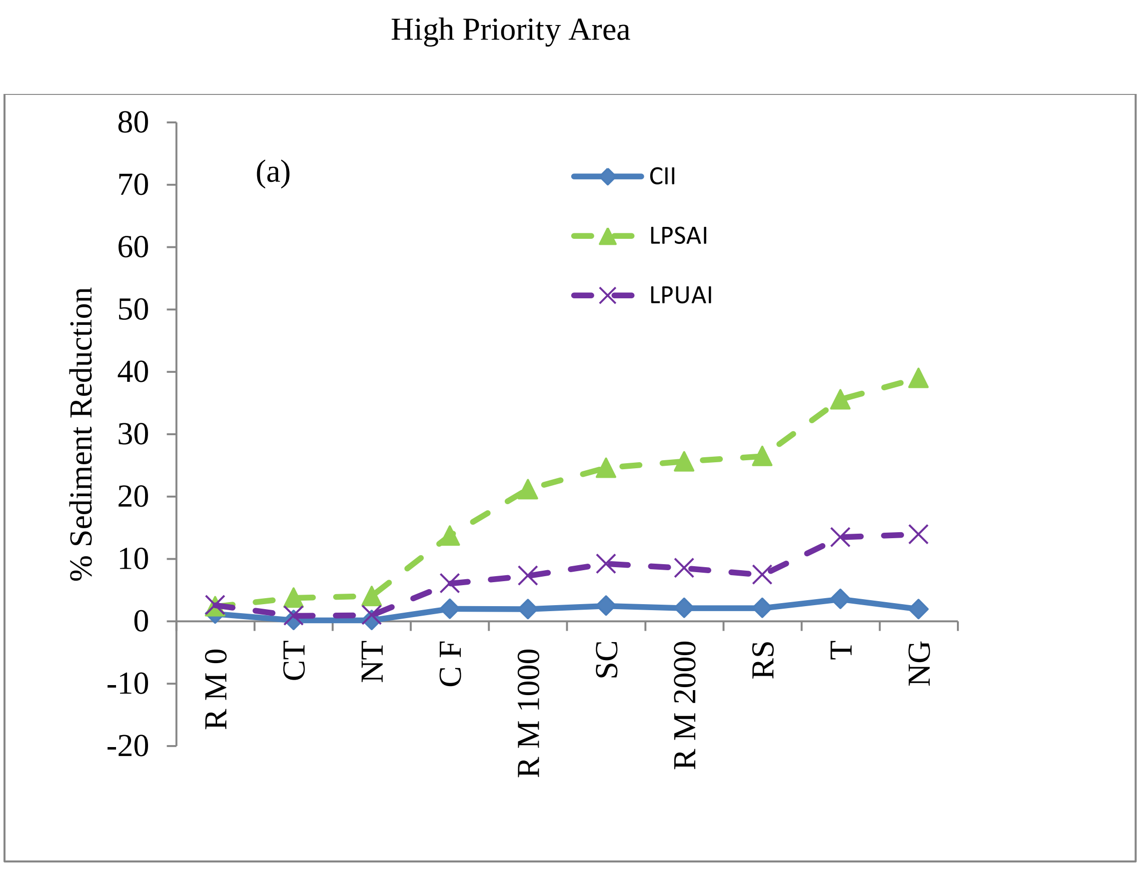

Figure 4-10. (a) Sediment reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Medium Priority Area

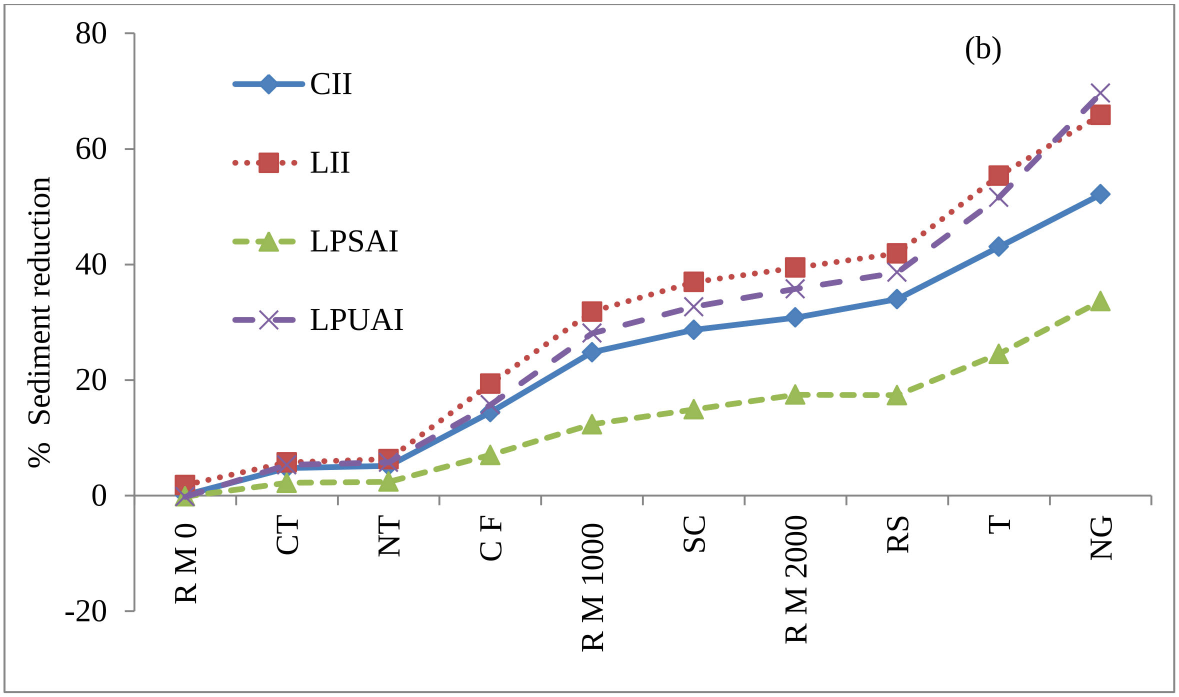

Figure 4-10. (b) Sediment reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Low Priority Area

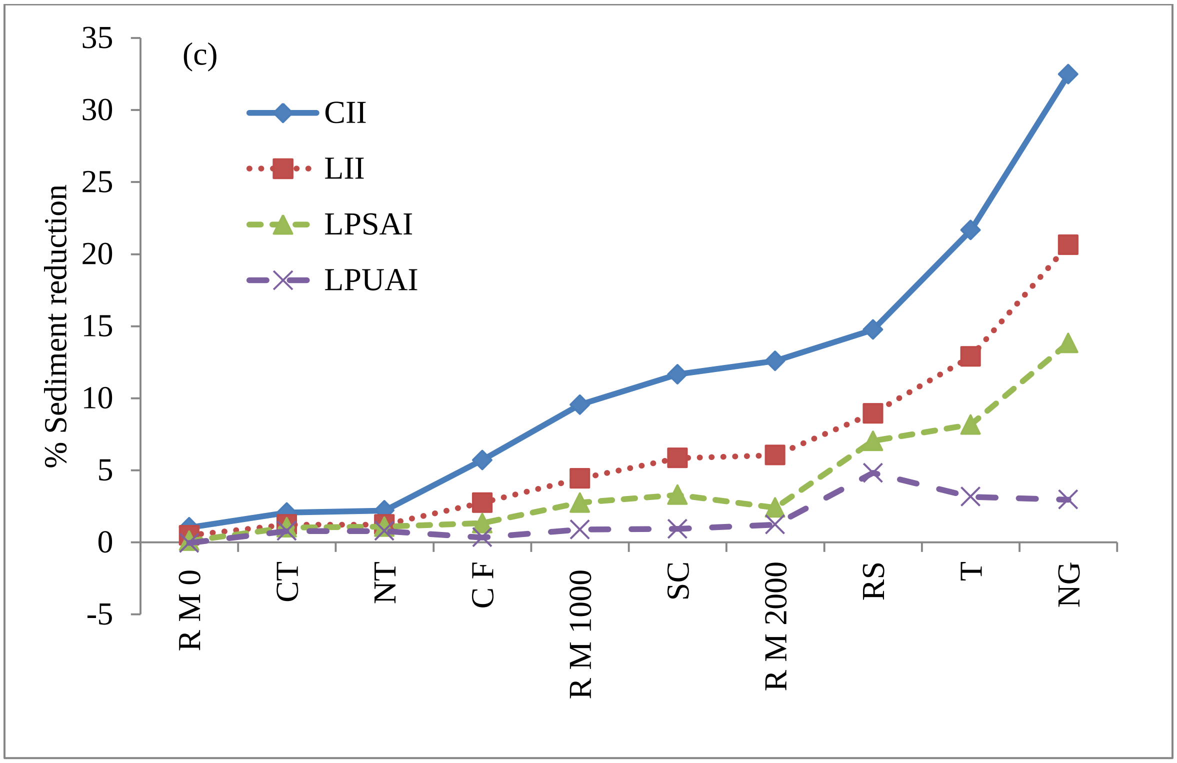

Figure 4-10. (c) Sediment reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

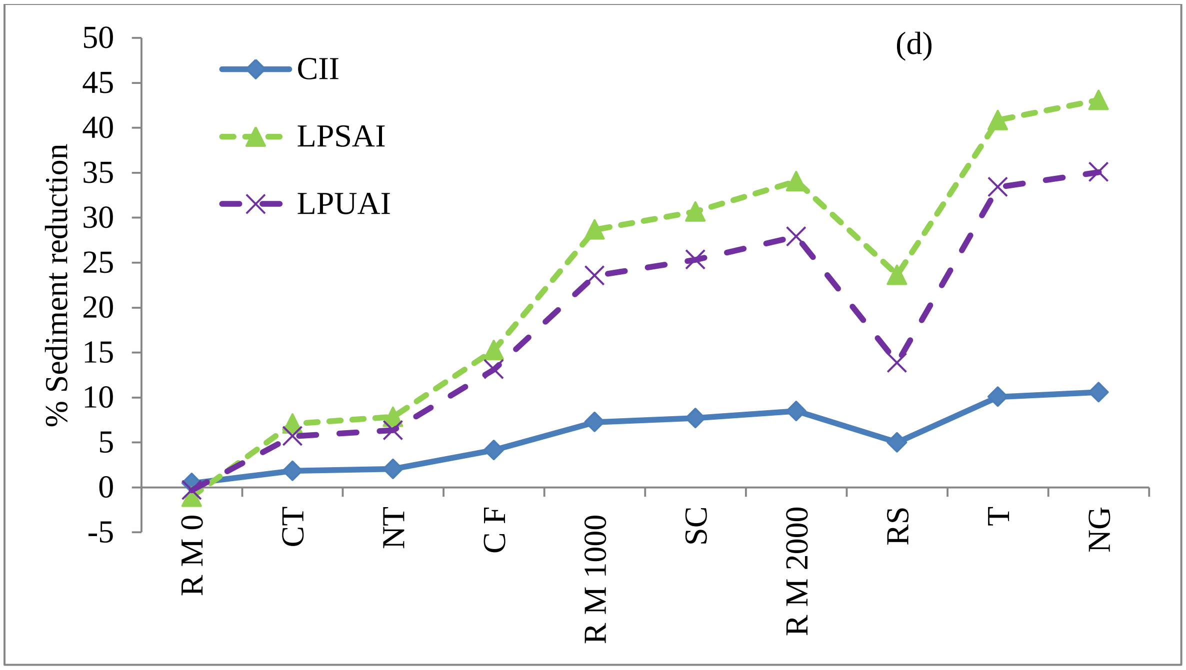

Figure 4-10. (d) Sediment reduction by BMPs in high priority area in subbasin for different targeting methods without normalizing the BMPs application area.

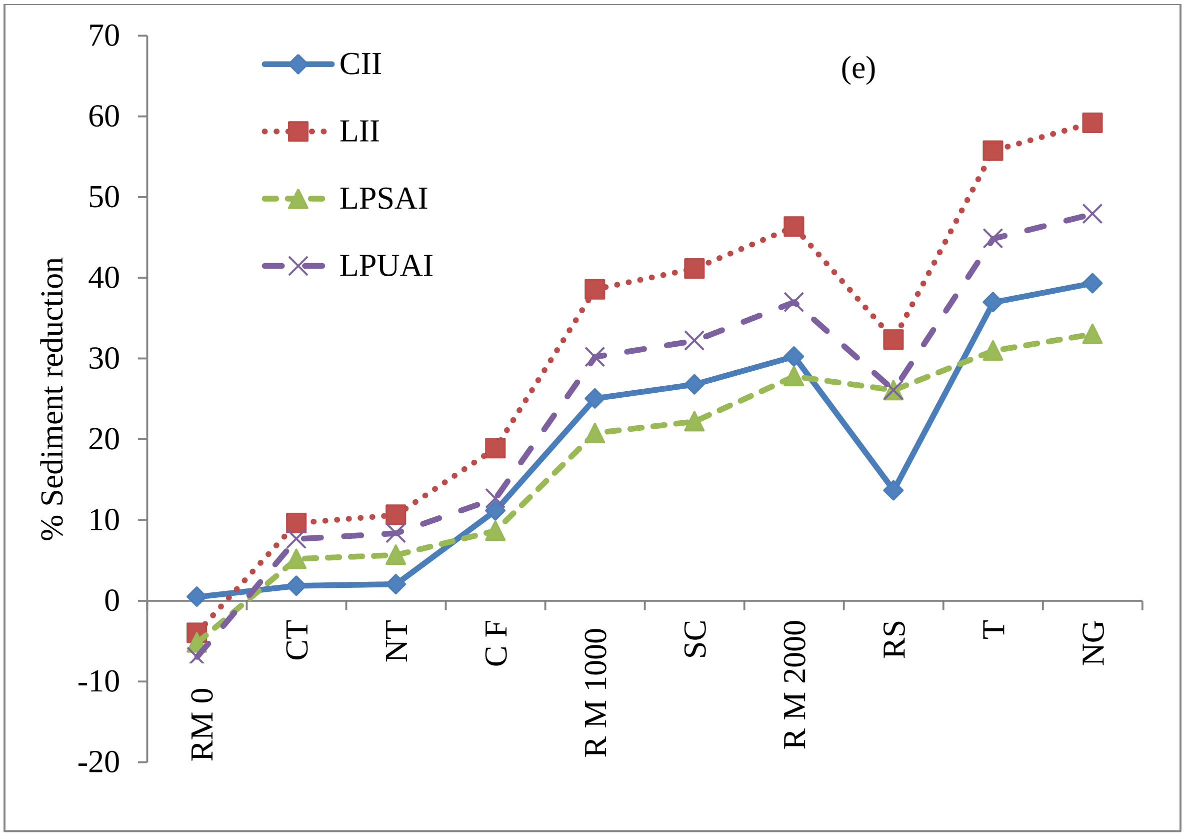

Figure 4-10. (e) Sediment reduction by BMPs in medium priority area in subbasin for different targeting methods without normalizing the BMPs application area.

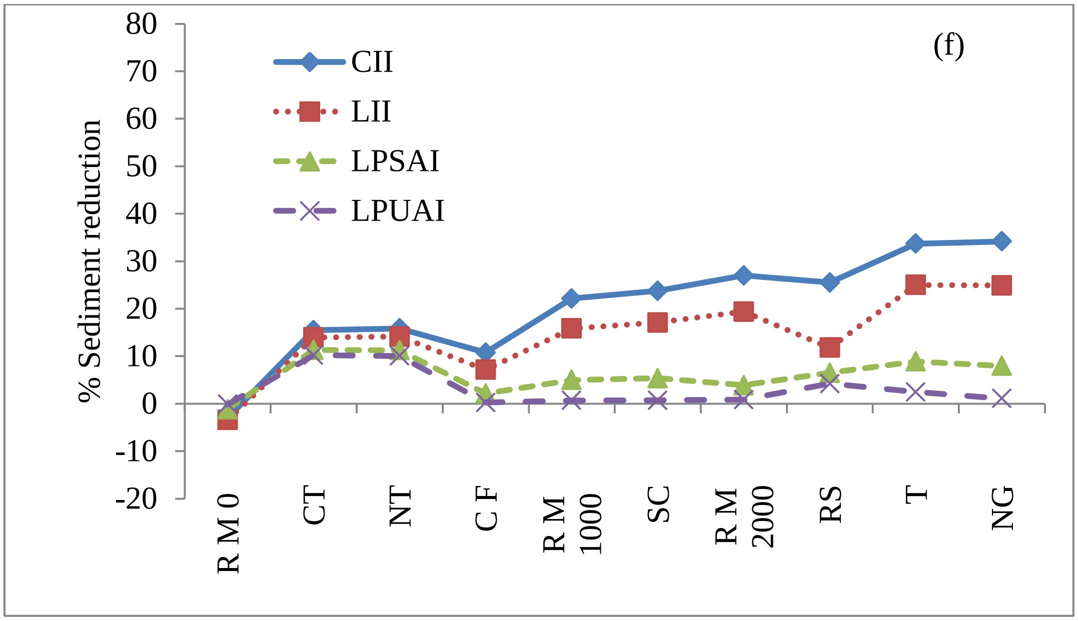

Figure 4-10. (f) Sediment reduction by BMPs in low priority area in subbasin for different targeting methods without normalizing the BMPs application area.

4.4.5.1.2 Sediment reduction after normalizing BMPs application area

The total BMP application area of each targeting scenario was divided by the amount of sediment reduction of each BMP in each targeting method in order to normalize the area of BMP application. The new percentage of sediment reduction in four targeting methods for the watershed outlet and the subbasin is presented in Figure 4-11.

High Priority Area

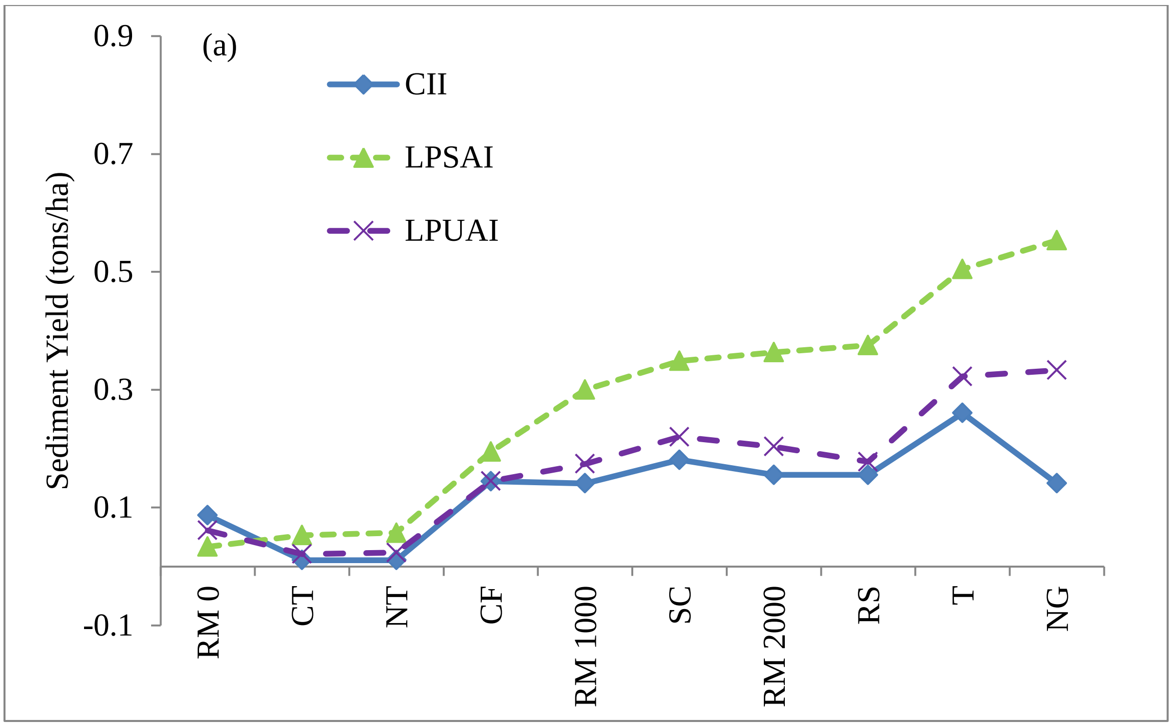

Figure 4-11. (a) Sediment reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

Medium Priority Area

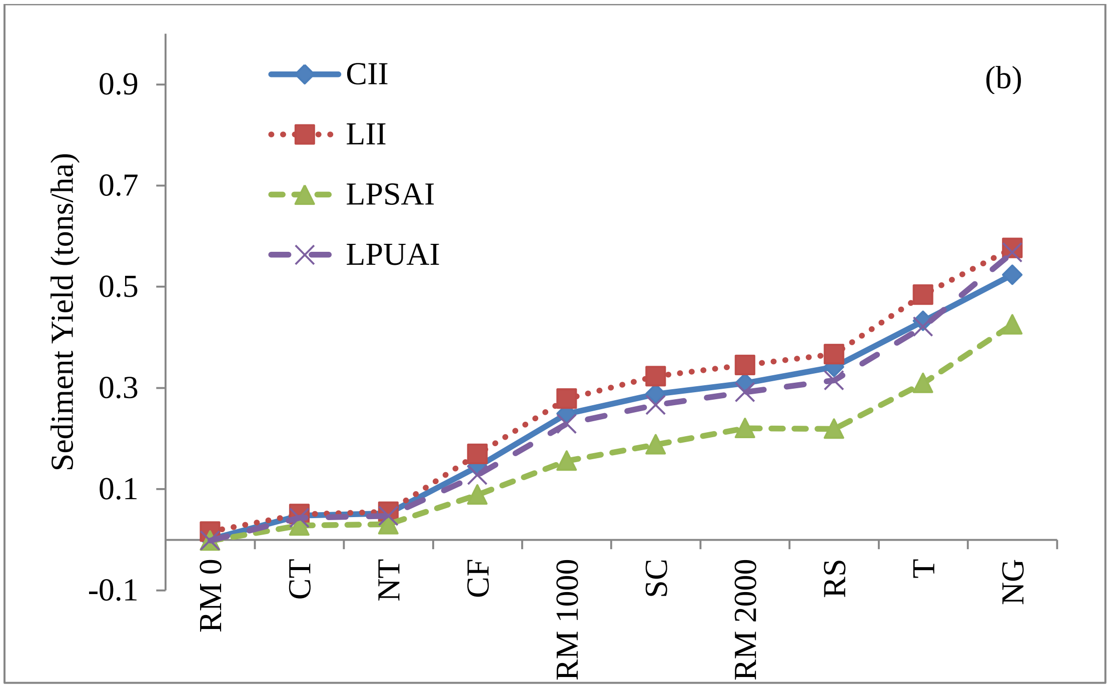

Figure 4-11. (b) Sediment reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

Low Priority Area

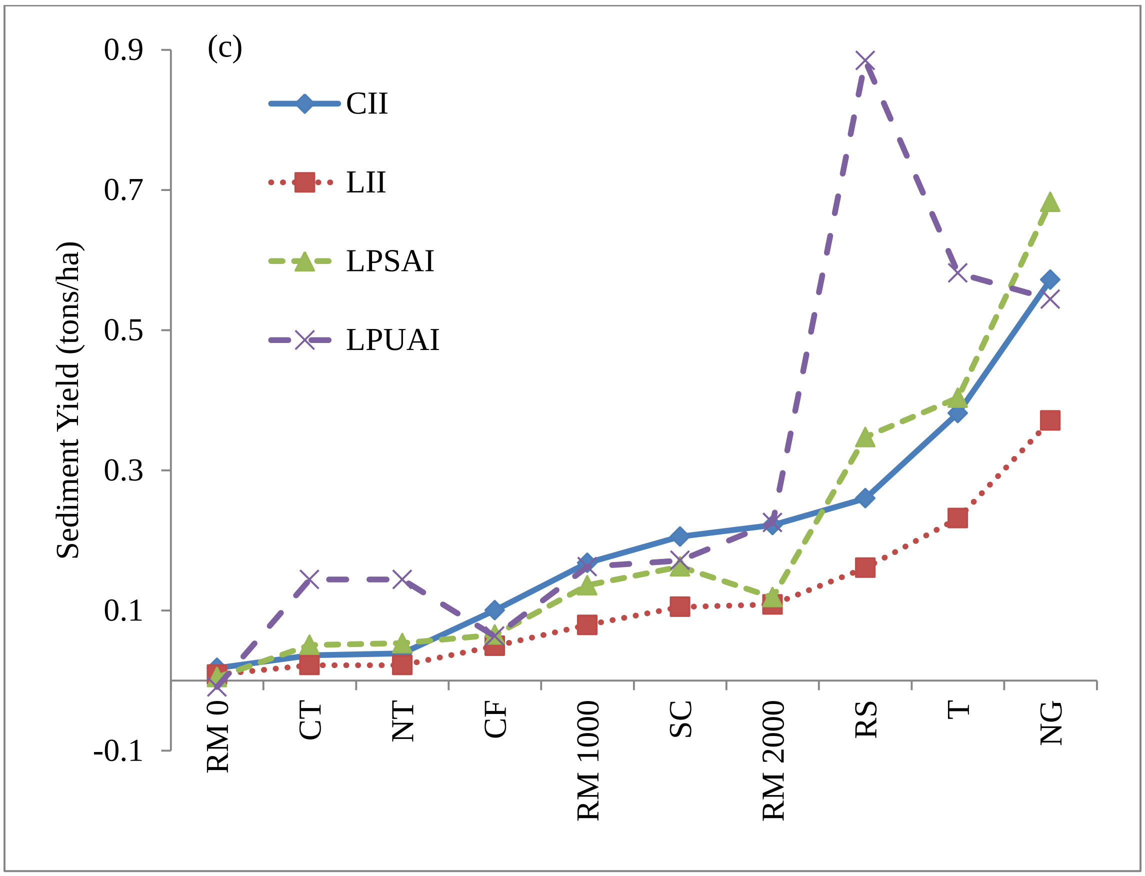

Figure 4-11. (c) Sediment reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

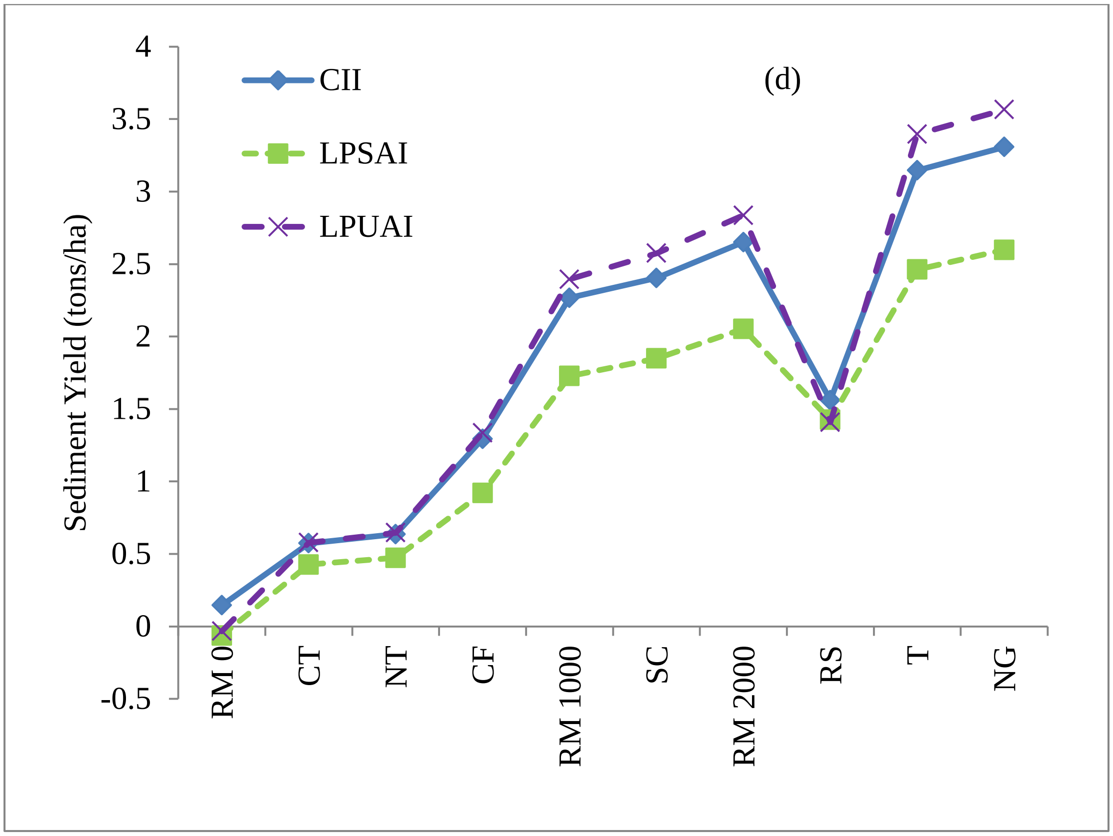

Figure 4-11. (d) Sediment reduction by BMPs in high priority area in subbasin for different targeting methods after normalizing the BMPs application area.

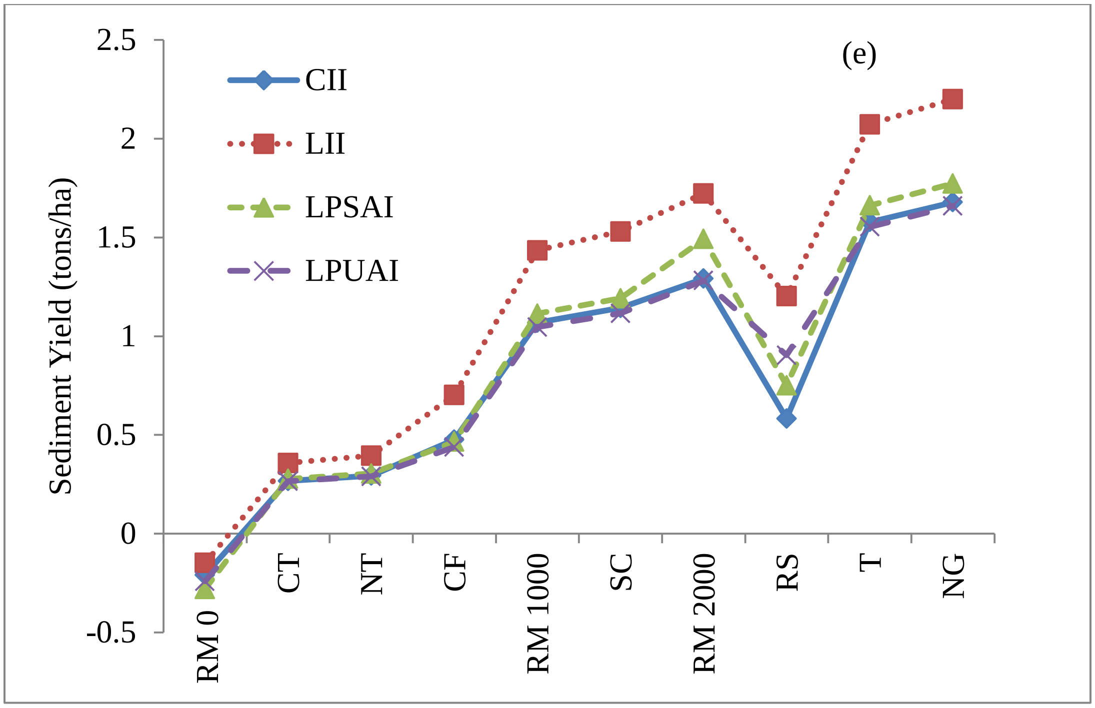

Figure 4-11. (e) Sediment reduction by BMPs in medium priority area in subbasin for different targeting methods after normalizing the BMPs application area.

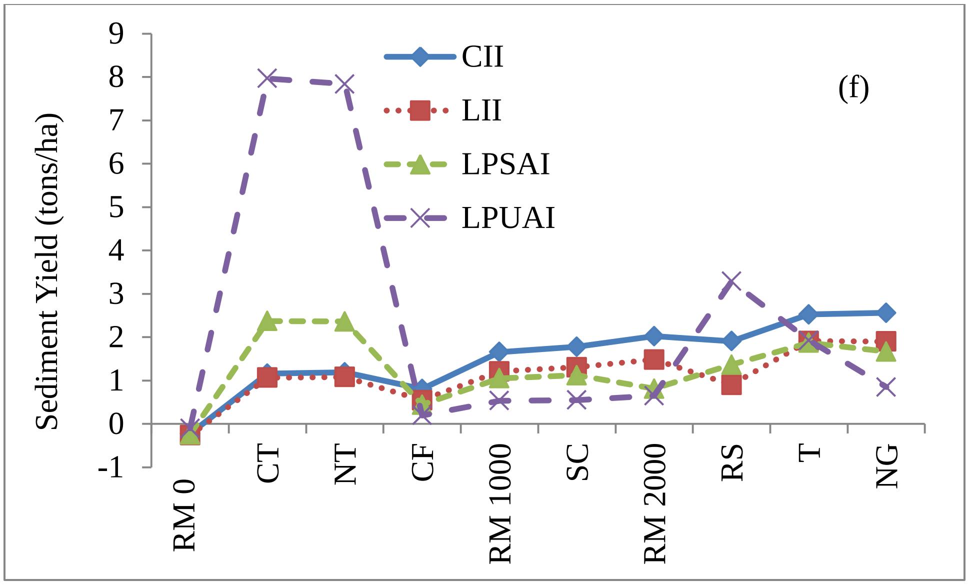

Figure 4-11. (f) Sediment reduction by BMPs in low priority area in subbasin for different targeting methods after normalizing the BMPs application area.

When normalizing for application area, sediment reduction at the watershed outlet had similar trends to the non-normalized reduction. Applying BMPs on the medium priority areas has the greatest impact when normalizing for application area (Figure 4-11a, b, and c). In addition, all targeting methods have relatively similar performance in sediment reduction for all three priorities. In the low priority area, recharge structures have the highest reduction in LPUAI because of the relatively low implementation area coupled with the fact that this BMP is implemented in the reach rather than the field. This indicates that recharge structures are highly effective if sediment reduction at the watershed outlet is a concern.

Normalized sediment reduction at the subbasin level also exhibits a similar trend to the non-normalized reduction (Figure 4-11d, e, and f). Similar to the reach results, the targeting methods had similar normalized percent sediment reduction. The BMP to note from high and medium priority (for all targeting methods) is recharge structures, which is much less effective at the subbasin than at the reach because of the manner in which it is implemented. Under low priority conservation tillage and no tillage have considerably higher normalized sediment reduction for the LPUAI method, which is also true for the non-normalized case. This is likely due to the limited area of agricultural land attributed to low priority in this method coupled with the relatively high sediment reduction under low priority for these BMPs.

4.4.5.2 TN Reduction

4.4.5.2.1 TN reduction without normalizing BMPs application area

At the watershed outlet, varying percent TN reduction was observed based on targeting method, priority area, and BMP (Figure 4-12a, b, and c). Overall, native grass and terraces have the highest reduction efficiencies, while no tillage and conservation tillage have the lowest. BMP application on high priority areas generally has the highest percent TN reduction at the watershed outlet, while low priority is the lowest. This indicates that targeting TN high priority areas is a viable solution to reducing TN loads at the watershed outlet, regardless of the targeting method. Meanwhile, there are two methods (LPUAI-medium priority and LII-low priority) that have much higher reduction efficiencies than other methods in the same priority. In the case of LPUAI this is because the method identified a large area of medium priority, therefore the BMPs were applied on a larger scale. For LII under low priority, the reduction efficiency is much higher because most agricultural land in this scenario was identified to be low priority, increasing BMP application area. This also indicates that LII may be misleading, because application on medium priority areas is much less efficient. Therefore, it may not always be optimal to place BMPs near the watershed outlet just because the TN load is higher at that location.

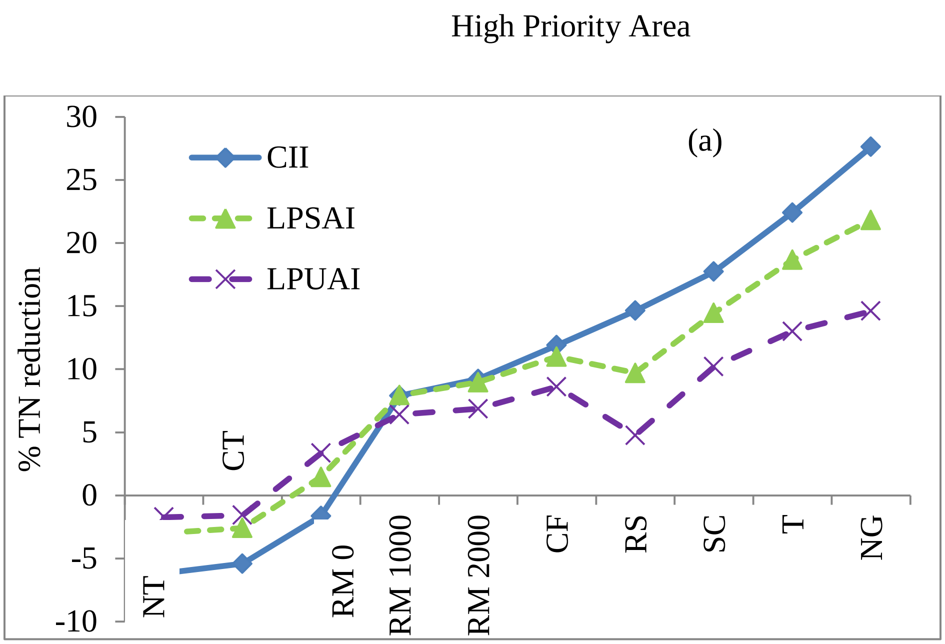

Figure 4-12. (a) TN reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Medium Priority Area

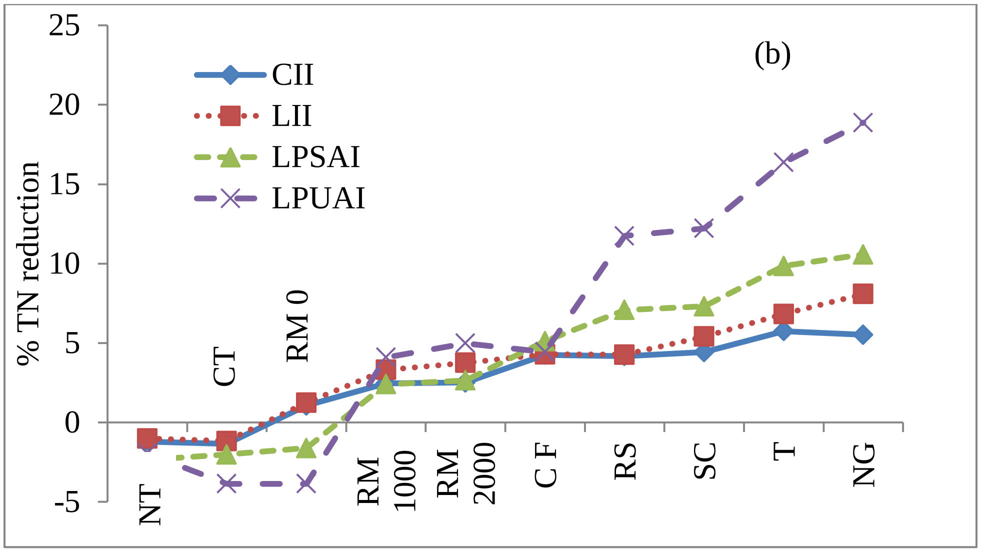

Figure 4-12. (b) TN reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Low Priority Area

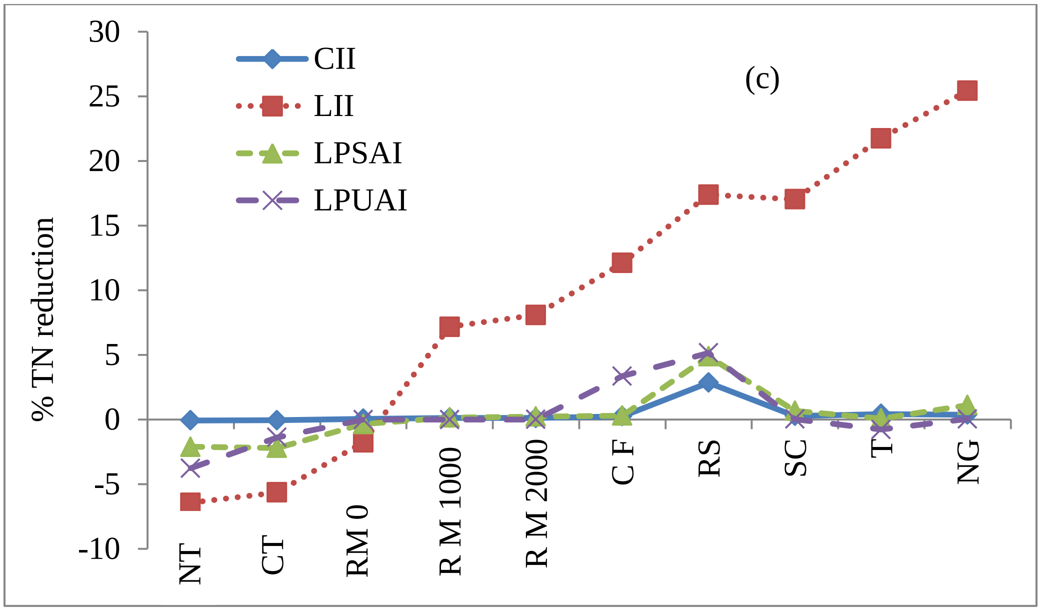

Figure 4-12. (c) TN reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

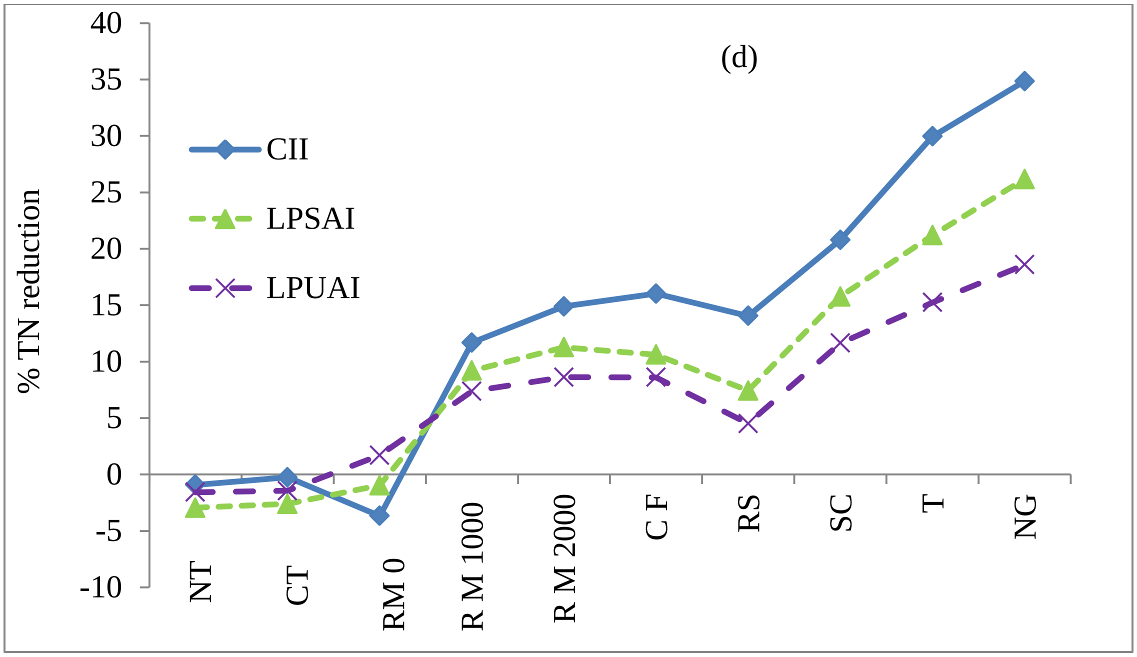

Figure 4-12. (d) TN reduction by BMPs in high priority area in subbasin for different targeting methods without normalizing the BMPs application area.

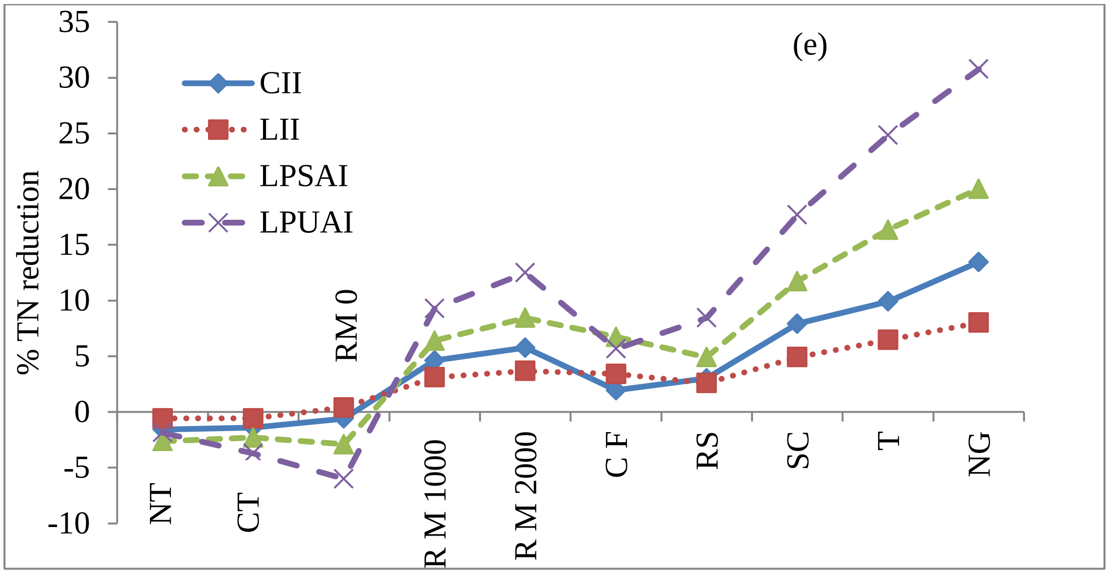

Figure 4-12. (e) TN reduction by BMPs in medium priority area in subbasin for different targeting methods without normalizing the BMPs application area.

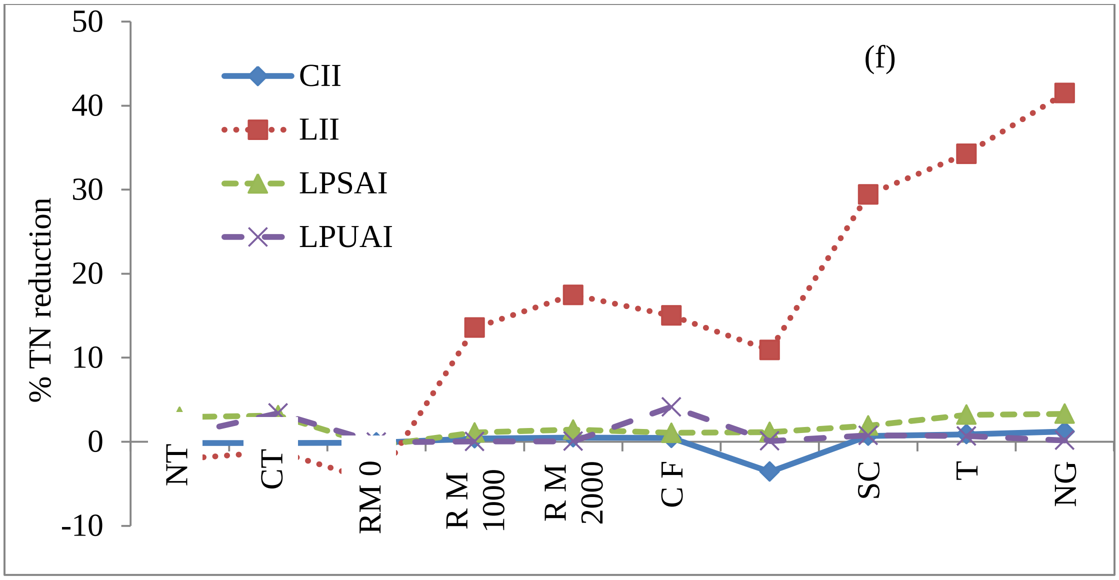

Figure 4-12. (f) TN reduction by BMPs in low priority area in subbasin for different targeting methods without normalizing the BMPs application area.

The subbasin level generally exhibits the same reduction patterns that are observed at the watershed outlet. Native grass and terraces have the highest percent TN reduction for any targeting method and priority, while no till, conservation tillage, and residue management (0 kg/ha) are generally the least effective. The contrast in efficiencies is likely due to the manner of intensive implementation for native grass and terraces. Overall, BMP application on high priority areas has the greatest percent TN reduction, while low priority has the lowest (except for the LII method). The LII method on low priority areas has higher reduction at the subbasin level primarily because this method identified most agricultural area as low priority. In most cases, there is a positive correlation between area of BMP application based on the targeting method and that method's percent TN reduction. However, recharge structures have a negative reduction of TN at the subbasin level, while a positive reduction was observed in the reach. This may be due to the fact that this BMP is implemented in the main channel (reach) rather than in the field.

4.4.5.2.2 TN reduction after normalizing BMPs application area

The BMPs application area for TN targeting scenario for four targeting methods were variable. Therefore, the percentage of TN reduction before normalization was divided by the total BMP application area in order to obtain the normalized percentage of TN reduction.

At the watershed outlet, the normalized percent TN reduction follows trends that are similar to the non-normalized reduction, although some trends are more pronounced (Figure 4-13a, b, and c). For example, the LII method on medium priority becomes the most effective because normalization reveals that the BMPs under this targeting scenario have the greatest reduction because of limited application area. Similarly, LPUAI on high priority becomes the most efficient after normalization because this method only identifies a small area of the watershed that is high priority. Therefore, it can be said that the LPUAI method requires less investment in application (due to the limited high priority area) while still producing large percent TN reduction at the watershed outlet. Low priority areas for the CII, LII, and LPSAI methods have percent TN reductions close

to zero for all BMPs, indicating their limited effectiveness at TN reduction at the watershed outlet when applied across broad low priority areas. Conversely, the LPUAI method on low priority identified a limited number of low priority areas defined as agriculture and observed increased reduction for contour farming and recharge structures.

High Priority Area

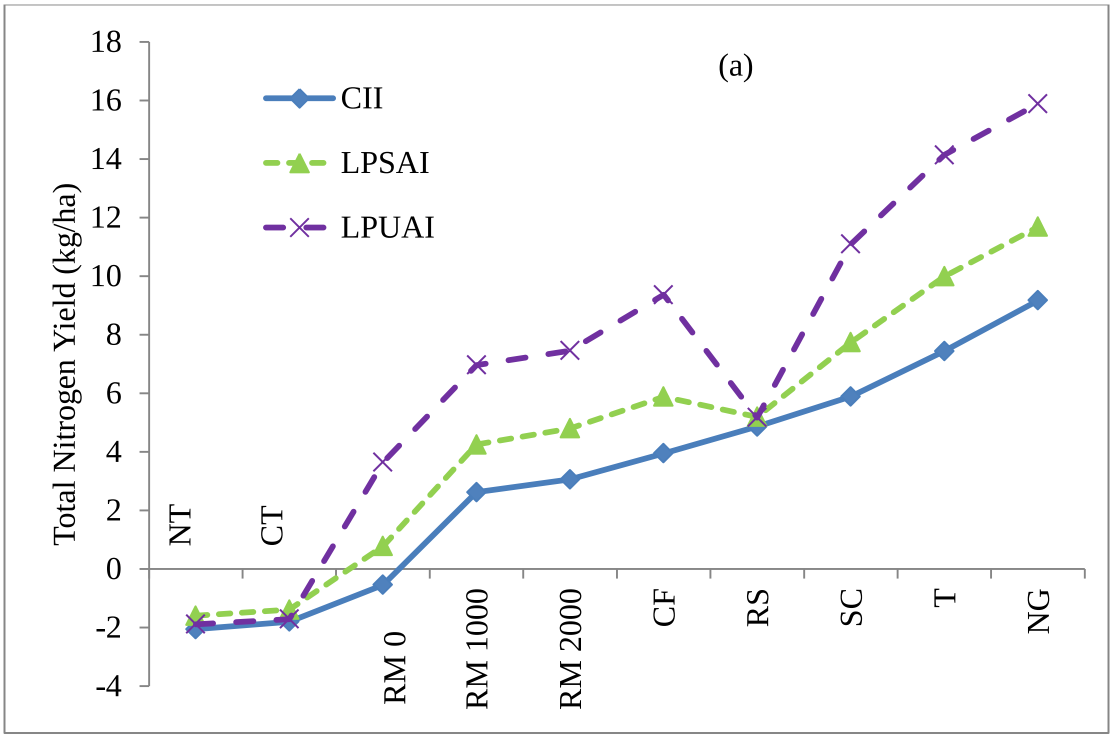

Figure 4-13. (a) TN reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

Medium Priority Area

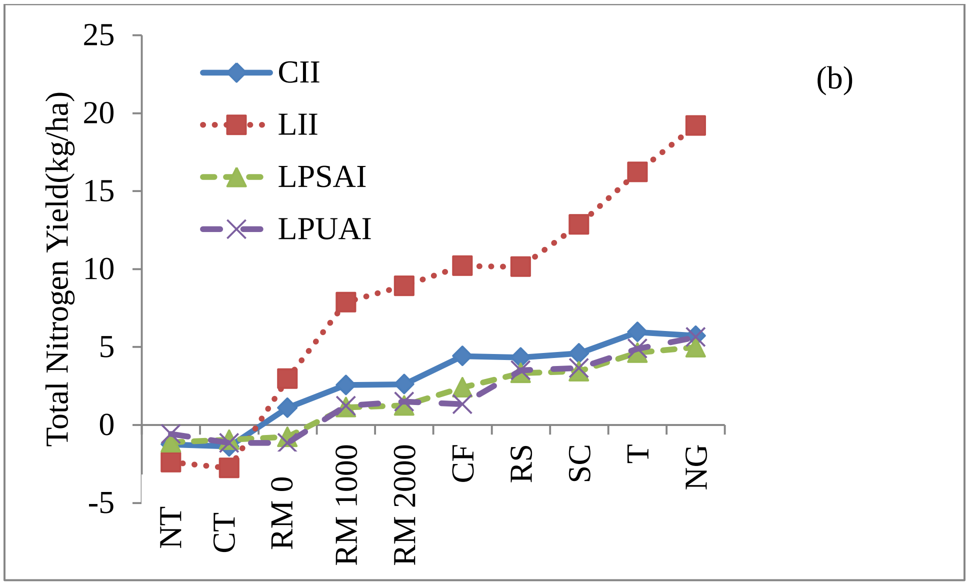

Figure 4-13. (b) TN reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

Low Priority Area

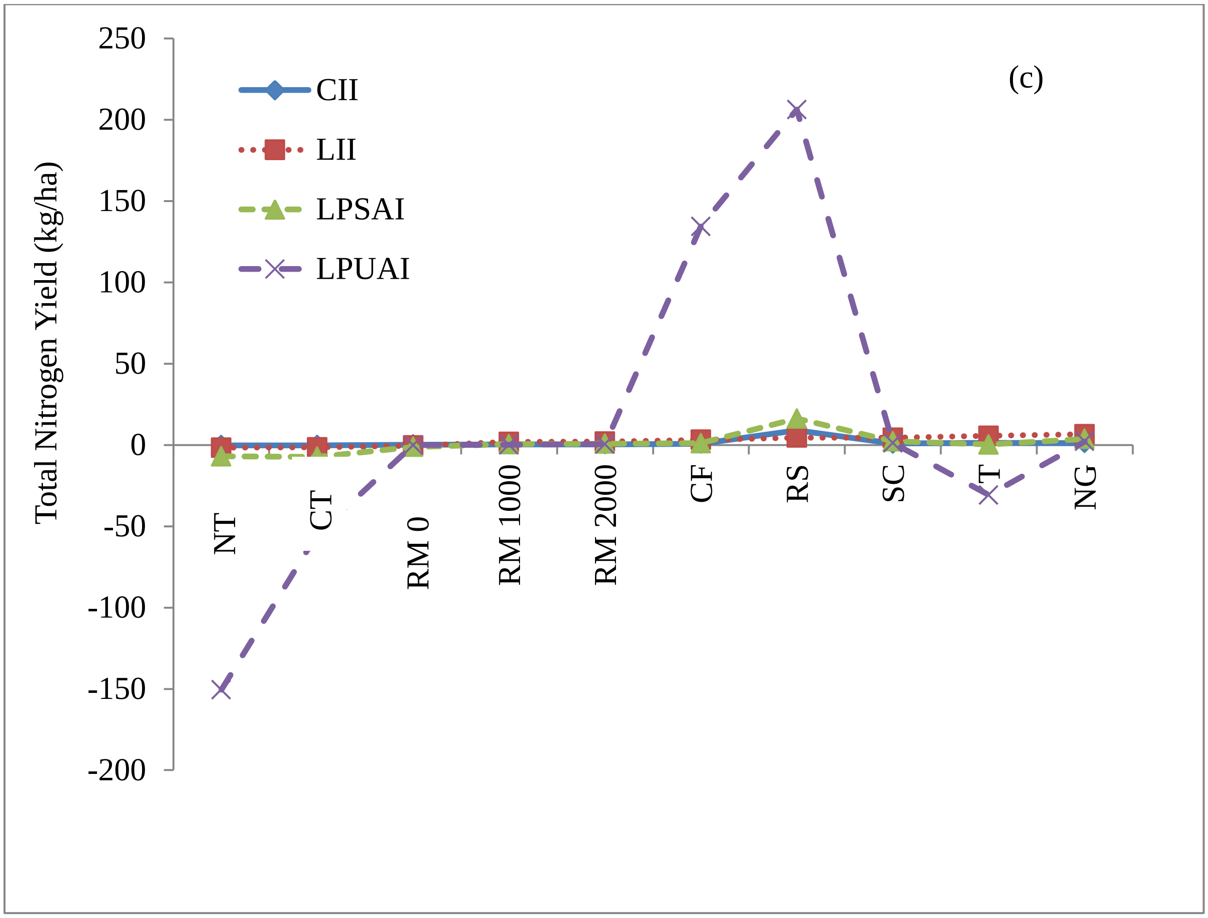

Figure 4-13. (c) TN reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

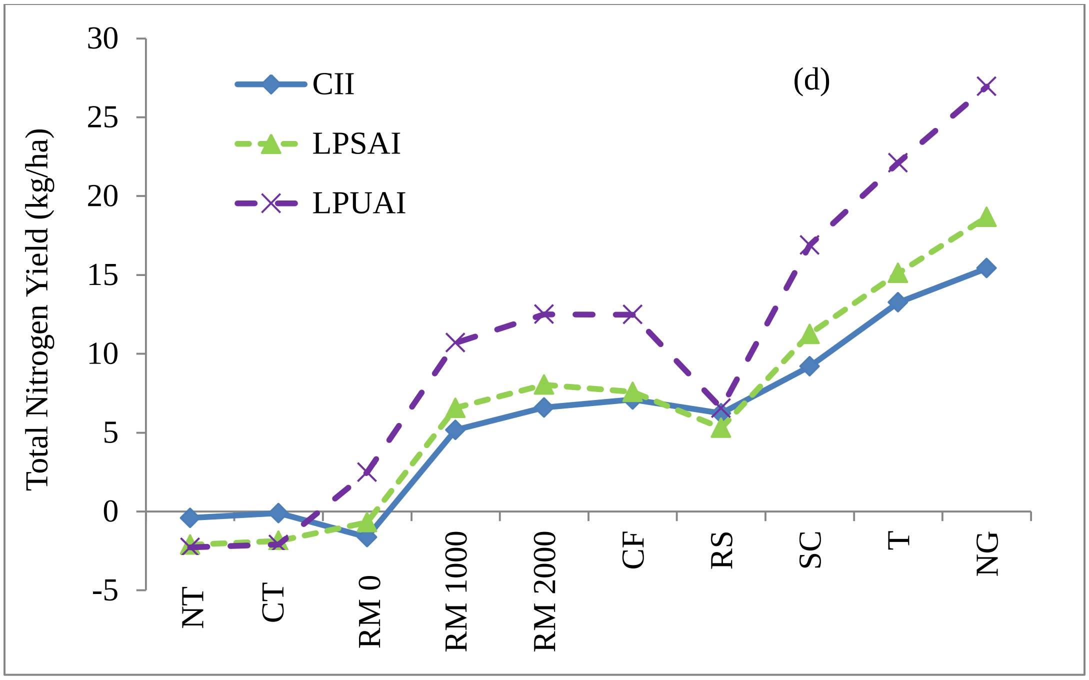

Figure 4-13. (d) TN reduction by BMPs in high priority area in subbasin for different targeting methods after normalizing the BMPs application area.

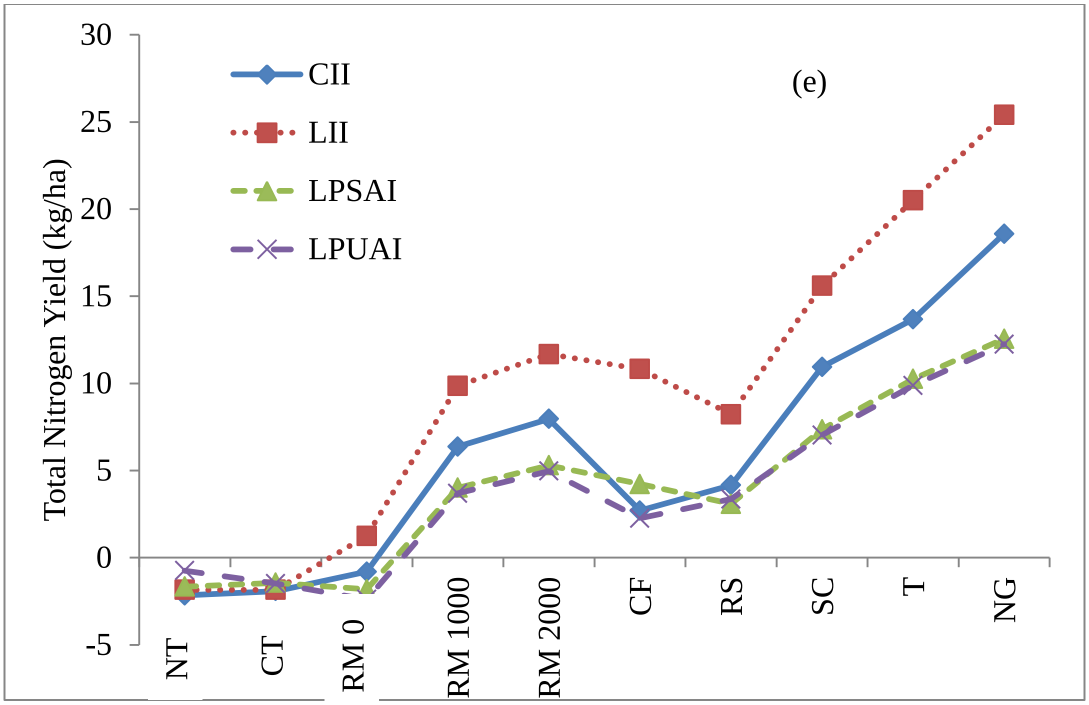

Figure 4-13. (e) TN reduction by BMPs in medium priority area in subbasin for different targeting methods after normalizing the BMPs application area.

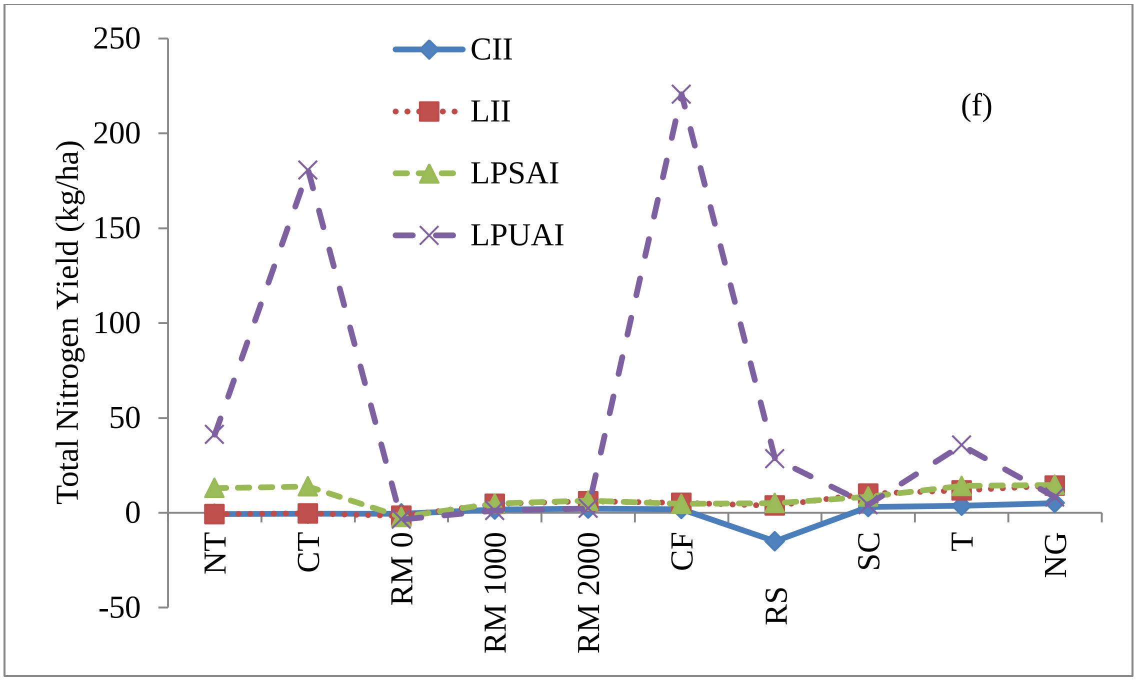

Figure 4-13. (f) TN reduction by BMPs in low priority area in subbasin for different targeting methods after normalizing the BMPs application area.

At the subbasin, trends observed in the non-normalized percent TN reduction are amplified in the areal normalization (Figure 4-13d, e, and f). Consistent with sediment, native grass and terraces are generally the most efficient. Under high priority, the LPUAI targeting becomes the most efficient because of the limited agricultural area identified as high priority. The situation is similar for the medium priority LII targeting method. This indicates that on a reduction per area basis, these two targeting methods have the highest efficiency. For low priority areas, the LPUAI method has predominantly higher reduction efficiencies because most land applicable for BMPs was identified as high or medium priority, therefore what is applied on low priority will have a large impact in this case.

4.4.5.3 TP Reduction

4.4.5.3.1 TP reduction without normalizing BMPs application area

Percent reduction of TP at the watershed outlet varies widely between targeting method and priority area (Figure 4-14a, b, and c). As with sediment and TN, native grass and terraces have the greatest percent reduction overall, while residue management, no tillage, and conservation tillage have the smallest percent reduction. Under high priority areas, CII and LPSAI are generally the most effective at TP reduction at the watershed outlet because the agricultural high priority areas identified are largest. Medium priority areas generally have less than 10% TP reduction for all BMPs and targeting methods. This indicates that regardless of targeting method, BMP placement on medium priority areas has limited impact at the watershed outlet. Most BMPs and targeting methods have close to 0% TP reduction, except for the LII method. The impact of BMP placement under LII is more substantial in this case because there is a large amount of agricultural land identified as low priority. A negative reduction of TP was observed by residue management (0 kg/ha), no till, and conservation tillage at both reach and subbasin level. This may be due to higher concentration of dissolved phosphorus in the runoff. A similar result was observed by Bundy et al. (2001) in which they found increased dissolve phosphorus concentration from no till corn fields.

Similar trends are observed at the subbasin level as those at the watershed outlet (Figure 4-14d, e, and f). BMP application on high priority areas generally has the greatest impact on percent TP reduction. The targeting methods have the most variable reductions under medium priority, which is likely because each method selected very different areas of medium priority agricultural land. For low priority, the reach based methods (CII and LII) have the greatest percent TP reduction, which is likely because these methods selected the most low priority area. This indicates that the reach based methods may not be applicable for TP reduction at the subbasin, because it is more beneficial to have greater reduction on areas identified as high priority because implementation is more likely to occur there.

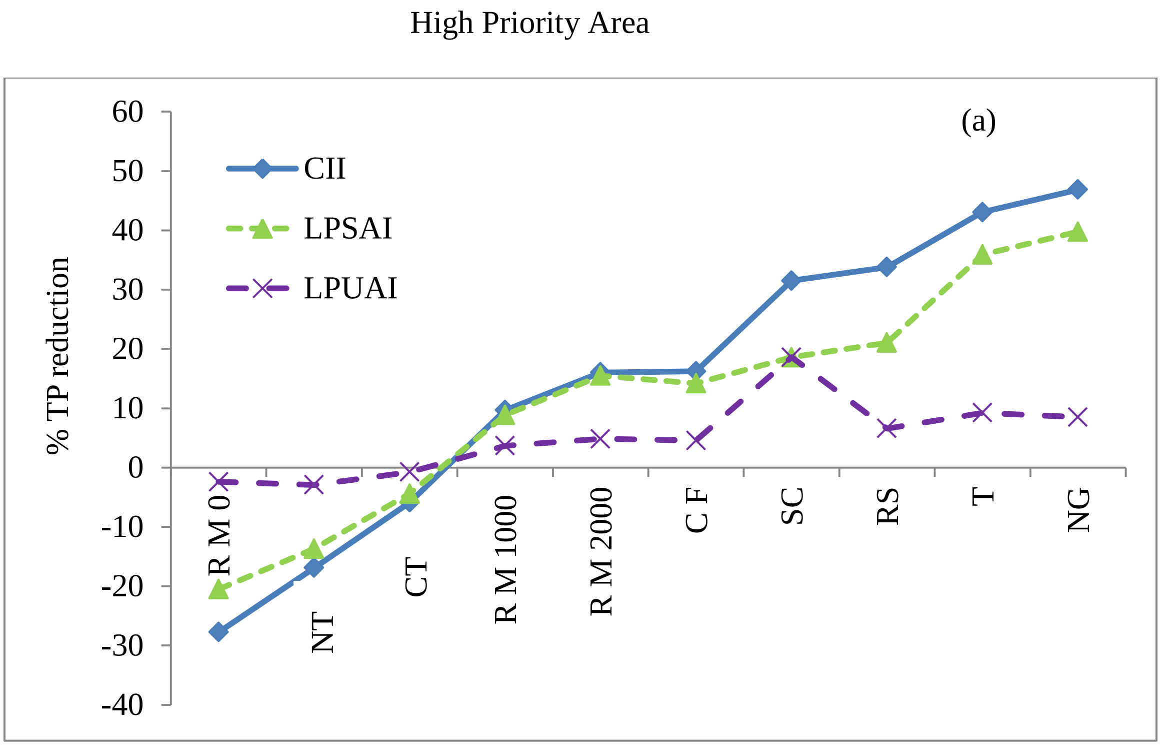

Figure 4-14. (a) TP reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Medium Priority Area

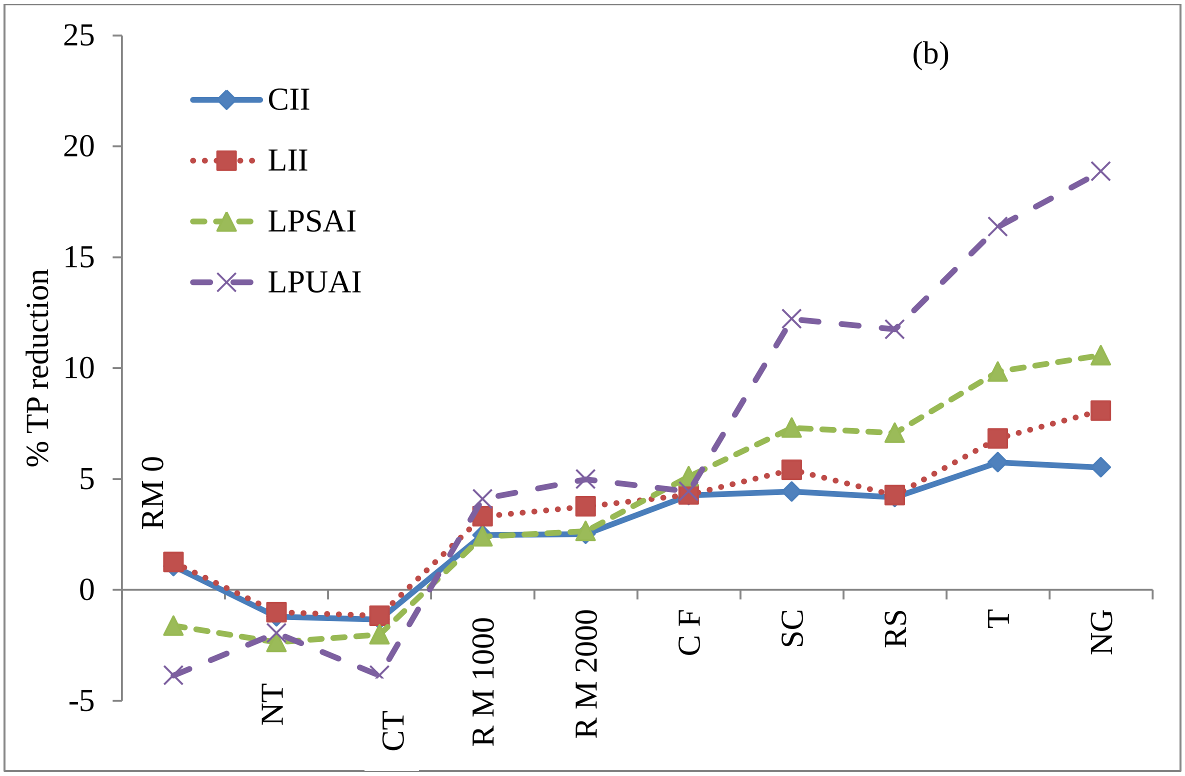

Figure 4-14. (b) TP reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

Low Priority Area

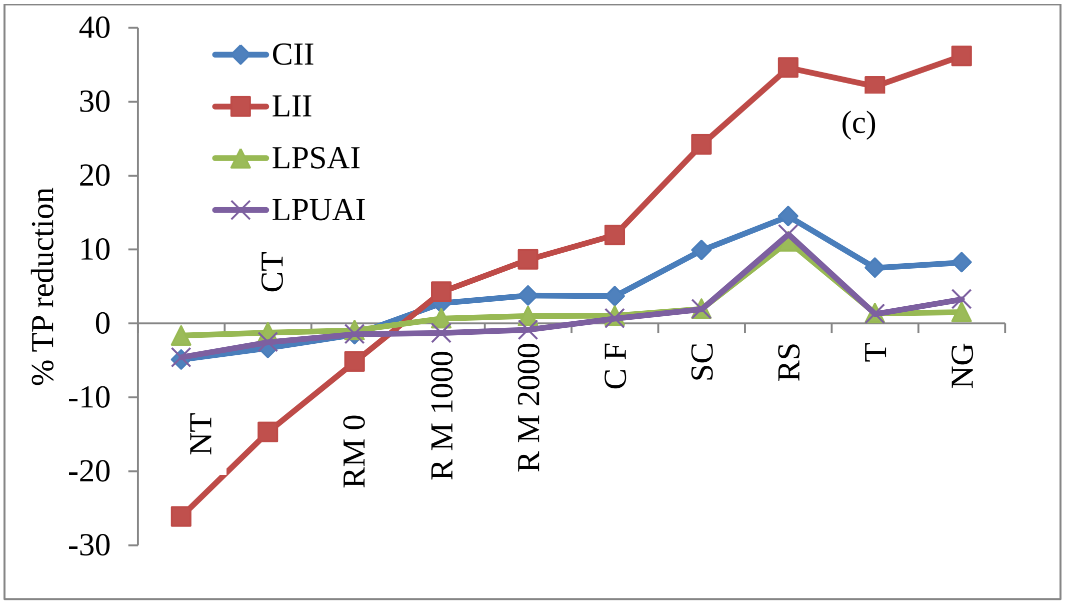

Figure 4-14. (c) TP reduction by BMPs in reach for different targeting methods without normalizing the BMPs application area.

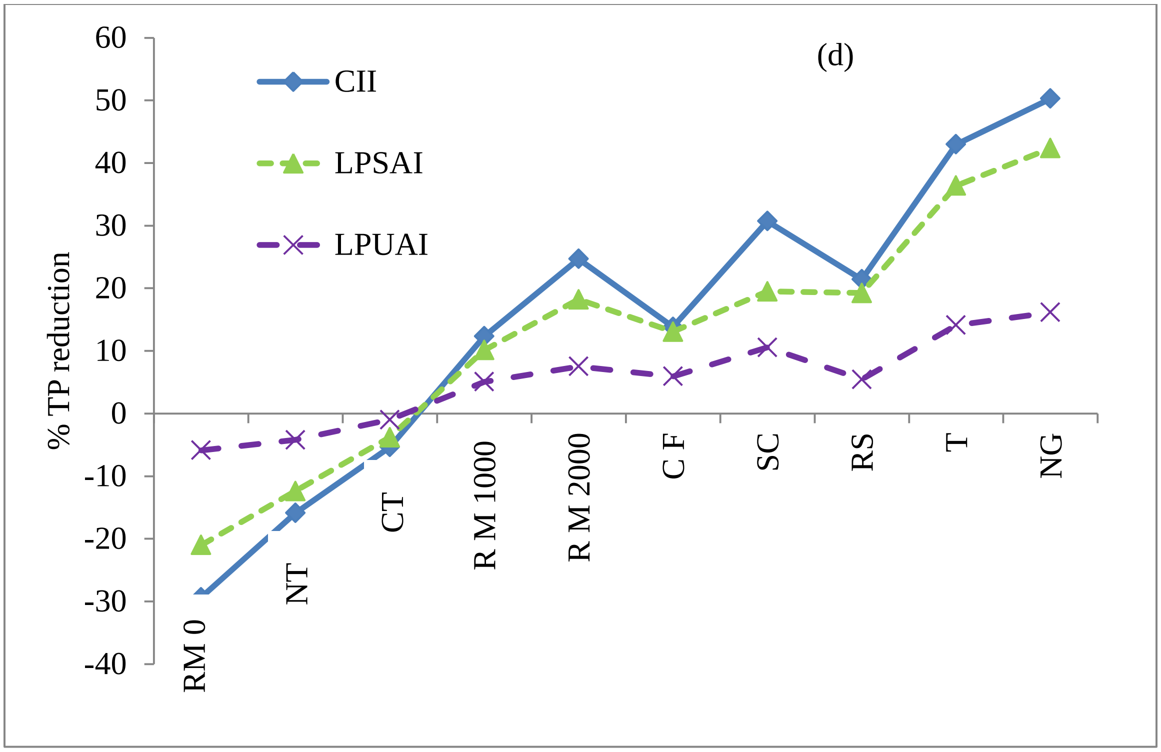

Figure 4-14. (d) TP reduction by BMPs in high priority area in subbasin for different targeting methods without normalizing the BMPs application area.

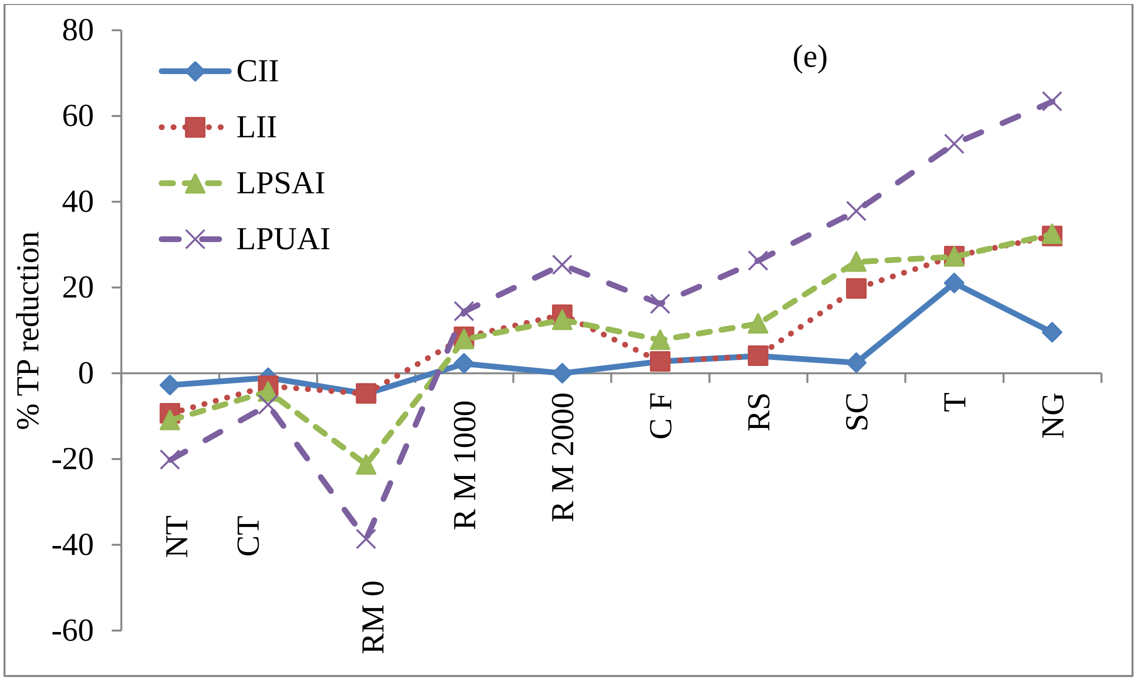

Figure 4-14. (e) TP reduction by BMPs in medium priority area in subbasin for different targeting methods without normalizing the BMPs application area.

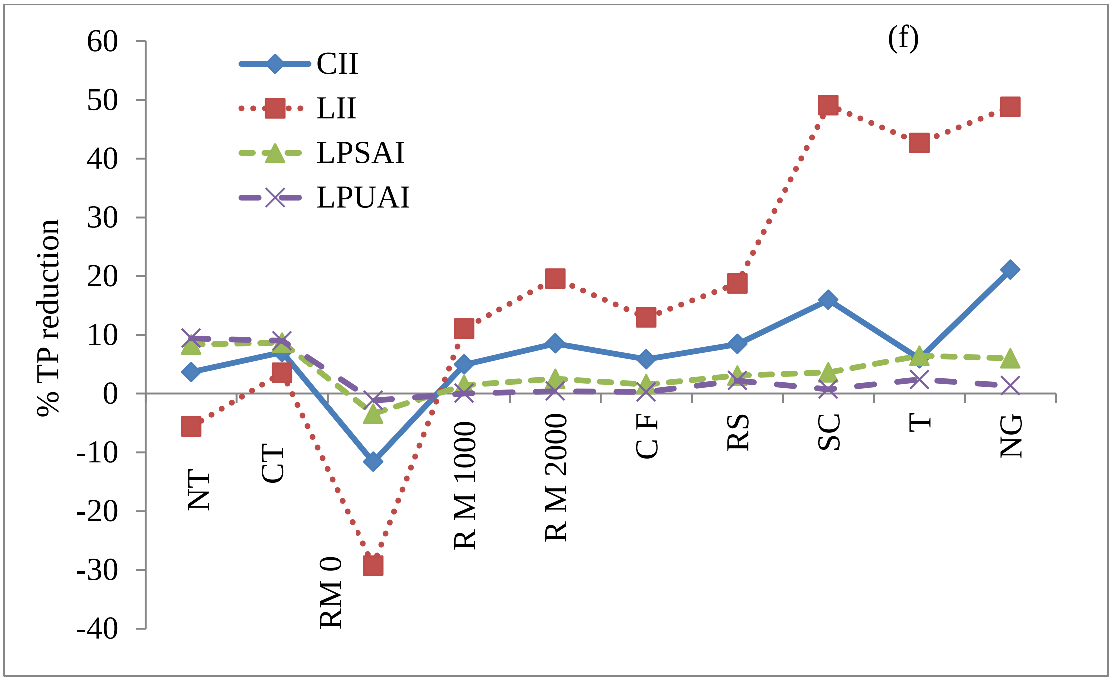

Figure 4-14. (f) TP reduction by BMPs in low priority area in subbasin for different targeting methods without normalizing the BMPs application area.

4.4.5.3.2 TP reduction after normalizing BMPs application area

Percent TP reduction at the watershed outlet normalized by area exhibits uniformity across targeting methods, while high, medium, and low priorities have similar efficiencies (Figure 4-15a, b, and c). Native grass and terraces are still the most efficient BMPs, although other BMPs have similar efficiencies. High and medium priority areas have similar results for all targeting methods, indicating that no BMP or targeting method is superior when examining percent TP reduction per area. In the case of low priority areas, recharge structures for LPUAI have significantly greater reduction efficiency, which is likely because recharge structures are implemented in stream and the amount of low priority area in this method is minimal. However, for some BMPs, such as no till, conservation tillage, residue management 0 kg/ha, residue management 1000 kg/ha, and residue management 2000 kg/ha, produced negative TP reduction at reach (Figure 4-15 c) based on LPUAI targeting method in low priority areas.

At the subbasin level, trends are similar to the reach for the normalized percent TP reduction (Figure 4-15d, e, and f). All priority areas have similar normalized percent TP reduction, although high priority areas have the greatest reduction. In addition, all targeting methods produce similar results when BMPs are applied. Therefore, on a per area basis, any targeting method or BMP is likely to have similar normalized percent TP reduction. The exceptions to this are no tillage and conservation tillage on low priority for the LPSAI and LPUAI methods, which is likely due to the limited area identified as low priority. Consequently, when targeting with the LPSAI or LPUAI it is advisable to implement conservation or no tillage practices to get the most percent TP reduction at the subbasin level.

High Priority Area

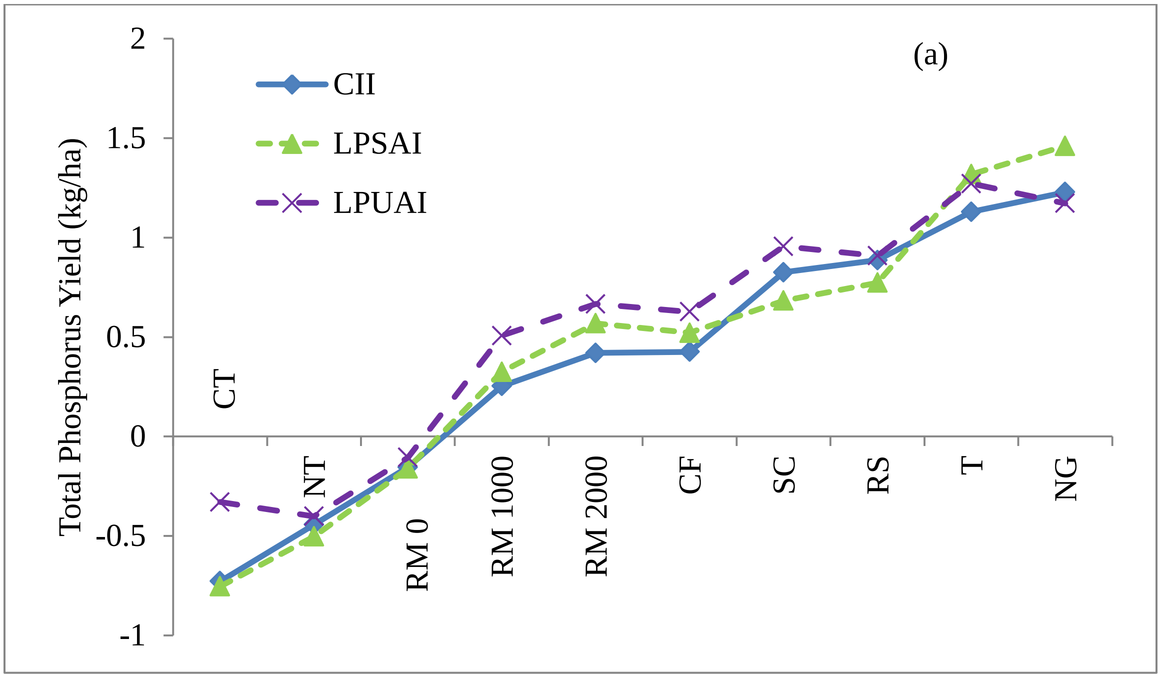

Figure 4-15. (a) TP reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

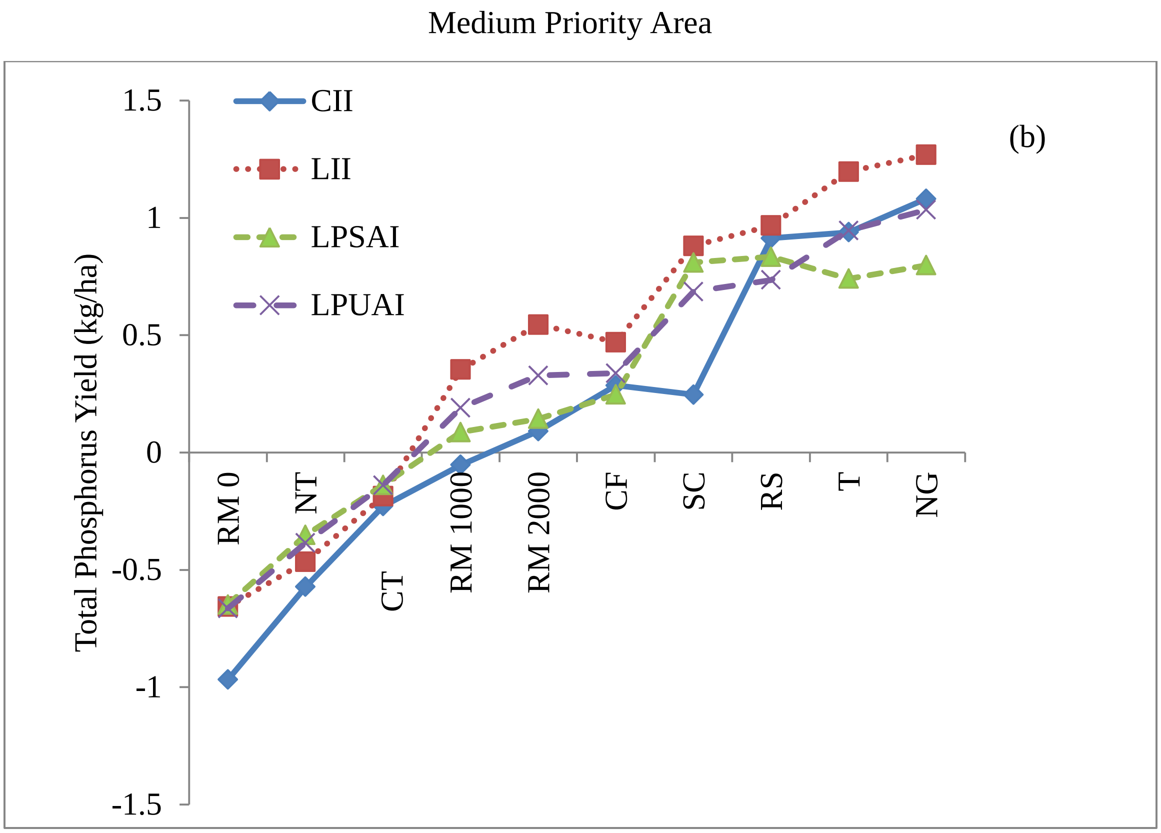

Figure 4-15. (b) TP reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

Low Priority Area

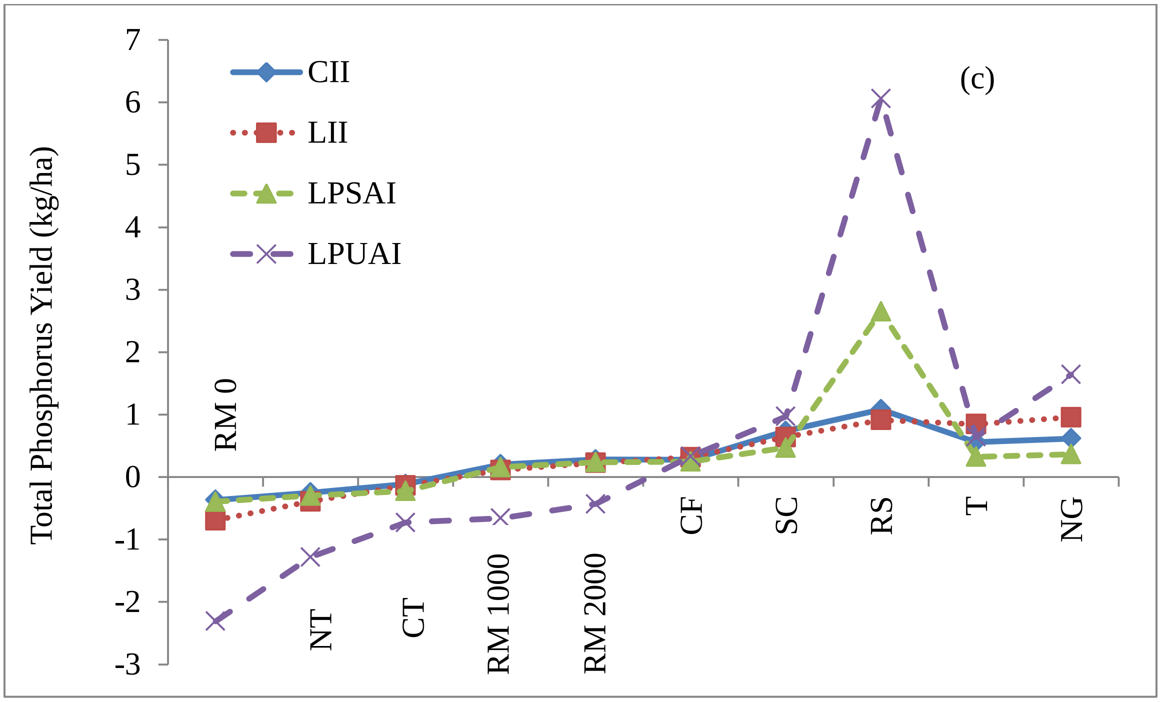

Figure 4-15. (c) TP reduction by BMPs in reach for different targeting methods after normalizing the BMPs application area.

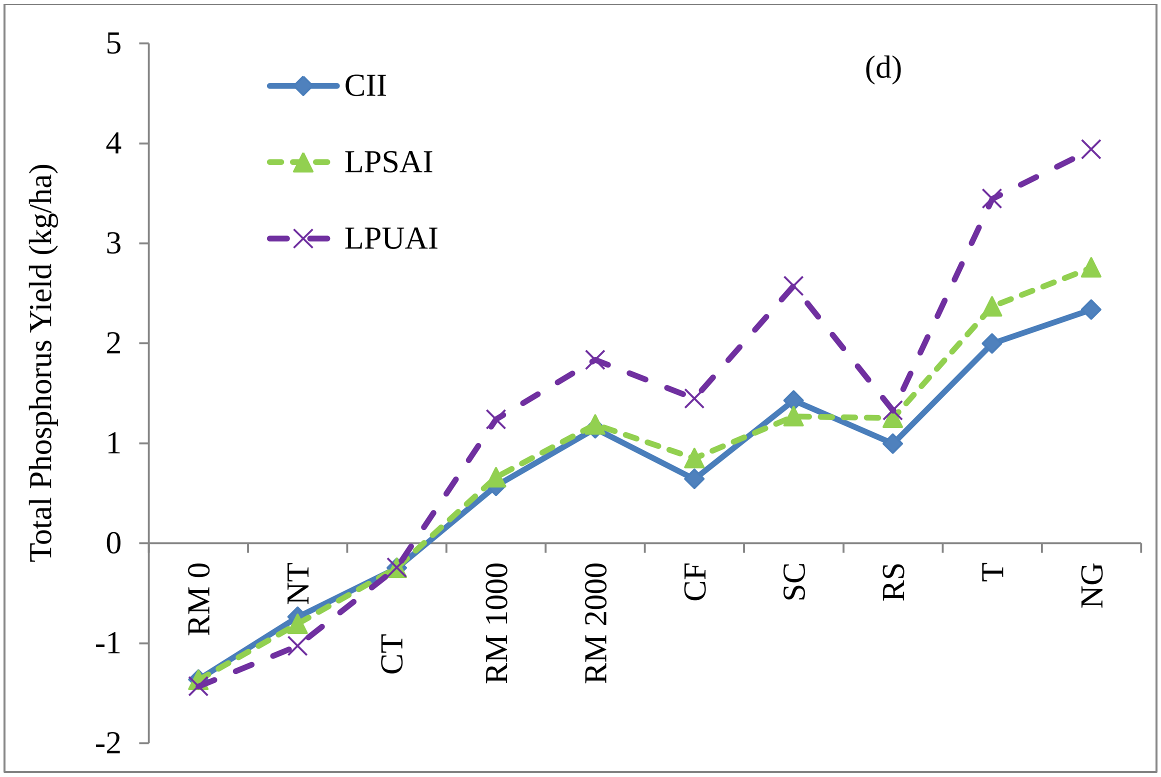

Figure 4-15. (d) TP reduction by BMPs in high priority area in subbasin for different targeting methods after normalizing the BMPs application area.

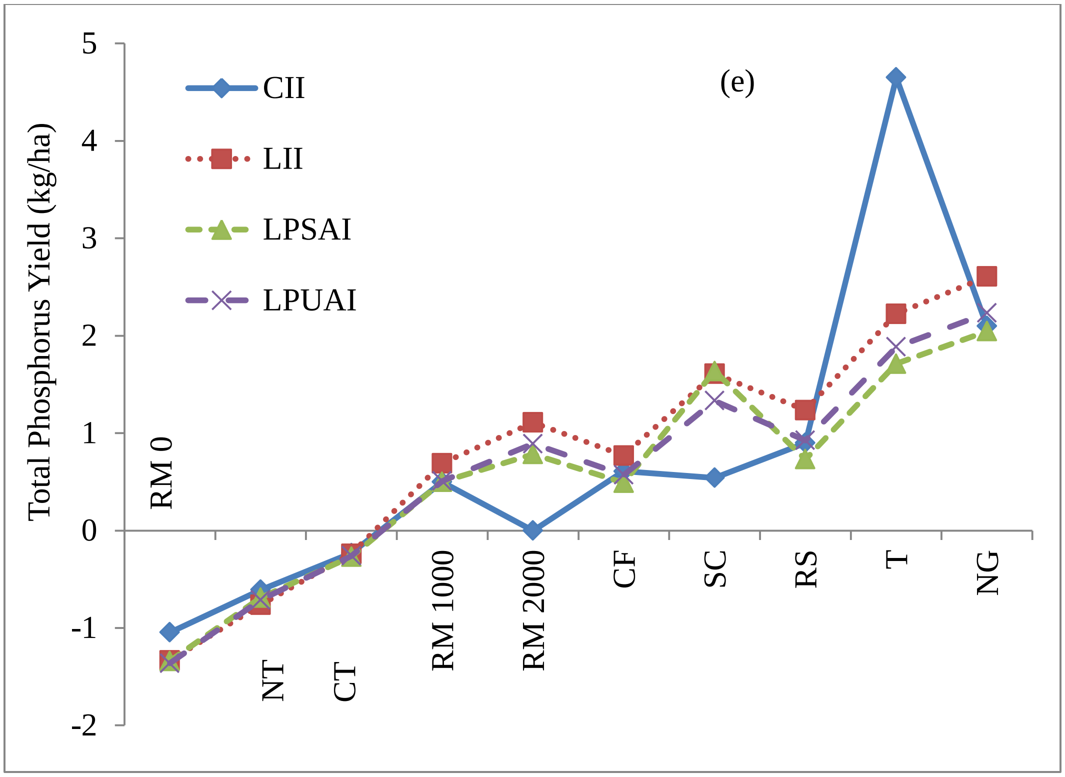

Figure 4-15. (e) TP reduction by BMPs in medium priority area in subbasin for different targeting methods after normalizing the BMPs application area.

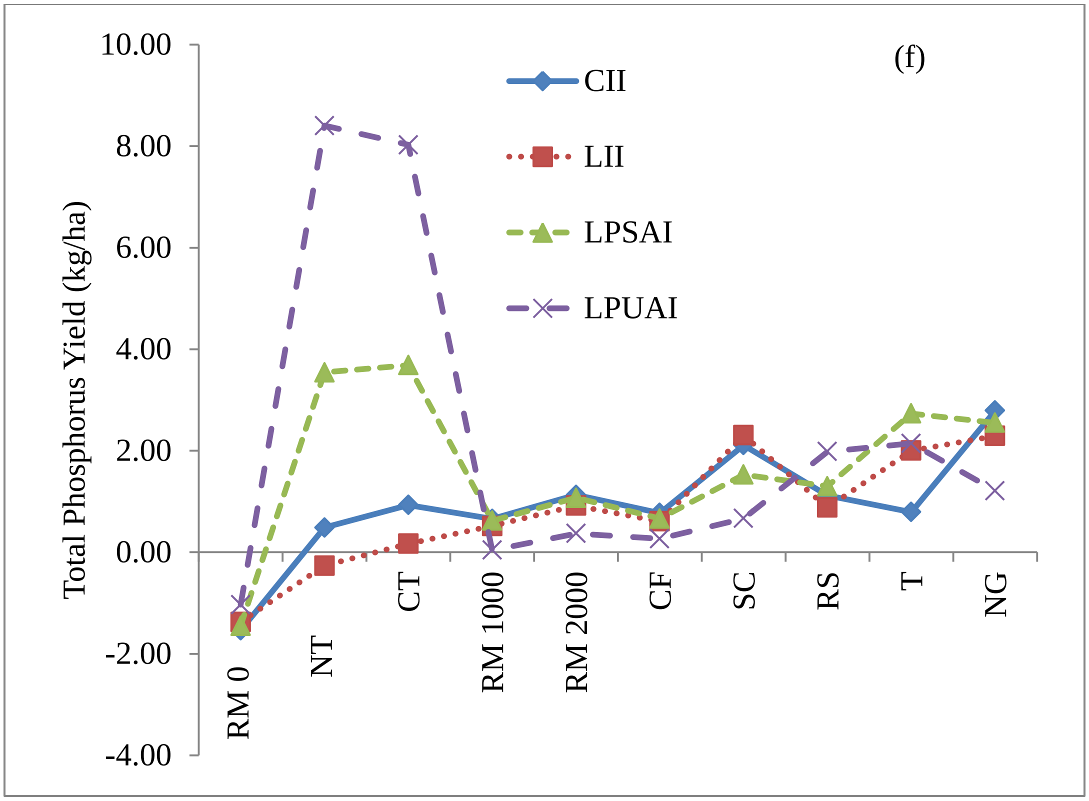

Figure 4-15. (f) TP reduction by BMPs in low priority area in subbasin for different targeting methods after normalizing the BMPs application area.

4.4.6 Evaluation of Relative Sensitivity Index among Targeting Methods

Evaluation of relative sensitivity index allows for comparison of the pollution reduction tendencies of the targeting methods combined with priority level. Eleven scenarios were plotted (all possible combinations of targeting method and priority area) in Figure 4-16. The median and the 25th and 75th percentile sensitivity index across all BMPs for each sensitivity scenario were included to identify variability in subbasin versus watershed outlet pollution reduction. The median relative sensitivity index for most sensitivity scenarios is close to one with little variability, indicating that reducing pollution at the subbasin level causes a proportional reduction at the watershed outlet. Meanwhile, CII-high and LPUAI-high have a high relative sensitivity index for all three pollutants, while the LII-medium scenario is highly variable for nutrients.

4.4.6.1 Sediment Targeting Scenario

For sediment relative sensitivity index, most scenarios had a median close to one with little variability (Figure 4-16a). The CII-high and LPUAI-high were the only sensitivity scenarios with large variability and median relative sensitivities greater than one. A high relative sensitivity index indicates that there is a much greater proportion of reduction occurring at the subbasin level rather than at the watershed outlet.

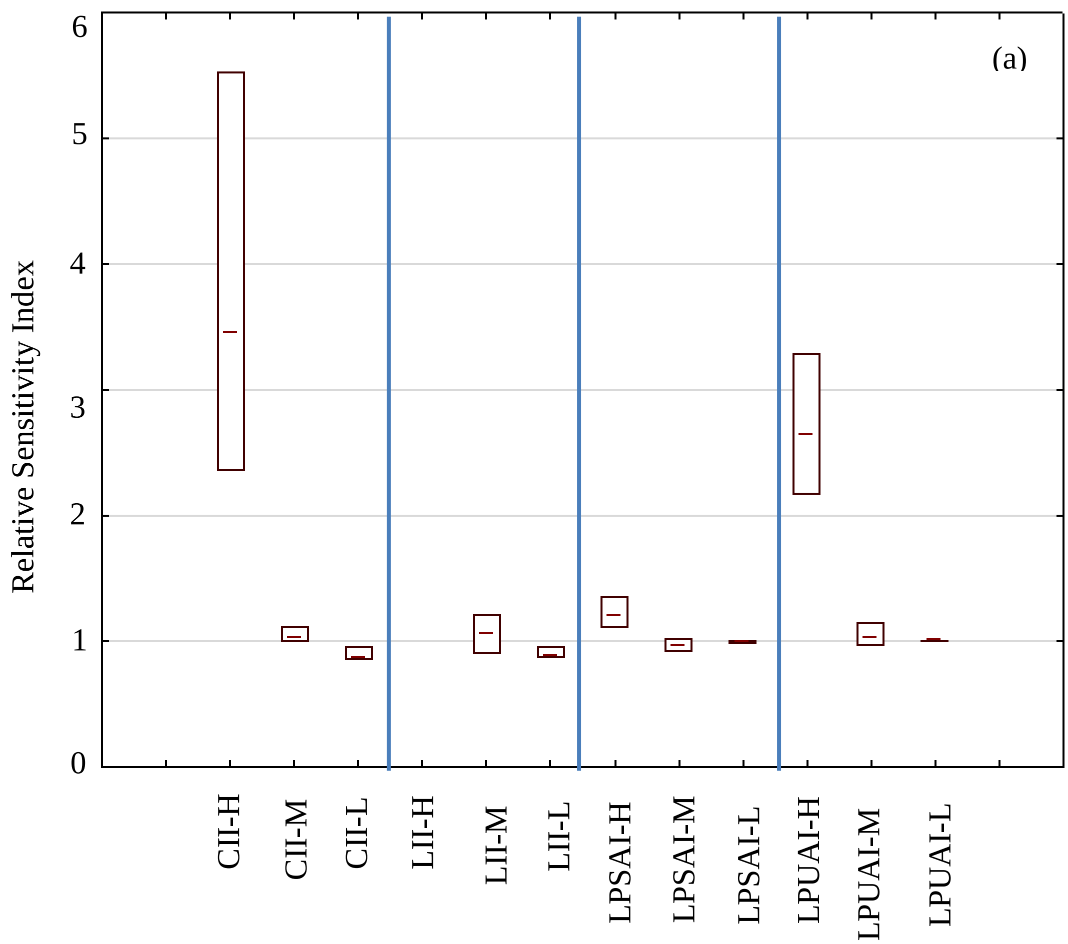

Figure 4-16. (a) BMP relative sensitivity index sediment.

CII-high has a high relative sensitivity index because of the targeting methodology; CII-high generally targets streams with low flows, so even relatively small loads will increase pollution concentration. This can be a very effective approach to protect sensitive aquatic ecosystems. As BMPs are implemented on the high priority areas identified by CII, reduction is high at the subbasin but there is not as great of an impact at the watershed outlet because only small upstream areas are targeted. This results in a higher proportion of reduction at the subbasin and consequently, a high relative sensitivity index. Variability of CII-high is also large, which is due to the difference in sediment reduction between BMPs at the subbasin level and at the watershed outlet. Percent reduction is similar among all BMPs at the watershed outlet, while native grass and terraces have much higher reduction efficiency at the subbasin than residue management (0 kg/ha) and conservation tillage (not shown in Figure 16). These trends create variability in the relative sensitivity index.

LPUAI-high has a large relative sensitivity index because it targets pollution generation at the subbasin level while ignoring pollution in the reach. Therefore, percent sediment reduction for all BMPs is larger at the subbasin level than at the watershed outlet, which creates a large relative sensitivity index. In addition, the variability is fairly large compared to other sensitivity scenarios because percent sediment reduction at the watershed outlet is relatively the same across all BMPs, while at the subbasin level native grass, tillage, and residue management (2000 kg/ha) have much higher percent sediment reduction than other BMPs.

4.4.6.2 TN Targeting Scenario

Overall, the TN scenario has less extreme sensitivity than the sediment scenario, while the variability is generally greater than the TP scenario (Figure 4-16b).

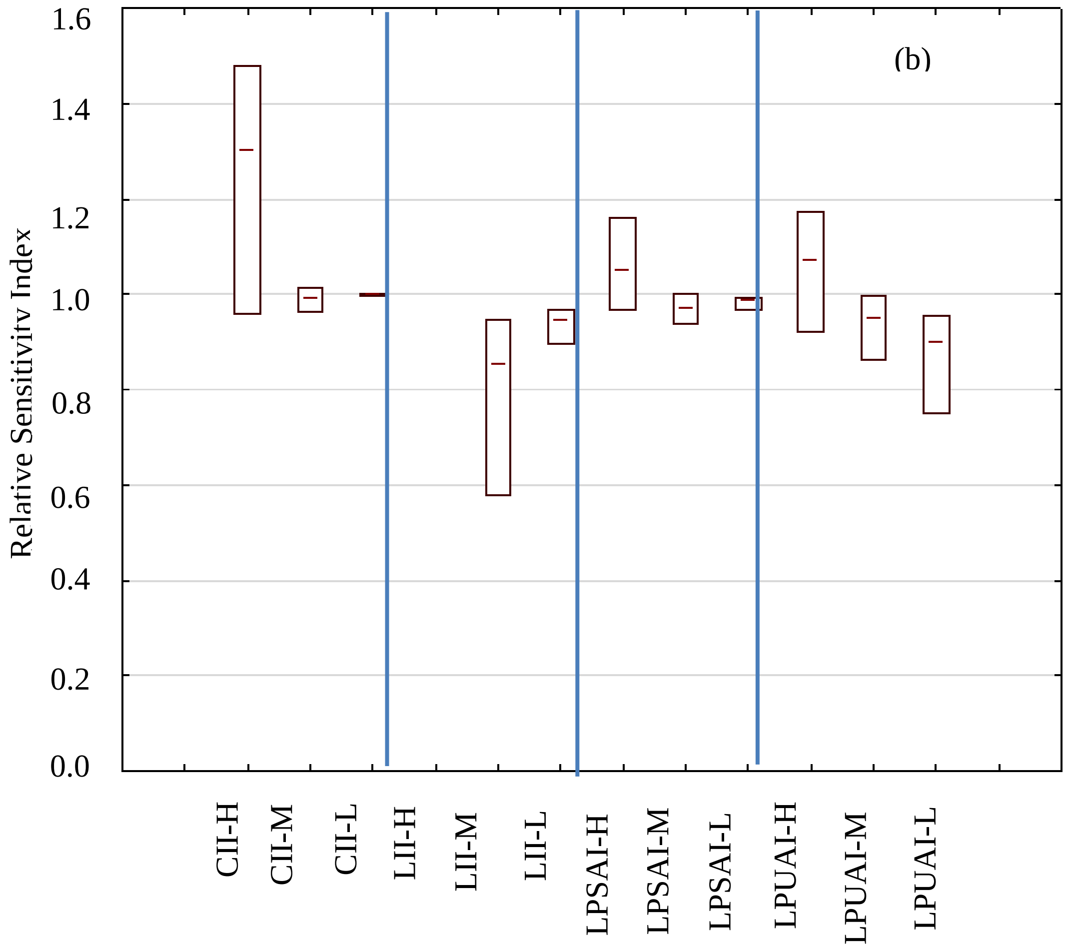

Figure 4-16. (b) BMP relative sensitivity index TN.

The median relative sensitivity index is close to one for all sensitivity scenarios, although the CII-high and LII-medium are greater than one and less than one, respectively. The CII-high sensitivity is generally higher for similar reasons as in the sediment sensitivity scenario.

LII-medium has a median relative sensitivity lower than one due to the targeting methodology. This method targets high stream loads while ignoring what is happening at the subbasin level. Therefore, it is likely that the proportion of reduction at the watershed outlet is greater than at the subbasin level. High range of sensitivity in the LII-medium scenario is due to variable percent TN reduction at the watershed outlet between BMPs, while at the subbasin level, there is less difference in reduction between BMPs (indicating that the most efficient BMPs have a greater impact at the watershed outlet).

4.4.6.3 TP Targeting Scenario

For TP, the relative sensitivity index for most sensitivity scenarios is close to one with little variability (Figure 4-16c). This indicates that percent TP reduction of BMPs is similar at the subbasin level and the watershed outlet for most of the sensitivity scenarios. Overall, sediment and TP are similar for most sensitivity scenarios because of the transport relationship between the two pollutants.

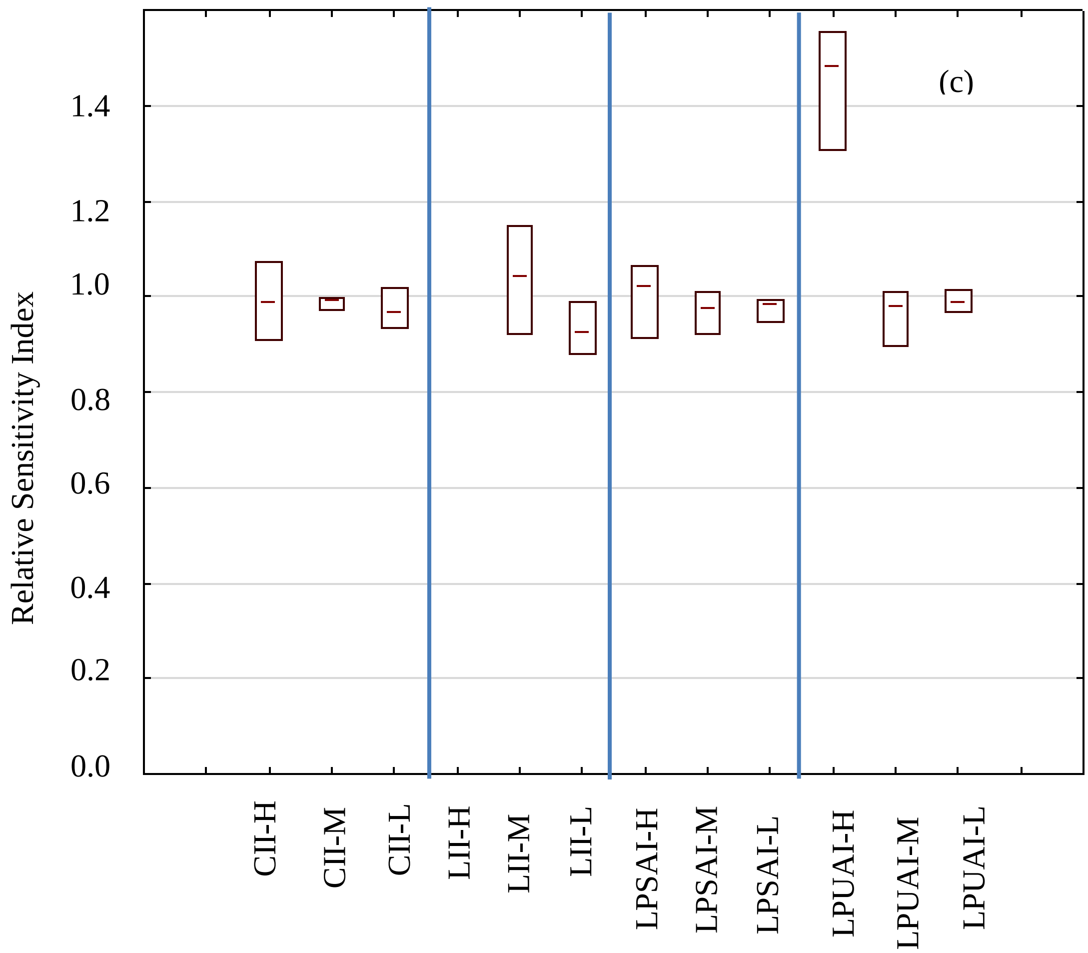

Figure 4-16. (c) BMP relative sensitivity index TP.

LPUAI-high is the only sensitivity scenario with a median sensitivity substantially larger than one, which is similar to the sediment case. This method targets pollution at the subbasin level rather than in the reach, therefore it is likely that the proportion of percent TP reduction is higher at the subbasin than at the watershed outlet. The variability of LPUAI-high is larger than other sensitivity scenarios because percent TP reduction is more variable at the subbasin level than at the watershed outlet. This indicates that BMP selection plays a more important role when the goal of implementation is TP reduction from the field than at the watershed outlet.

4.5 CONCLUSION

BMPs are one of the primary options in maintaining surface water quality. Informed placement of BMPs plays an important role in achieving maximum pollution reduction while minimizing costs. The objectives of this research were to (1) identify CSAs using multiple targeting techniques and pollutants, (2) assess the sensitivity of BMPs to different targeting methods, and (3) evaluate the impact of BMP application in CSAs at subbasin and watershed scales. In the SRW, four targeting methods (CII, LII, LPSAI, and LPUAI) were used in SWAT to prioritize BMPs for sediment, TN, and TP reduction. Ten BMPs (RM 0 kg/ha, CT, NT, CF, RM 1000 kg/ha, RM 2000 kg/ha, SC, RS, T, and NG) were implemented for each targeting method.

Initially, priority area selection between targeting methods for the entire SRW was compared for sediment, TN, and TP. In the sediment targeting scenario, the LPSAI targeting methods had the largest high priority areas, while LII had the least. For TN and TP, CII had the greatest high priority area, while LII had the least. The CII targeting method characterized large high priority area due to numerous smaller tributaries within the SRW. Low flow in the tributaries combines with pollutant load from agricultural lands, thereby causing high pollutant concentrations. Conversely, the LII targeting method consistently identified the smallest area of high priority area because of less load carrying capacity of smaller tributaries compared to the main channel in the watershed. Therefore, only subbasins near the SRW outlet were identified as high priority. The LPSAI targeting method categorized the greatest high priority area for sediment targeting scenario because of the combination of selecting large subbasin areas with pollutant loads from agricultural lands. The characterization of priority areas in LPUAI targeting method primarily depends on the pollutant load from agricultural areas, but is normalized by subbasin area.

Therefore, this method produced less high priority areas when compared to the LPSAI targeting method.

The targeting methods were also compared for sediment, TN, and TP on agricultural lands (available land for BMP implementation). This allows us to quantify the capability of each targeting method to identify agricultural lands as a NPS source. Trends in high priority area selection were similar for the entire SRW and agricultural lands. In the sediment targeting scenario, the LPSAI targeting method had the greatest high priority area for agricultural lands in the watershed, while the LII had the least. Under the TN and TP targeting scenarios, the CII targeting method had the highest high priority area for agricultural land whereas the LII targeting method had the least. The LPSAI targeting method produced larger high priority area because the method is based on field generated pollutant load across an area. Therefore, large subbasins primarily composed of agricultural lands are likely to be high priority. In contrast, the LII targeting method had the least high priority area due to the method itself, as it targets the pollutant load on the reach, without considering the field. The CII targeting method had the highest amount of agricultural high priority area both for TN and TP targeting scenario likely because of low flow conditions receiving pollutants from agricultural lands, creating higher than average concentrations.

When applying BMPs to the priority areas based on the four targeting methods, varying results were observed. Sediment, TN, and TP reduction was compared at the subbasin level and at the watershed outlet for each BMP/targeting method combination. Comparing BMPs across all targeting scenarios, native grass and terraces were generally the most effective at pollution reduction, where residue management (0 kg/ha), conservation tillage, and no tillage were consistently the least effective at both the subbasin and watershed outlet. This result is likely due to the manner of BMP implementation, where native grass and terraces are more intensive compared to adjustment of tillage practices. The LPSAI method was most effective in reducing sediment at the watershed outlet when applying BMPs on high priority areas compared to other targeting methods due to a combine effect of the method itself and the greatest amount of high priority areas. A similar trend was observed after normalization of BMP application area both at outlet and subbasin level. The CII targeting method was most effective in reducing TN at the subbasin level and watershed outlet by applying BMPs in the high priority area because of greater BMP application area. However, after normalization of BMP application area the LPUAI targeting method reduced a greater amount of TN both at the outlet and subbasin level, indicating that the most reduction per BMP implementation will occur under this scenario. Like the TN targeting scenario, the CII targeting method was most effective in reducing TP compared to other targeting methods because of greater agricultural high priority areas, and therefore more area in which BMPs were implemented. After normalization of BMP application area no targeting method was superior when comparing the TP reduction per area at the watershed outlet. The results of the BMP implementation based on targeting method indicate that selection of targeting method and BMP must be done with care and will depend on the goal of policymakers and watershed managers.

BMP relative sensitivity index was compared among all targeting methods and priority areas. Understanding the relative sensitivity index indicates whether the targeting method and priority with applied BMPs is more sufficient at pollution reduction at the subbasin or watershed outlet, and to what proportion. Except for two scenarios (CII-high and LPUAI-high), the overall relative sensitivity index for the sediment targeting scenarios was approximately one, indicating that reduction at the reach and subbasin is proportional. This result was due to the targeting methodology itself. CII-high targets low flow streams with high concentration (not necessarily load), which results in implementation in many areas, reducing sediment production from the field, although the impact is not strongly observed at the watershed outlet. LPUAI targets the load from the subbasin rather than the watershed outlet; therefore the effects of BMP implementation are less likely to be observed at the watershed outlet. Relative sensitivity index was similar for the TN scenario, although LII-medium relative sensitivity index was less than one, indicating that reduction is more apparent at the watershed outlet than it is at the subbasin level. The LII method targets stream loads at the watershed outlet rather than load from the subbasin, causing sensitivity less than one. Overall, relative sensitivity index was approximately one for the TP targeting scenario, except for LPUAI-high. The higher relative sensitivity index in LPUAI-high was due to a greater proportion of TP reduction in subbasin level compared to the watershed outlet because the targeting method aims at reducing pollutant at subbasin rather than the outlet.

This study compared targeting methods under different priority areas based on targeting pollution type (sediment, TN, and TP) to develop possible BMP implementation decisions. No single method was found to be significantly better or worse for priority area selection and pollutant type, although each method produced different high and medium priority areas. In addition, utilization of a specific targeting method should be based on the goals stated in a BMP implementation project. For example, when the goal of project is to protect aquatic health, it may be useful to use a method that focuses in-stream pollutant concentration. Conversely, if preventing sedimentation of a reservoir is the goal of a BMP implementation project, selecting the targeting method that focuses on load reduction in the stream may be more appropriate. Further studies need to be completed to address spatial variability of priority areas with respect to time, climate change, and land use change.

5. ANALYSIS OF BEST MANAGEMENT PRACTICE EFFECTIVENESS AND SPATIOTEMPORAL VARIABILITY BASED ON DIFFERENT TARGETING STRATEGIES.

5.1 ABSTARCT

In this study, ten best management practices (BMPs) were modeled for agricultural areas in the Saginaw River Watershed using the Soil and Water Assessment Tool based on four targeting methods (Load per Subbasin Area Index (LPSAI), Load per Unit Area Index (LPUAI), Concentration Impact Index (CII), and Load Impact Index (LII). The effective BMPs both for targeting and non-targeting pollutants were contour farming (except total nitrogen reduction during total phosphorus targeting scenario), residue management 1000 kg/ha and 2000 kg/ha, strip cropping, recharge structures, terracing, and native grass. In contrast, conservation tillage and no tillage did not reduce significant amount of pollutants for any combination of targeting methods and priority areas. In regard to spatial correlation between targeting methods, a strong relationship was found between the LPSAI and LPUAI methods both for the sediment and total nitrogen targeting scenarios. In addition, a similar result was found between the CII and LPSAI targeting methods. Regarding the spatiotemporal variability of BMP implementation plan, a distinct change in priority area was observed in the case of native grass implementation by the end of the second year; however, this impact was minimal for contour farming due to less pollutant reduction efficiency compared to native grass.

5.2 INTRODUCTION

Degradation of water quality in recent decades is a major concern for society, which is further compounded by land use change and intensified agricultural practices. According to the US Environmental Protection Agency (2009), 44% out of 3.5 million miles of the nation's rivers and streams were impaired. Excessive nutrient loading into waterbodies originates from different sources such as improper application of fertilizer, animal wastes, irrigation water, frequent plowing, forestry, and urban development. This leads to eutrophication, resulting in diminished water quality (TNRCC, 1999). Accumulation of surplus nutrients, primarily phosphorus and nitrogen, enhances excessive algal growth. Algal bloom in waterbodies decreases light availability and increases organic matter production, resulting in degradation of habitat, decreased fishery production, and substantial economic impact. Additionally, eutrophication decreases property value, disrupts recreation and tourism, and creates taste and odor problems resulting in increased drinking water treatment costs (Dodds et al., 2009).

Improving water quality through implementing best management practices (BMPs) on agricultural lands is currently receiving increase interest. BMPs are a widely accepted method to control pollution from agricultural activities within a watershed (Arabi et al., 2007). However, the effectiveness of BMPs varies from site to site and with the type of BMP applied (Giri et al., 2012a). Considering resource and time constraints, it is impractical to develop best management strategies through field studies. Therefore, watershed managers prefer modeling for development of watershed management plans. Meanwhile, BMP implementation on all agricultural lands is not required as application of BMPs at critical source areas (CSAs) may reduce the pollutants to acceptable levels (Maringanti et al., 2009). CSAs generate a disproportionate amount of pollutants in the watershed, which is a combination of land use, soil type, slope, and proximity to the waterbodies. Targeting CSAs is more effective and resource efficient than randomly implementing BMPs throughout a watershed. Therefore, identification of CSAs is essential to optimize nonpoint source (NPS) pollution reduction. Preferential implementation of BMPs on CSAs is known as the targeting approach.

Models such as the Soil and Water Assessment Tool (SWAT), Hydrological Simulation Program Fortran (HSPF), Annualized Agricultural Nonpoint Source (AnnAGNPS), Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS-2000), Watershed Assessment Model (WAM), and Water Erosion Prediction Project (WEPP) have been used for developing BMP implementation plans. Among these models, SWAT is preferred because its built-in equations describe various agricultural components such as tillage operations, fertilizer and pesticide applications, vegetative filter strips, and crop rotations in more detail than other models. SWAT has been widely used to assess the effectiveness of BMPs on the watershed scale (Arnold et al., 1998; Gassman et al., 2007, Arabi et al., 2007, Arabi ei al., 2008, Panagopoulos et al., 2011). Several studies have used the SWAT model in targeting watershed CSAs for BMP implementation (Panagopoulos et al., 2011, Ghebremichael et al.,2010, Jha et al., 2010; Maringanti et al., 2009; Parajuli et al., 2008; Schilling and Wolter, 2009; Tuppad et al., 2010; White et al., 2009). However, these studies did not address the spatiotemporal impacts (change in space and time) of BMP implementation plans or explore BMP effectiveness on both targeted pollutants and non-targeted pollutants.

5.2.1 CSA Identification

Ghebremichael et al. (2010) used the SWAT model to identify and quantify phosphorus CSAs in the Rock River watershed, which is the primary phosphorus contributor to Lake Champlain. They found that more than 50 % of the sediment and TP originated from corn fields, and another 20-25% of TP was coming from other row crops. Overall, 24% of the watershed area contributed 80% of TP. Tuppad et al. (2010) used random and targeting methods for implementation of BMPs (reduced tillage, edge of field vegetative filter strips, and contoured terraces) in the Smoky Hill watershed in Kansas. The BMPs were implemented on 10%, 26%, 52%, and 100% of the total targeted cropland and the pollutant reduction efficiencies were compared at the outlet of the watershed. CSAs were defined based on the total pollution load per unit area. They observed that the targeting method was more effective compared to the random method. White et al. (2009) identified CSAs and quantified sediment and TP loads at the watershed scale in Oklahoma using the SWAT model. Within each hydrologic response unit (HRU), CSAs were identified based on threshold unit area load and then HRUs were ranked from highest to lowest based on the sediment and phosphorus yields. They observed that approximately 22% of the sediment and phosphorus load originated from only 5% of the agricultural land. Diebel et al. (2008) implemented BMPs using four allocation approaches: aggregated/targeted, aggregated/random, dispersed/targeted, and dispersed/random. These allocation approaches were evaluated by two methods: modeled pollutant reduction index and water quality change index. The proportion of phosphorus load reduction after BMP implementation is known as the modeled pollutant reduction index, while the proportion of the watershed having significant reduction of stream phosphorus concentration is called the water quality change index. For modeled pollutant reduction index and water quality change index, the targeted approach performed better compared to the random approach for both methods.

Few studies have looked at the performance of BMPs based on different CSA identification methods. This study is unique because 1) the effects of targeting for a particular pollutant on non-targeted pollutants are considered; 2) no studies have addressed the impact of gradual BMP implementation on spatial variability of CSAs despite the fact that in reality, it is very common that BMP implementation plans are applied in a gradual manner over the course of multiple years; and 3) spatial correlation (similarity in identifying location) was calculated to determine the relationship between priority area and targeting methods. In this study, a statistical model was used to remove time series autocorrelation among the dataset, while comparing the base with the BMP scenario in order to determine the BMP effectiveness. The objectives of this study were to 1) determine the most effective BMPs both for targeting and non-targeting pollutants based on different targeting methods while minimizing the area devoted to BMP implementation; 2) evaluate the spatial correlation among the targeting methods in categorization of priority area (high, medium, and low) based on targeting pollutant; and 3) assess the spatiotemporal variability of CSAs.

5.3 MATERIALS AND METHODS

5.3.1 Study Area

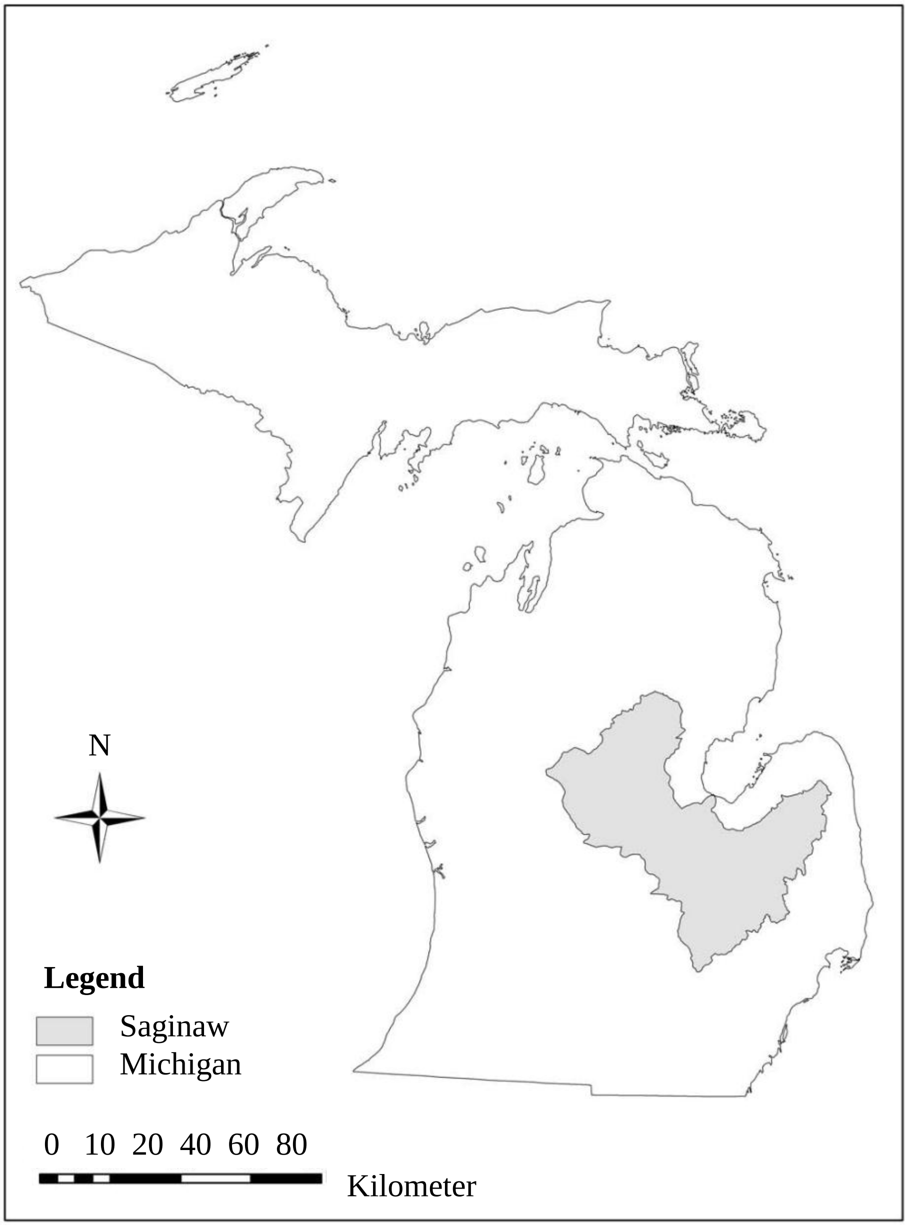

Figure 5-1. Location of Saginaw River Watershed.

The study was conducted on the predominantly agricultural lands of the Saginaw River Watershed (SRW). The SRW (Figure 5-1) is located in east central Michigan, and is one of the most diverse areas of Michigan having agriculture, manufacturing, tourism, outdoor recreation, and wildlife habitat. This is the largest six digit hydrologic unit code (HUC)- watershed in Michigan (040802), and is the nation's largest contiguous freshwater coastal wetland system (USEPA, 2009). The SRW flows northward and finally drains into Lake Huron. The total watershed area in this study is 15,263 km^2 with approximately 42% forest, 23% agriculture, 17% pasture, 11% wetland, while the remaining is high, medium, and low density urban. Corn and soybeans are the most predominant crops in the watershed.

5.3.2 Model Description

In this study, SWAT was used to identify the critical source areas of sediment, total nitrogen (TN), and total phosphorus (TP). The SWAT model is developed by the USDA-ARS, and is a physically-based, spatially distributed watershed scale model (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007). The SWAT model estimates flow, sediment, nutrients, and pesticides on a watershed scale based on land use, soil type, and management operations. A watershed in SWAT is divided into subbasins and further divided into HRUs based on homogeneous land use, soil, slope, and management practices. Hydrology, soil characteristics, plant growth, weather, nutrients, pesticides, and land management practices are major model components (Gassman et al., 2007).

5.3.3 Data Sources

Different types of physiographic data such as topography, land use, soil, and stream network are required by the SWAT model. The Better Assessment Science Integrating point and Nonpoint Sources (BASINS) program was used to attain the topography data in the form of the digital elevation model (DEM). The 2008 Cropland Data Layer was obtained from the USDA's National Agricultural Statistics Service (NASS, 2008) in order to represent the land use in the watershed. The State Soil Geographic Database (STATSGO) was used to represent the watershed soil characteristics. The STATSGO dataset was developed by the National Cooperative Soil Survey and was linked to tabular data containing soil chemical and physical properties at a scale of 1:250,000. The United States Geological Survey (USGS) National Hydrography Dataset (NHD) was used to define the stream network in the watershed in order to improve the hydrologic segmentation and subwatershed boundary delineation.

Daily streamflow data were downloaded for USGS gauging station 04157000 for streamflow calibration and validation. The water quality data were obtained from the Michigan Department of Environmental Quality station 090177. In this study, 19 precipitation stations and 11 temperature stations were used to represent the precipitation and temperature data required by the SWAT. Twenty years (1990-2009) of observed daily precipitation (19 stations) and temperature (11 stations) data were obtained from the National Climatic Data Center. The SWAT weather generator program was used to generate the remaining required meteorological data (wind speed, relative humidity, and solar radiation).

Agricultural management operations for corn and soybeans were developed based on common practices in the region in order to assess the fate and transport of sediment and nutrients in the watershed. The common practices include tillage and fertilizer applications. The continuous corn rotation period is six years, out of which corn is planted for five years and soybean is planted in the final year. The continuous soybean rotation period is three years in length, and consists of two years soybean planting and a final year of corn planting.

5.3.4 Sensitivity Analysis and Calibration

The most influential parameters on model output (obtained in sensitivity analysis) are required for use during the model calibration process. Sensitivity analysis ranks parameters in terms of the sensitivity of model outputs to the input parameters. Latin Hypercube One factor-at-a-time (LH-OAT) sampling is used to perform the sensitivity analysis in the SWAT model (van Griensven et al. 2006). In this study, a sensitivity analysis was performed to estimate the model parameters sensitive to streamflow, sediment, TN, and TP. Complete sensitivity analysis, calibration, and validation results are presented in Giri et al. (2012a). Calibration and validation were performed for streamflow, sediment, TN, and TP on a monthly time step with a two-year model warm-up.

5.3.5 Best Management Practices in SWAT

The ten BMPs modeled on agricultural lands were contour farming (CF), terraces (T), recharge structure (RS), conservation tillage (CT), no tillage (NT), native grass (NG), residue management (0 kg/ha) (RM 0), residue management (1000 kg/ha) (RM 1000), residue management (2000 kg/ha) (RM 2000), and strip cropping (SC)One BMP was used at a time to assess the impact of BMP effectiveness on pollution reduction. After modeling BMPs in the

SRW, the results were compared to the base scenario (no BMPs implemented) to evaluate the pollution reduction effectiveness of each. The BMPs were implemented in SWAT according to procedures in various published literatures (USDA, 1996; USDA-NRCS, 2005; Arabi et al., 2007; Nejadhashemi and Mankin, 2007; Tuppad and Srinivasan, 2008; Tuppad et al., 2010; USDA, 2010; USDA-NRCS, 2011; Woznicki et al., 2011).

5.3.6 Spatial targeting Methods

Implementation of BMPs throughout the watershed is impractical, expensive, and time consuming. Proper utilization of limited resources is achieved through the right selection criteria. Hence, the primary step before BMP implementation is to identify CSAs of pollutants in the watershed. In this study, four targeting methods – CII, LII, LPSAI, and LPUAI were evaluated in prioritization of the SRW for three targeting pollutants (sediment, TN, and TP). A total of 12 targeting scenarios were studied (all combinations of targeting methods and targeting pollutants). Using these four targeting methods, the watershed was categorized into high (H), medium (M), and low (L) priority areas for all pollutants. The categorization was based on the natural breaks method of data classification, where different classes are formed based on natural groupings of a dataset. Similar values of data form a group that attempts to maximize the differences between the groups, resulting into a relatively substantial difference between the data values of any two groups.

In addition to the effect of each targeting method on the targeted pollutant, the effectiveness of BMPs on non-targeted pollutants was also evaluated. For example, a BMP such as no tillage was implemented in the priority areas aiming at maximum sediment reduction (primary pollutant).

Meanwhile, the effectiveness of the BMPs on TN and TP reduction (secondary pollutants) was also estimated.

5.3.6.1 Concentration Impact Index

High priority areas are identified based on the pollutant concentration level in the reach (Tuppad and Srinivasan, 2008). This method considers pollutant load from both the subwatershed as well as the upstream subwatersheds. This method addresses aquatic health localized pollution in low and high flows.

5.3.6.2 Load Impact Index

The LII method identifies high priority areas based on the total pollutant load from the reach (Tuppad and Srinivasan, 2008). Like the CII targeting method, this method also considers pollutants from the subwatershed as well as the upstream watershed. This method represents cumulative load up to the point of interest, and is useful in establishing waste water treatment plants and water withdrawal processes.

5.3.6.3 Load Per Subbasin Area Index

High priority areas are identified based on total pollutant load from each subbasin. The total pollutant load of each subbasin is calculated by multiplying subbasin area with pollutant load per unit area of that subbasin. This method identifies the subbasins with the largest amount of pollutant discharge into the stream, resulting in identifying local concerns. Hence, this method can be used to identify hot spots for excessive loads, which endanger aquatic species.

5.3.6.4 Load Per Unit Area Index

The LPUAI method identifies the high priority areas based on average pollutant load per unit area from each subbasin (Tuppad and Srinivasan, 2008; Giri et al., 2012a). This method is useful to identify local concerns within an area.

5.3.7 Statistical Analysis

5.3.7.1 Temporal Analysis

A statistical analysis was conducted to detect temporal autocorrelation when comparing BMP effectiveness on both targeting and non-targeting pollutants with respect to base calibrated scenarios. Therefore, autocorrelation functions (ACFs) for sediment, TN, and TP with and without BMPs were created. However, we are only presenting the sediment function here (Figure 5- 2). A similar procedure was performed for TN and TP. Figure 5-2 a, b show that sediment load datasets without and with BMP scenarios have a strong time series autocorrelation at lag 1 (the time step where the data failed to keep up the trend), which prevents the usage of a general two-sample paired t-tests for the comparison of significant differences between two datasets since the independent assumption is violated. Therefore, a modified paired t-test (Napier-Munn and Meyer, 1999) was used to compare monthly sediment, TN, and TP loads at the watershed outlet. In addition, comparisons were conducted among the priority areas (H vs. H + M, H+M vs. H+M+L) for the same time period.

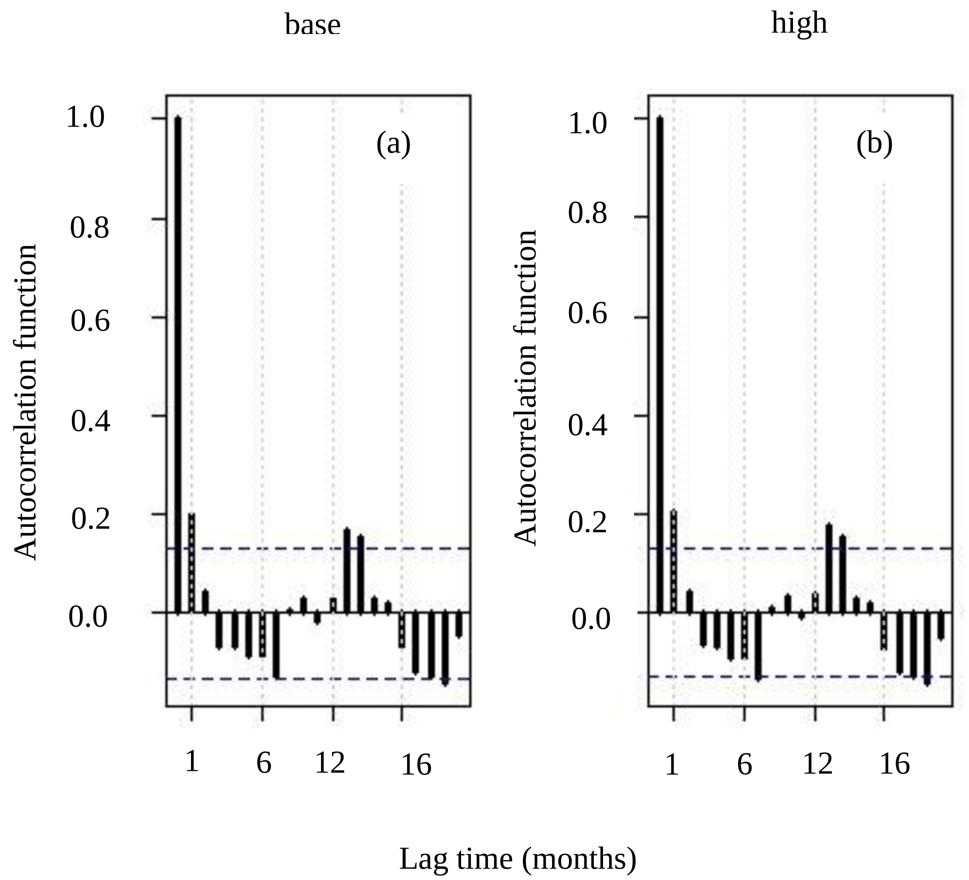

Figure 5-2. (a) ACF-sediment base scenario and (b) ACF-high priority area . Bar beyond the confidence band (dashed horizontal line) show significance at that time lag.

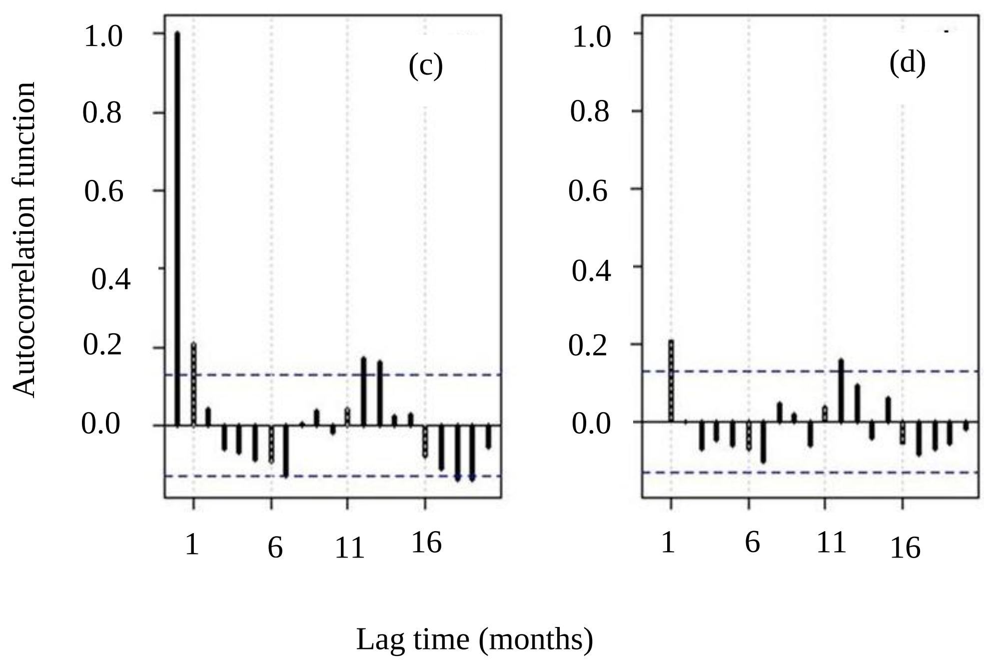

Figure 5-2. (c) ACF-pooled series of sediment base and high priority area and (d) Partial ACF-pooled series. Bar beyond the confidence band (dashed horizontal line) show significance at that time lag.

In order to hold the normality assumption, a log transformation was performed on each dataset before the analysis. In addition, an autocorrelation coefficient (Φ) was introduced in the modified paired t-test autoregressive model of order one AR (1) to nullify the effect of temporal autocorrelation among the pooled series. According to the AR (1) model, the time series data can be modeled using the following equation:

$$X_t = \Phi X_{t-1} + e_t \quad (5\text{-}1)$$

Where X_t is the mean at time t, X_{t-1} is the mean at time t-1, and e_t is the white noise.

In this modified t-test, a special sampling technique for pooling two series was followed, where the pollution load output of the current month of base scenario was compared with the load output of the next month of BMP implementation scenario, and so on (Napier-Munn and Meyer, 1999). For example, the base load output of January was compared with the load output of February of the no-till BMP implementation scenario on high priority areas. Figure 5-3 represents the pooled time series for pollution generated under base (black circle) and high priority area (white circle) scenarios. The ACF and partial autocorrelation function (PACF) or pooled series are shown in Figure 5- 2 c, d. Figure 5-2d demonstrates that the strongest partial autocorrelation in the time series occurs at lag 1 and is significant for each cycle, which suggests that the AR (1) model for the pooled series is suitable. After the special sampling, the modified t-test was performed in R using the following equations:

$$t= \frac{\bar{d}}{S_d/\sqrt{n}} \times \frac{1}{\sqrt{k}} \tag{5-2}$$

$$K = 1 - \frac{\phi}{1+\phi}\left[1 - \left(\frac{1-\phi^{2n}}{n(1-\phi^2)}\right)\right] \tag{5-3}$$

Where $\bar{d}$ is the mean difference for all pairs, S_d is the standard deviation of the differences, and n is the number of pairs

Again, normality of the sample dataset was verified. If normality was satisfied, the modified t-test value was taken into account, else the outliers were removed from the datasets and the modified t-test was performed again.

5.3.8 Spatial Correlation

The spatial correlation analysis was performed to determine the similarities of targeting methods in identifying priority areas. Each targeting method was used to categorize SRW subbasins into high, medium, and low priority areas. The possible combinations of two targeting methods were compared against their categorization of priority area for each pollutant. The total number of common subbasins was calculated between two targeting methods for all possible combinations of priority areas and pollutions. A squared contingency table with r = 3 categories was prepared between two targeting methods. This was repeated for all targeting methods and pollutants. An example of a contingency table with rounded proportions and marginal sums is presented Table 5-1.

Table 5-1. Contingency table between CII and LPSAI targeting methods based on the TN targeting scenario. The number in the parenthesis represents the ratio of counts in that category (e.g. number of subbasins identified as high priority) to the total number of counts (total number of subbasins).

CII/LPSAI Counts (%)	High	Medium	Low	Sum
High	7 (0.028)	10 (0.039)	16 (0.063)	33 (0.130)
Medium	1 (0.004)	15 (0.059)	48 (0.189)	64 (0.252)
Low	0 (0.000)	5 (0.020)	152 (0.598)	157 (0.618)
Sum	8 (0.031)	30 (0.118)	216 (0.850)	254 (1.000)

Table 5-1 was prepared to investigate the agreement (spatial similarity) between two targeting methods (CII vs. LPSAI). Perfect agreement occurs when all nonzero counts fall in the main diagonal cells (the targeting methods match exactly). The sum of the proportion in the main-diagonal cell was calculated as the estimated probability of agreement. However, most contingency tables had a large number of observations for low-low category. Therefore, a high proportion of main-diagonal entries in the contingency table may be misleading in determining the actual agreement beyond chance, because it is difficult to create a sufficient predictor model due to a high concentration of data falling in the low-low category. The Cohen's kappa coefficient (parameter to measure agreement between two methods in categorical data) was calculated as an agreement measure assuming independence between two methods (Cohen, 1960). The large-sample asymptotic variance (variance when sample size approaches infinity) was also calculated to obtain the 95% confidence interval, as the sample size n is sufficiently large (Fleiss et al., 1969). Having the Cohen's kappa coefficient closer to one represents a stronger agreement between two methods. A zero-value kappa indicates that the agreement occurs by chance, and a negative value depicts that the agreement is even weaker than expected by chance. Moreover, since the three categories have ordinal responses from high to low levels, disagreements of high vs. low levels are considered more severe than that for medium vs. low levels. The weighted kappa with squared weights can be considered as an intra-class correlation coefficient (Fleiss and Cohen, 1973). The weighted kappa behaves similarly to kappa, ranging from negative values to 1 with perfect agreement. The 95% confidence intervals from a large-sample standard error of weighted kappa were also calculated (Fleiss et al., 1969).

However, summarizing a contingency table with one single index can lead to a significant loss of information. Therefore, an agreement plus linear-by-linear association model (Agresti, 1988) was fitted to each contingency table to quantitatively investigate the class agreement and association between two methods, which is presented in Equation 5-4.

$$\log m_{ij} = \mu + \lambda_i^A + \lambda_j^B + \beta u_i u_j + \delta(i,j) \qquad 1 \leq i,j \leq r = 3 \tag{5-4}$$

Where i, j values 1, 2, 3 correspond to high, medium, and low priority areas, respectively, for two methods, m_{ij} is the expected counts falling cell (i,j), μ is the grand mean, λ_i^A is the effect due to the i^{th} level of method 1, λ_j^B is the effect due to the j^{th} level of method 2, β is the expected baseline association and u_i, u_j are the fixed scores of the ordered categories from high to low level. The uniform association score $\{u_i = i\}$ was considered, which incorporates no extra assumptions beyond equal intervals between categories; $\delta(i,j) = \delta$ for $i = j$ and 0 otherwise, with δ the agreement parameter. This model is a special case of log-linear quasi-symmetric models. It involves the effects of individual method (A and B), which are nuisance parameters in our case, and an agreement term which takes values δ only for main-diagonal cells, plus a linear-by-linear association term with effect β. The interested parameters are β and δ. A non-significant β indicates that there is no extra association beyond that due to exact agreement, while a non-significant δ suggests no extra agreement beyond that due to the baseline association. Both non-significances indicate independence of two methods.

The model was fitted in the statistical software R (version 2.13.2). The likelihood ratio statistic, G^2, as a measure of model goodness-of-fit was calculated using R and reported. In general, a smaller G^2 indicates that the fitted values from the model are not deviated from the observed counts. The residual degree of freedom was calculated as 2 using the equation $r^2-(r-1)\times 2-3$ for $r = 3$. The interested parameters β and δ with standard errors were estimated and are significant if the associated p-values are less than 0.1. Furthermore, the local indistinguishable parameter (Equation 5-5) under uniform association was calculated for each contingency table, which is equal to $e^{(\beta+2\delta)}$.

$$\tau_{i,i+1} = \frac{m_{i,i} m_{i+1,i+1}}{m_{i,i+1} m_{i+1,i}}, i = 1,2 \qquad (5\text{-}5)$$

5.3.9 Spatiotemporal Variability of Priority Area

We hypothesize watershed priority areas change with time, especially after the establishment of BMPs. In order to analyze the variability of the priority area after BMP implementation in the SRW watershed, two BMPs (contour farming and native grass) were selected because the manner in which they are implemented are quite different. The BMPs were implemented only in the high priority areas of the SRW for two consecutive years for all targeting methods and pollutions. For example, native grass is planted on high priority areas before year one (base scenario), which leads to new high priority areas at the beginning of year two, on which native grass is subsequently applied. The base scenario was the same for both BMP implementation scenarios.

5.4 RESULTS AND DISCUSSIONS

5.4.1 Determining the Most Effective BMPs for Targeting and Non-targeting Pollutants

The objective of this section was to determine the most effective BMPs for primary and secondary pollutants when applied on agricultural lands. The results presented in this study are based on pollutant reduction at the watershed outlet.

5.4.1.1 BMP Pollutant Removal Efficiency (Sediment Targeting Pollutant)

Sediment reduction varies between targeting methods, type of BMP applied, and the priority area the BMP was applied on. Table 5-2 presents significant differences in sediment reduction for each BMP between various priority area targets and methods. Native grass, terraces, recharge structures, residue management (2000 kg/ha), strip cropping, residue management (1000 kg/ha), and contour farming were effective in sediment reduction; whereas conservation tillage and no tillage were not effective even when the BMP implementation area increased from H to H+M+L priority areas (Table 5-2). The insignificant sediment reduction in the case of conservation tillage and no tillage may be due to the fact that fewer soil disturbances (conservation tillage) and minimum soil disturbances (no tillage) did not create a larger impact of sediment delivery into the stream. Residue management (0 kg/ha) showed a mixed effectiveness in sediment reduction based on the priority areas. Native grass, terraces, and recharge structure reduced significant amounts of sediment when the base scenario was compared to priority areas as well as among the priority areas, most likely due to the intensive nature of the application of these BMPs. When the sediment reduction in priority areas are compared among the targeting methods, no BMPs reduced a significant amount of sediment in the high priority area of the CII targeting methods while some BMPs reduced significant amount of sediment in the high priority area of other targeting methods (Table 5-2). This result was due to less area of high priority implementation in CII (Table 5-3) than the other targeting methods and using a concentration basis whereas other targeting methods are based on a pollutant load basis. When priority areas (H+M vs. H+M+L) were compared, only two and three BMPs reduced significant amounts of sediment compared to the H+M priority area in the LPUAI and LPSAI targeting methods, respectively (Table 5-2). It indicates that BMP application on H+M would be the wise decision for both the LPUAI and LPSAI targeting methods, rather than additionally including implementation on low priority areas. Overall, LPSAI had higher significant sediment reduction counts (highlighted cells in Table 5-2), indicating that this method is the most effective.

Table 5-2. P-values for BMPs based on the AR (1) model for different targeting methods based on sediment targeting (sediment).

Scenario	CT	NT	RM 0	CF	RM 1000	SC	RM 2000	RS	T	NG
CII Targeting Method										
B vs. H	2.3E-01	2.3E-01	1.7E-01	0.14	1.5E-01	1.3E-01	1.4E-01	1.5E-01	1.0E-01	1.7E-01
B vs. H+M	1.4E-01	1.4E-01	6.3E-02	5.9E-04	5.2E-05	1.7E-06	2.9E-06	8.0E-08	6.4E-15	3.3E-13
B vs. H+M+L	1.1E-01	1.0E-01	2.8E-02	1.2E-05	2.0E-07	3.1E-10	8.0E-10	1.1E-12	0.0E+00	0.0E+00
H vs. H+M	1.4E-01	1.4E-01	9.3E-02	1.4E-03	1.3E-04	6.6E-06	8.5E-06	2.1E-07	5.2E-10	9.5E-13
H+M vs. H+M+L	2.0E-01	2.0E-01	1.2E-01	1.5E-02	7.6E-03	7.2E-04	1.4E-03	9.7E-05	3.4E-09	0.0E+00
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	1.2E-01	1.2E-01	3.8E-02	7.9E-05	2.8E-06	3.0E-08	4.5E-08	7.2E-10	0.0E+00	0.0E+00
B vs. H+M+L	1.1E-01	1.0E-01	2.8E-02	1.2E-05	2.0E-07	3.1E-10	8.0E-10	1.1E-12	0.0E+00	0.0E+00
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	2.3E-01	2.4E-01	1.9E-01	7.6E-02	6.5E-02	2.1E-02	3.4E-02	2.3E-01	3.1E-05	4.1E-13
LPSAI Targeting Method										
B vs. H	1.6E-01	1.5E-01	5.5E-02	1.6E-03	4.4E-04	4.5E-05	7.7E-05	2.7E-05	1.4E-07	5.6E-08
B vs. H+M	1.2E-01	1.2E-01	3.1E-02	2.8E-05	9.1E-07	3.1E-09	5.3E-09	1.4E-10	0.0E+00	0.0E+00
B vs. H+M+L	1.1E-01	1.0E-01	2.8E-02	1.2E-05	2.0E-07	3.1E-10	8.0E-10	1.1E-12	0.0E+00	0.0E+00
H vs. H+M	1.9E-01	2.0E-01	1.4E-01	1.4E-02	4.9E-03	4.7E-04	6.1E-04	1.0E-04	4.4E-08	7.6E-13
H+M vs. H+M+L	2.4E-01	2.5E-01	2.2E-01	1.2E-01	1.1E-01	5.9E-02	9.6E-02	1.3E-02	1.0E-03	2.9E-10
LPUAI Targeting Method										
B vs. H	2.1E-01	2.1E-01	9.8E-02	3.8E-02	3. 66E-02	1.8E-02	2.7E-02	3.3E-02	5.4E-03	7.8E-03
B vs. H+M	1.1E-01	1.1E-01	2.8E-02	1.4E-05	2.8E-02	6.0E-10	1.7E-09	2.5E-11	0.0E+00	0.0E+00
B vs. H+M+L	1.1E-01	1.0E-01	2.8E-02	1.2E-05	2.8E-02	3.1E-10	8.0E-10	1.1E-12	0.0E+00	0.0E+00
H vs. H+M	1.3E-01	1.3E-01	8.6E-02	4.0E-04	1.6E-05	1.4E-07	2.5E-07	2.2E-09	1.5E-15	0.0E+00
H+M vs. H+M+L	2.5E-01	2.6E-01	2.5E-01	1.7E-01	1.9E-01	1.3E-01	1.6E-01	4.4E-02	3.1E-02	2.08E- 01

*Cells having darker color are significantly different at p <0.05 level of significance based on the AR (1) model. Abbreviations: conservation tillage (CT), no tillage (NT), residue management 0 kg/ha (RM 0), contour farming (CF), residue management 1000 kg/ha (RM 1000), strip cropping (SC), residue management 2000 kg/ha (RM 2000), recharge structures (RS), terraces (T), and native grass (NG).

Table 5-3. BMP implementation area for sediment targeting scenario.

Targeting method	H (ha)	H+M (ha)	H+M+L(ha)
CII	27,648	230,043	345,423
LII	-	232,351	345,423
LPSAI	143,319	304,258	345,423
LPUAI	84,977	334,345	345,423

5.4.1.2.1 BMP Removal Efficiency for TN

The TN reduction trend (when targeting sediment) among the BMPs was similar to sediment reduction, varying between the BMPs, priority areas, and the targeting methods (Table A-1in the Appendix). Native grass, terraces, recharge structure, residue management (1000 and 2000 kg/ha), strip cropping, and contour farming reduced significant amounts of TN. Conservation tillage and no tillage were not effective in TN reduction in any combination of priority area and targeting method. The statistically insignificant TN reduction in these BMPs may be due to an increase in organic matter (nutrients) because of diminished soil disturbances, while the nutrients in organic matter can still be released into the soil.

Significant differences in TN reduction while targeting sediment between various priority areas and methods are presented in Table 5-4. TN reduction was insignificant in high priority areas vs. base for CII, while significant TN reduction was observed in the high priority areas of LPSAI and LPUAI for most BMPs. This result was due to the considerably smaller BMP implementation area in CII compared to the LPSAI and LPUAI (Table 5-3), and because CII targets high concentration rather than load, leading to less load reduction at the outlet. When comparing to the priority areas (H+M vs. H+M+L) among the targeting methods, most of the BMPs in CII reduced significant amounts of TN, whereas the BMPs did not reduce significant amounts of TN both in the LPSAI and LPUAI targeting methods. This depicts BMP implementation in H+M+L of the LPSAI and LPUAI targeting methods does not significantly reduce TN compared to H+M application. Therefore, we can optimize TN reduction by applying BMPs only to H+M priority areas of LPSAI and LPUAI and still achieve similar results as applying BMPs on all areas.

Table 5-4. P-values for BMPs based on the AR (1) model for different targeting methods based on sediment targeting for non-targeted TN.

Scenario	CT	NT	RM 0	CF	RM 1000	SC	RM 2000	RS	T	NG
				CII Targeting Method						
B vs. H	3.4E-01	3.4E-01	1.9E-01	1.1E-01	1.4E-01	9.3E-02	1.4E-01	4.7E-01	6.1E-02	5.9E-02
B vs. H+M	1.4E-01	1.4E-01	6.3E-02	3.1E-04	7.2E-03	2.5E-05	9.5E-03	2.3E-03	5.7E-08	2.9E-08
B vs. H+M+L	1.1E-01	1.0E-01	2.8E-02	3.1E-08	6.1E-04	3.8E-10	3.9E-04	1.1E-04	6.1E-12	1.2E-08
H vs. H+M	5.3E-01	5.4E-01	1.9E-01	2.7E-03	2.7E-02	4.1E-04	1.7E-02	8.4E-03	3.3E-06	5.9E-07
H+M vs. H+M+L	4.4E-01	3.9E-01	6.3E-02	2.8E-02	8.4E-02	1.9E-02	1.0E-01	5.7E-02	2.9E-03	1.6E-02
				LII Targeting Method						
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	5.9E-01	5.9E-01	3.1E-02	5.8E-06	1.4E-03	2.3E-06	9.2E-04	6.5E-03	1.7E-09	9.5E-09
B vs. H+M+L	8.4E-01	8.7E-01	3.3E-02	3.1E-08	6.1E-04	5.8E-02	3.9E-04	1.1E-04	6.1E-12	1.2E-08
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	2.6E-01	3.9E-01	2.5E-01	1.0E-01	1.7E-01	5.8E-02	1.8E-01	2.2E-02	1.6E-02	4.3E-02
				LPSAI Targeting Method						
B vs. H	5.0E-01	5.1E-01	4.4E-02	5.6E-04	6.3E-03	1.2E-04	4.7E-03	4.3E-02	2.7E-06	8.4E-07
B vs. H+M	6.2E-01	6.4E-01	3.2E-02	1.9E-07	8.8E-04	3.2E-07	2.6E-06	2.9E-03	7.4E-11	9.8E-10
B vs. H+M+L	8.4E-01	8.7E-01	3.3E-02	3.1E-08	6.1E-04	3.8E-10	3.9E-04	1.1E-04	6.1E-12	1.2E-08
H vs. H+M	3.6E-01	3.3E-01	2.0E-01	3.5E-02	9.0E-02	8.1E-03	3.6E-03	4.5E-02	8.1E-04	4.0E-04
H+M vs. H+M+L	4.2E-01	3.6E-01	4.4E-01	2.1E-01	4.5E-01	3.3E-01	5.3E-01	5.2E-02	1.8E-01	1.2E-01
				LPUAI Targeting Method						
B vs. H	4.1E-01	4.1E-01	9.2E-02	1.4E-02	4.9E-02	9.4E-03	4.9E-02	1.0E-01	2.6E-03	3.3E-03
B vs. H+M	6.3E-01	6.5E-01	2.9E-02	8.1E-08	6.0E-04	1.4E-09	6.0E-04	2.3E-03	5.5E-08	6.3E-10
B vs. H+M+L	8.4E-01	8.7E-01	3.3E-02	3.1E-08	6.1E-04	3.8E-10	3.9E-04	1.1E-04	6.1E-12	1.2E-08
H vs. H+M	5.0E-01	5.0E-01	4.6E-01	7.7E-04	1.2E-02	8.4E-05	1.2E-02	1.3E-02	1.8E-07	4.8E-07
H+M vs. H+M+L	4.0E-01	3.5E-01	4.8E-01	4.3E-01	5.1E-01	4.4E-01	2.8E-01	3.1E-02	3.1E-01	1.8E-01

Cells having darker color are significantly different at $p < 0.05$ level of significance based on AR (1) model.

5.4.1.2.2 BMP Pollutant Removal Efficiency for TP (Targeting Sediment)

TP reduction also varies among the BMPs, types of priority area, and targeting methods. Table 5-5 represents the p-value of TP reduction by BMPs in different priority areas and targeting methods based on the AR (1) model. BMPs such as native grass, terraces, recharge structure, residue management (1000 and 2000 kg/ha), strip cropping, and contour farming reduced significant amounts of TP, whereas conservation tillage, no till, and residue management (0 kg/ha) did not reduce when targeting sediment. The insignificant TP reduction by these BMPs associates with insignificant sediment reduction, likely due to their related transport mechanisms (Table 5-2). Similar results were demonstrated by Bundy et al. (2001), where dissolved phosphorus concentration from a corn field increased when implementing no tillage practices.

When TP reduction was compared among the priority areas with base scenarios, a significant TP reduction was observed by BMPs in all the priority areas among all targeting methods (Table 5-5). Among the targeting methods CII was most effective in counts (combination of significant TP reductions for priority area/BMPs), indicating its overall superior TP reduction abilities among targeting methods (when targeting sediment). TP reduction compared among H+M vs. H+M+L of the LPUAI targeting method, an insignificant TP reduction was found in most of the BMPs due to the smallest increase in BMP implementation area from H+M to H+M+L (Table 5-3).

Table 5-5. P-values for BMPs based on the AR (1) model for different targeting methods based on sediment targeting for non-targeted TP.

Scenario	CT	NT	RM 0	CF	RM 1000	SC	RM 2000	RS	T	NG
CII Targeting Method										
B vs. H	6.9E-02	1.1E-01	8.1E-02	1.3E-02	2.0E-02	6.9E-03	1.8E-02	5.0E-03	3.2E-03	7.7E-15
B vs. H+M	2.6E-01	9.3E-01	9.2E-01	2.5E-06	1.7E-03	1.5E-09	8.9E-05	1.0E-10	0.0E+00	0.0E+00
B vs. H+M+L	3.4E-01	6.3E-01	8.9E-01	2.0E-08	2.8E-04	1.8E-14	9.7E-06	0.0E+00	0.0E+00	0.0E+00
H vs. H+M	2.2E-01	8.0E-01	9.4E-01	2.4E-05	5.3E-03	5.3E-08	4.7E-04	6.3E-09	1.8E-13	4.0E-04
H+M vs. H+M+L	7.7E-02	1.2E-01	1.1E-01	1.3E-02	5.9E-02	1.1E-03	5.1E-02	4.7E-06	5.1E-06	3.3E-01
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	2.8E-01	9.4E-01	6.3E-01	5.4E-07	4.4E-04	4.3E-11	2.7E-05	3.2E-11	0.0E+00	2.2E-16
B vs. H+M+L	3.4E-01	6.3E-01	8.9E-01	2.0E-08	2.8E-04	1.8E-14	9.7E-06	0.0E+00	0.0E+00	0.0E+00
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	8.6E-02	1.4E-01	4.2E-01	2.5E-02	1.1E-01	2.9E-03	8.3E-02	8.6E-02	3.8E-05	1.0E-04
LPSAI Targeting Method										
B vs. H	1.8E-01	6.8E-01	4.9E-01	1.1E-05	1.6E-03	4.2E-08	2.5E-04	1.5E-05	4.1E-11	1.2E-10
B vs. H+M	3.1E-01	7.7E-01	8.7E-01	1.0E-07	2.9E-04	5.2E-13	1.2E-05	3.7E-13	0.0E+00	2.2E-16
B vs. H+M+L	3.4E-01	6.3E-01	8.9E-01	5.8E-06	2.8E-04	1.8E-14	9.7E-06	0.0E+00	0.0E+00	0.0E+00
H vs. H+M	1.2E-01	2.4E-01	3.2E-01	1.3E-02	1.4E-02	4.1E-04	5.7E-03	1.3E-05	1.3E-07	6.5E-07
H+M vs. H+M+L	7.7E-02	1.0E-01	3.5E-01	7.8E-02	1.8E-01	3.3E-02	2.2E-01	7.2E-05	4.8E-03	1.6E-02
LPUAI Targeting Method										
B vs. H	9.9E-02	2.4E-01	1.4E-01	4.1E-04	6.4E-03	5.5E-05	3.5E-03	4.0E-04	2.7E-05	5.4E-05
B vs. H+M	3.2E-01	7.1E-01	9.4E-01	1.5E-06	2.0E-04	7.7E-14	7.5E-06	8.5E-14	0.0E+00	0.0E+00
B vs. H+M+L	3.4E-01	6.3E-01	8.9E-01	2.0E-08	2.8E-04	1.8E-14	9.7E-06	0.0E+00	0.0E+00	0.0E+00
H vs. H+M	2.3E-01	7.7E-01	9.4E-01	3.7E-05	3.4E-03	5.0E-09	4.1E-04	8.7E-08	6.6E-16	1.0E-12
H+M vs. H+M+L	7.5E-02	9.0E-02	3.3E-01	1.1E-01	9.15E-02	7.9E-02	2.3E-01	2.3E-04	3.1E-01	7.4E-02

Cells having darker color are significantly different at p <0.05 level of significance based on AR (1) model.

This indicates that the implementation of a BMP on only H+M priority areas of the LPUAI targeting method is enough to make a significant TP reduction, so additional resources do not need to be invested on low priority areas to get achieve significant reduction.

5.4.1.2 Targeting Component (TN)

In targeting TN, similar trends were observed for the non-targeted components as in the case for sediment targeting (and its effects on non-targeted components). Table 5-6 describes the summary of the targeting component (TN) and non-targeting components (sediment and TP) for each BMP, targeting method, and priority comparison. In addition, the total number of significant reductions for each targeting method and component combination are presented, where the method with the highest number is the most effective for the pooled set of BMPs and priority area combinations. This summarizes results obtained from the supplementary material Table A-1, Table A-2, and Table A-3 in the appendix. All BMPs excluding conservation tillage and no tillage reduced a significant amount of TN, sediment, and TP. Residue management 0 (kg/ha) exhibited mixed effect (significant reduction in some priority areas/targeting methods and insignificant reduction in others) in sediment and TN reduction.

Table 5-6. Summary of targeting component (TN) and non-targeting components (sediment and TP).

		Targeting component	Non-targeting components	
		TN	Sediment	TP
Significant BMPs		CF,RM 1000, SC, RM 2000, RS, T, NG	CF, RM 1000, SC, RM 2000, RS, T, NG	CF, RM 1000, SC, RM 2000, RS, T, NG
Insignificant BMPs		CT, NT	CT, NT	CT, NT, RM 0
Mixed effects		RM 0	RM 0	-
Significant reductions	B vs. H	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI	CII,LPSAI, LPUAI
	B vs. H+M	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
	B vs. H+M+L	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
	H vs. H+M	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI
	H+M vs. H+M+L	LII	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
Total significant reductions	CII	24/30	23/30	21/30
	LII	11/30	9/30	14/30
	LPSAI	23/30	23/30	21/30
	LPUAI	23/30	23/30	21/30

Table 5-7. BMP implementation area for TN targeting scenario.

Targeting method	H(ha)	H+M(ha)	H+M+L(ha)
CII	242318	319972	345423
LII	-	33865	345423
LPSAI	150276	321195	345423
LPUAI	73943	343408	345423

Examining significant reduction when comparing priority areas, a significant TN reduction was observed between H+M and H+M+L based on the LII targeting method, which indicates that including BMP implementation on low priority areas significantly impacts reduction. However, all BMPs (except recharge structure in CII and LPSAI) did not show a significant TN reduction based on the rest of the three targeting methods due to a smaller increase of the BMP application area from H+M to H+M+L priority area (Table 5-7). This suggests that the application of BMPs up to the H+M priority area is effective in TN reduction based on the CII, LPSAI, and LPUAI targeting methods. Comparing all targeting methods, CII was most effective in reducing targeted TN (24/30) and non-targeting sediment (23/30) and TP (21/30), where the counts indicate the combinations of BMP and targeted areas that reduced significant amounts of pollutant from the no-BMP scenario. For example, for CII reducing non-targeting sediment TN (23/30), seven BMPs had significant reductions in base vs. H, eight BMPs had significant reductions in both base vs. H+M and base vs. H+M+L, which adds to 23 total significant reductions.

5.4.1.3 Targeting Component (TP)

The results of TP targeting and non-targeting components (sediment and TN) are presented in Table 5-8. This table summarized the results obtained from the supplementary material Table A-4, Table A-5, and Table A-6 in the Appendix. Overall, the majority of BMPs were effective in reduction of TP and the non-targeted components, while conservation tillage and no tillage did not exhibit significant reductions. Contour farming had mixed results when reducing TN, while residue management and contour farming reduced significant amounts of TP and sediment.

Table 5-8. Summary of targeting component (TP) and non-targeting components (sediment and TN).

		Targeting component	Non-targeting components	
		TP	Sediment	TN
Significant BMPs		CF, RM 1000, SC, RM 2000, RS, T, NG	CF, RM 1000, SC, RM 2000, RS, T, NG	RM 1000, SC, RM 2000, RS, T, NG
Insignificant BMPs		CT, NT, RM 0	CT, NT	CT, NT
Mixed effect		_	RM 0	CF, RM 0
Significant reduction	B vs. H	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI
	B vs. H+M	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
	B vs. H+M+L	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
	H vs. H+M	CII, LPSAI, LPUAI	CII, LPSAI, LPUAI	LPSAI, LPUAI
	H+M vs. H+M+L	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI	CII, LII, LPSAI, LPUAI
Total significant reductions	CII	21/30	21/30	20/30
	LII	14/30	14/30	15/30
	LPSAI	21/30	22/30	20/30
	LPUAI	21/30	18/30	20/30

However, it showed a mixed result among targeting methods in reducing TN. Residue management (0 kg/ha) did not reduce significant amounts of TP but had mixed results among targeting methods in the reduction of sediment and TN. Overall, CII and LPSAI targeting methods were most effective in reducing TP and the non-targeting components in this scenario. None of the BMPs reduced significant amounts of sediment and TN in the CII high priority area; however, they reduced significant amounts of TP, suggesting that the BMP implementation for targeting TP does not have the added benefits or reduction of non-targeting pollutants. Except for the LII targeting method, no other targeting methods reduced significant amounts of TN between the H+M and H+M+L priority areas. This demonstrates that BMP implementation up to the H+M priority area of these targeting methods is adequate for significant TN reduction. Out of all targeting methods, LPSAI had the highest number of significant reduction options for sediment and TP targeting scenarios, while CII, LPSAI, and LPUAI had highest number of options for TN targeting scenario.

5.4.2 Spatial Correlation among the Priority Methods

The objective of this section was to determine the spatial correlation between priority areas of targeting methods based on the targeting pollutant. In this manner it can be determined if there are statistically significant differences between the priority areas that a targeting method identifies. The agreement between two targeting methods is determined through kappa and weighted kappa coefficients and an agreement plus linear-by-linear association model. The kappa and weighted kappa coefficients being closer to one indicate stronger agreement between two methods, while zero value represents that agreement occurs by chance, and a negative value depicts the agreement as weaker than expected by chance. A stronger agreement was found between CII and LPSAI, and LPSAI and LPUAI for sediment and TN targeting scenarios. However, there is no agreement between most of the targeting methods for the TP targeting scenario.

5.4.2.1 Sediment Targeting Scenario

Parameters required for the spatial correlation analysis between all targeting methods while considering sediment as the targeting pollutant are presented in A-7 (Appendix). When the CII and LPSAI targeting methods were compared, the G^2 was relatively small (9.65), indicating that the fitted value from the model is nearly equal to the actual value. This is demonstrated in Table 5-9, which compares the common subbasins selected for high/medium/low priority between CII and LPSAI from SWAT (actual) and by the developed spatial model. For example, the fitted value for low-low is 221.9, whereas the actual value is 223.

Table 5-9. Comparison of actual vs. modeled counts based on the agreement plus linear-by-linear association model: CII and LPSAI targeting methods (sediment).

CII / LPSAI	High counts: Actual (Model)	Medium counts: Actual (Model)	Low counts: Actual (Model)
High	2 (3.052)	0 (0.461)	2 (0.488)
Medium	4 (1.436)	8 (8.00)	2 (4.564)
Low	2 (3.512)	11 (10.539)	223 (221.948)

The estimated β is 0.79 with a moderately significant p-value (0.09) under the 90% confidence interval (Table A-7 in the Appendix). The estimated δ is 1.41 with a highly significant p-value (0). Therefore, the calculated local indistinguishable parameter (τ) i+1 = 36.91 (Table A-7) can be interpreted as: if LPSAI gives a result in category i+1 rather than i (say medium rather than high, or low rather than medium), CII is about 37 times more likely to give a result in the category i+1 rather than i, which suggests a strong agreement. This result is further supported by the results provided by the kappa coefficient 0.5 (0.33, 0.67) and weighted kappa coefficient 0.56 (0.36, 0.76) (Table A-7). Both the kappa and weighted kappa confidence intervals do not contain zero, indicating that there is a significant agreement beyond that expected by chance between the categorization of the watershed into H, M, and L priority areas by CII and LPSAI. Therefore, it can be concluded that these two targeting methods select similar subbasins to be H, M, and L priority.

Excluding CII vs. LPSAI and LPSAI vs. LPUAI, all other comparisons between targeting methods in the sediment scenario did not show significant spatial agreement because p-values of either β or δ were not significant (< 0.10). Similarity between LPSAI and LPUAI exists likely because they both target sediment loads from the subbasin. In the majority of the comparisons, the targeting methods behave differently when targeting sediment by selecting diverse priority areas.

5.4.2.2 TN Targeting Scenario

Like the sediment targeting scenario, the CII and LPSAI targeting methods are presented. The G^2 was 0.33 (Table A-7 in the Appendix), indicating the model fitting value is approximately equal to the actual values, which can be observed in Table 5-10 comparing the actual and model priority counts for the targeting methods. The estimated β is highly significant, whereas the estimated δ is moderately significant under the 90% CI. Hence, the chance of CII giving selecting a subbasin in category i+1 rather than i (medium rather than high, or low rather than medium) is 10 times higher when LPSAI selects a subbasin in category i+1 rather than i, suggesting a strong agreement between the methods.

Similarly, LPSAI selecting a subbasin in category i+1 rather than i is 21 times higher when LPUAI selects a subbasin in category i+1 rather than i. As was the case with sediment targeting, the CII vs. LPSAI and LPSAI vs. LPUAI are the only methods with significant spatial agreement for TN targeting. Therefore, all other combinations of targeting methods are likely to produce differing H, M, and L priority areas, illustrating the necessity of selecting a targeting method that aligns with stakeholders' specific goals in mind.

Table 5-8. Comparison of actual versus modeled counts based on agreement plus linear-by-linear association model: CII and LPSAI targeting methods (TN).

CII / LPSAI	High counts: Actual (Model)	Medium counts: Actual (Model)	Low counts: Actual (Model)
High	7 (6.86)	10 (10.29)	16 (15.85)
Medium	1 (0.991)	15 (15)	48 (48.009)
Low	0 (0.150)	5 (4.71)	152 (152.140)

5.4.2.3 TP Targeting Scenario

Unlike the sediment and TN targeting scenario, the G^2 is zero between all targeting methods except the CII vs. LII and CII vs. LPUAI targeting methods (Table A-7 in the Appendix). This result suggests that the model is saturated (model predictions are similar to actual values) as G^2 is zero due to data sparseness (zeroes in non-diagonal elements of the contingency tables). The sparseness of the data causes computational problems, which leads into problems in model fitting. Hence, the parameters (β, δ, and τ) estimated for all pair wise comparisons except CII vs. LII and CII vs. LPUAI are unreliable. Only, the kappa and weighted kappa coefficients were used to measure the agreement for such pairs. However, when the CII and LII targeting methods were compared, the G^2 was found to be 1.53 (Table A-7), suggesting a good model fit, which is further supported from the observation in Table 5-11.

Table 5-9. Comparison of actual versus modeled counts based on agreement plus linear-by-linear association model for CII and LII targeting methods (TP).

C2 / LII	High counts: Actual (Model)	Medium counts: Actual (Model)	Low counts: Actual (Model)
High	0 (0.305)	4 (3.101)	21 (21.594)
Medium	0 (0.288)	0 (0)	14 (13.712)
Low	6 (5.406)	36 (36.899)	173 (172.695)

However, both β and δ are highly non-significant (Table A-7 in the Appendix). This is further supported by the negative kappa and weighted kappa coefficients, indicating a strong disagreement between the categorization of priority areas between CII and LII targeting methods. The disagreement is likely due to the CII targeting method being based on pollutant concentration, while LII is based on the pollutant load. Overall, no conclusions can be drawn for the spatial correlation of most targeting methods for TP. The exceptions are CII vs. LII and CII vs. LPUAI, which were spatially dissimilar in selecting H, M, and L areas.

5.4.3 Spatiotemporal Variability of Priority Areas

The objective of this section was to understand the variability of priority areas with respect to the time of BMP implementation. Native grass and contour farming were selected because these BMPs demonstrated the highest and lowest pollutant reduction efficiencies among studied BMPs with significant reductions. The process begins by implementing BMPs in the high priority areas based on the CII, LPSAI, and LPUAI targeting methods for two successive years. The LII targeting method was not used in this analysis due to lack of agricultural lands identified as high priority. Overall, the high priority areas of both sediment and TP scenarios changed faster over implementation years than in the TN scenario. A greater variability of high priority areas was observed in native grass compared to contour farming in all scenarios and targeting methods.

The findings of this section will help policymakers and stakeholders to develop better implementation strategies based on time and location of BMPs installment. This scenario reflects the manner in which implementation projects are completed over a number of years, which is closer to reality.

5.4.3.1 Sediment Targeting Scenario

Subbasin priority area designations were altered in each year of implementation for contour farming and native grass for all applicable targeting methods, as demonstrated in the Appendix Figure A-8, Figure A-9, and Figure A-10. Considering year zero, BMPs are only implemented on the high priority areas. When native grass is implemented, most high priority areas are reclassified to medium or low priority areas. However, in order to achieve the highest rate of pollution reduction while targeting smaller areas, the area of study was reclassified to high, medium, and low again for the next round of BMP implementation. Meanwhile, the specific pollutant concentration or load intervals of each priority change between each year of implementation. Contour farming is not as effective as overall, as most high priority areas did not change until year two, when they are converted to medium priority. In addition, some medium priority areas become high priority because the definition of high priority changes with time.

For CII, the high and medium priority areas of both BMPs were nearly equal after the first year of BMP implementation (Figure A-8). However, different priority areas were observed for both BMPs after the second year of implementation. A greater high priority area was found in contour farming compared to the native grass applied scenario. In fact, the high priority area of native grass is not visible in the map (year two) due to the very small area selected as high priority in year zero. This result was due to greater sediment reduction efficiency of native grass compared to contour farming. Variability of the priority area changes rapidly for most effective BMPs (e.g. native grass); while it changes slowly for less effective BMPs (e.g. contour farming).

Medium and high priority areas of both BMPs were different after BMP implementation under LPSAI (Figure A-9). A comparatively smaller high priority area was observed in the native grass implementation scenario compared to contour farming due to greater sediment reduction in case of native grass. Also, a distinct change in the high priority area of native grass was observed between the first and second year of BMP implementation. However, a minimal change in the high priority area was observed in contour farming between the first and second year of BMP implementation.

Like the CII and LPSAI targeting methods, less high priority areas were found in native grass compared to contour farming after one year of BMP implementation under LPUAI (Figure A-10). However, after the second year of BMP implementation, the high priority areas of contour farming were smaller than the native grass. This was due to the conversion of more high priority areas (after year one) of contour farming implementation into medium priority areas and alteration of medium priority areas (after year one implementation) of native grass into high priority areas.

5.4.3.2 TN Targeting Scenario

The pattern of priority areas in this scenario was similar to the sediment targeting scenario, as shown in the Appendix Figure A-11, Figure A-12, and Figure A-13. Based on the CII targeting method, the high priority area of contour farming was greater than the high priority area of native grass for both the first and second years of implementation (Figure A-11). This was due to comparatively less TN reduction by contour farming than native grass (Table A-2). In the LPSAI targeting method, smaller high priority areas were observed in native grass compared to the contour farming applied scenario after year one of implementation (Figure A-12). However, a comparatively greater high priority area was found in the native grass applied scenario compared to the contour farming scenario after the second year due to presence of greater medium priority area after one year of BMP implementation and conversion of those medium priority areas to high priority areas after the second year. Like the CII targeting method, a similar pattern of high priority areas was found among the BMPs based on the LPUAI targeting method (Figure A-13). The conversion of a high priority area to a medium priority area by BMPs was slower than the sediment targeting scenario for all targeting methods.

5.4.3.3 TP Targeting Scenario

CII high priority areas of native grass (year one and two) were smaller compared to the contour farming priority area (Figure A-14 in the Appendix) after the first year due to comparatively more significant TP reduction under native grass. However, the medium priority area of native grass was greater than contour farming for both of the years due to the conversion of low to medium priority during both years of BMP implementation. In the LPSAI (Figure A-15 in the Appendix) and LPUAI (Figure A-16 in the Appendix) targeting methods, native grass had less high priority areas compared to contour farming in both years due comparatively greater TP reduction than for native grass. In most of the native grass scenarios, high priority areas decreased gradually to the point where less high priority areas were observed by the end of second year. However, the high priority areas of contour farming did not show a significant change by the end of second year due to less effective TP reduction. Like the sediment targeting scenario, a faster conversion of a high priority area to medium priority area was observed in this scenario by native grass.

5.5 CONCLUSION

The objectives of this research were to 1) determine the most effective BMPs both for targeting and non-targeting pollutants based on different targeting methods while minimizing area devoted to BMP implementation; 2) evaluate the spatial correlation among the targeting methods in categorization of priority area (high, medium, and low) based on targeting pollutant; and 3) assess the spatiotemporal variability of CSAs. Four targeting methods (CII, LII, LPSAI, and LPUAI) were used in SWAT to prioritize BMP implementation in the Saginaw River Watershed for sediment, TN, and TP reduction at the watershed outlet. Ten BMPs, namely conservation tillage, no till, residue management (0 kg/ha), contour farming, residue management (1000 kg/ha), residue management (2000 kg/ha), strip cropping, recharge structures, terraces, and native grass were implemented for each targeting method.

BMP effectiveness among targeting methods and priority areas for targeted and non-targeted pollutants was compared using autocorrelation functions and modified paired t-tests that account for temporal autocorrelation. Most BMPs (excluding no tillage and conservation tillage) exhibited at least some significant pollutant reduction (targeted and non-targeted) for all targeting methods. As BMP implementation areas increased from high+medium to high+medium+low priority areas, significant pollutant reduction was not present. This indicates that BMP implementation up to the high+medium priority area is enough to achieve significant pollutant reduction. Overall, LPSAI had the most significant reductions for sediment and TP, while CII was most effective for targeting TN.

Spatial correlation among the targeting methods was determined by kappa and weighted kappa coefficients with an agreement plus linear-by-linear association model. A strong agreement was found between LPSAI and LPUAI targeting methods when categorizing the priority areas into high, medium, and low in the SRW for both sediment and TN targeting scenarios, likely because these methods target pollutant loads. However, a similar result was found between the CII and LPSAI targeting methods even though both methods are based on different principles (CII is based on pollutant concentration in the reach, LPSAI is based on pollutant load in the subbasin) for both sediment and TN targeting scenarios. In the TP targeting scenario, strong disagreement between CII and LII was observed, indicating that these methods target TP differently. Examining spatial correlation between targeting methods highlights their similarities and differences. By considering spatial correlation, policymakers and stakeholders can better understand which critical source area targeting method will achieve their specific watershed management plan goals.

The spatiotemporal variability of priority areas primarily depends on the effectiveness of a BMP. By implementing BMPs on high priority areas in consecutive years, realistic BMP implementation scenarios were achieved. In all targeting methods, the defining factors of priority area changed with each implementation year. A distinct change in the high priority area of native grass was observed by the end second year, while a minimal change in high priority areas was found in the case of contour farming due to greater pollutant reduction efficiency of native grass. Therefore, the high priority area of native grass changes rapidly compared to contour farming. Examining spatiotemporal variability emulates realistic BMP implementation plans and allows for the understanding of how critical source areas will be altered as BMPs are put into practice.

6. APPLICATION OF ANALYTICAL HIERARCHY PROCESS FOR EFFECTIVE SELECTION OF AGRICULTURAL BEST MANAGEMENT PRACTICES.

6.1 ABSTARACT

In this study an analytical hierarchy process (AHP) was used for ranking best management practices (BMPs) in the Saginaw river watershed based on environmental, economic, and social factors. Three spatial targeting methods were used for placement of BMPs on critical source areas (CSAs). The environment factors include sediment, total nitrogen, and total phosphorus reductions at the subbasin level and the watershed outlet. Economic factors were based on total BMP cost, including installation, maintenance, and opportunity costs. Social factors were divided into three favorability rankings (most favorable, moderately favorable, and least favorable) based on area allocated to each BMP. Equal weights (1/3) were considered for the three main factors while calculating the BMP rank by AHP. In this study three scenarios were compared. A comprehensive approach in which environmental, economic, and social aspects are simultaneously considered (*Scenario 1*) versus more traditional approaches in which both environmental and economic aspects were considered (*Scenario 2*) or only environmental aspects (sediment, TN, and TP) were considered (*Scenario 3*). In *Scenario 1,* only stripcropping (moderately favorable) was selected on all CSAs at the subbasin level, whereas stripcropping (49 to 69 % of CSAs) and residue management (most favorable, 31 to 51% of CSAs) were selected by AHP based on the watershed outlet and three spatial targeting methods. In *Scenario 2*, native grass was eliminated by moderately preferable BMPs (stripcropping) both at the subbasin and watershed outlet levels due the lower BMP implementations cost compared to native grass. Finally, in *Scenario 3*, at subbasin level, the least socially preferable BMP (native grass) was

selected in 100% of CSAs due to greater pollution reduction capacity compared to other BMPs. At watershed level, nearly 50% the CSAs selected stripcropping, and the remaining 50% of CSAs selected native grass and residue management equally.

6.2 INTRODUCTION

NPS pollution is the primary source of water quality problems in the United States (USEPA, 2003). In the past few decades, NPS pollution generated from agricultural activities have become the primary contributor to water quality impairments in rivers and lakes (USEPA, 2005). Higher agricultural yields obtained by increasing nutrient application have resulted in environmental concerns such as eutrophication (Shen et al., 2013). Additionally, in order to meet energy security needs, the rapid growth of bioenergy crop production will likely jeopardize aquatic ecosystems (Love et al., 2011; Yousefpour, 2013).

Implementing BMPs on agricultural lands to improve water quality is a well-known method (Giri et al., 2012a). However, BMP performance depends on placement, timing, and selection procedures (Giri et al., 2012b). Effective BMP implementation strategies cannot be achieved without simultaneous consideration of economic and social aspects of these strategies. To address these concerns, watershed management decision making plans should consist of evaluating, balancing, and making trade-offs between these components and available alternative management practices (Kaplowitz and Lupi, 2012). Multi-criteria decision analysis (MCDA) is a widely accepted method to address these challenges (Yatsalo et al., 2007). The multi-attribute utility theory (MAUT), multi-attribute value theory (MAVT), and analytical hierarchy process (AHP) are examples of MCDA methods, which use optimization algorithms to solve complex decision making problems (Linkov and Steevens, 2013). In particular, AHP uses systematic evaluation criteria based on pairwise comparison and expert knowledge (Young et al., 2009).

Several studies in water resources have used AHP to support decision making. Young et al. (2009) introduced AHP for selection of BMPs to reduce pollutant loadings downstream from a small parking lot in a residential/commercial development area. The selection of BMP ranking was obtained through pairwise comparison of selection criteria, BMPs among themselves, and BMPs against selection criteria (aesthetic benefit, limiting the BMP installation site to less than one acre, total suspended solid removal, total phosphorus removal, and total nitrogen removal). The pairwise comparison of selection criteria generated a criteria priority vector (weight of individual criteria), while the pairwise comparison of BMPs produced a BMP decision matrix. Finally, the BMP decision matrix was multiplied by the criteria priority vector to generate the priority BMP ranking. The final ranking of BMPs suggested bioretention, porous pavement, and storm water filtering systems were the most effective BMPs in descending order. Calizaya et al. (2010) used AHP to solve MCDA and to identify a sustainable water resources management plan in the Lake Poopo basin, Bolivia. The MCDA structure consisted of three major objectives (economic, social, and environmental issues), 10 conflicts (lower level objectives and sub-criteria), seven instruments to solve the conflicts (alternatives), and implementing actors (organizations). They evaluated the solutions from the MCDA based on the active participation of stakeholders. Forty five pairwise comparisons were included in the MCDA structure. The weights used in this study for environmental, social, and economic criteria were 0.62, 0.33, and 0.06, respectively, and were obtained by stakeholder participation. The most effective instruments of this MCDA structure were educational training program, formation of local water management organizations, and stakeholder involvement; whereas the most effective implementing actor was local government. Garfi et al. (2011) used AHP in multi-criteria analysis (MCA) to improve strategic environmental assessment of water programs in developing countries and validated for a semi-arid region in Brazil. Both general and specific criteria were selected to determine the best alternative among the One Million Cisterns Project and the Spring Assessment Program for water management. The goal of the study was to improve drinking water supplies to communities living in a semi-arid region. The final criteria were further divided into 11 general sub-criteria for human development and 12 technical sub-criteria for water supply. The relative weights were determined by pairwise comparison among the sub-criteria of each respective group. The results of this study showed that the Cisterns Project were more effective compared to the Spring Assessment Program considering economic, social, political, and environmental aspects.

A number of studies have applied AHP for decision support in water resources. A few of those studies have used AHP to determine the most effective BMP implementation, primarily in urban areas. It shows that AHP can be used multiobjective BMP implementation plan effectively. However, this study is unique because it focuses on evaluating suitable application of BMPs on agricultural lands on a large scale, which to the best of our knowledge has not been done. The specific objectives for this study were to: (1) evaluate the cost of pollution reduction associated with BMP installation both at subbasin level and the watershed outlet and (2) identify the best BMP type and implementation site using AHP while considering social, economic, and environmental issues based on different spatial targeting methods.

6.3 MATERIALS AND METHODS

6.3.1 Study Area

This study was conducted on the SRW, which is located in east central Michigan (Figure 6-1). It consists of six subwatersheds: Tittabawassee, Shiawassee, Pine, Flint, Cass, and Saginaw. This watershed is one of the most diverse watersheds in Michigan, consisting of agriculture, manufacturing, tourism, wildlife habitat, and outdoor recreation (Giri et al., 2012a). The Saginaw River flows towards north direction and finally drains into Lake Huron. This watershed contains nation's largest contiguous freshwater coastal wetland (USEPA, 2009). The mean, minimum, and maximum watershed elevations are 242 m, 177 m, and 457 m, respectively. The total watershed area is 15,263 km^2, of which 42% forest, 23% agriculture, 17% pasture, 11% wetland, and 7% urban. It is one of the predominant agricultural-based watersheds in Michigan, with predominantly corn and soybean cropping rotations.

Figure 6-1. Location of Saginaw River Watershed.

6.3.2 Model Description

In order to evaluate the BMP effectiveness in reducing NPS pollution in the SRW, a physically based, spatially distributed, watershed-scale model (Arnold et al., 1998; Neitsch et al., 1998; Neitsch et al., 2005) known as SWAT was used. Primary model components include hydrology, soil, landuse, plant growth, nutrients, pesticides, management practices, and weather (Gassman et al., 2007). SWAT calculates flow, sediment, nutrients, and pesticides transport both over land and in-stream based on the physiographic, meteorological, and land-management characteristics of the watershed. The watershed is divided into subbasins and further divided into hydrologic response units (HRUs) based on the homogeneous landuse, soil type, slope, and management practices.

6.3.2.1 Data Sources

The SWAT model requires input data such as topography, land use, soil, and stream network. Topography data in the form of digital elevation model (90m×90m) was obtained through the Better Assessment Science Integrating point and Nonpoint Sources (BASINS) software. Landuse data at 56m resolution 2008 Cropland Data Layer) for the watershed was obtained from USDA's National Agricultural Statistics Service (NASS, 2008). To represent the soil characteristics in the watershed, the State Soil Geographic Database (STATSGO) was used, which was developed by the National Cooperative Soil Survey. The stream network in the form of a National Hydrography Dataset was obtained from the United States Geological Survey (USGS) to improve hydrologic segmentation and subwatershed boundary delineation in the SRW.

For stream flow calibration and validation in the watershed, daily stream flow data was obtained from USGS gauging station 04157000. Water quality data (sediment, TN, and TP) were obtained from Michigan Department of Environmental Quality (MDEQ) for station 090177. Climatic data for 19 precipitation and 11 temperature stations were downloaded from the National Climatic Data Center (NCDC) for twenty years (1990-2009). The data for remaining climatic parameters (wind speed, relative humidity, and solar radiation) were generated from the SWAT weather generator.

In order to assess the fate and transport of sediment and nutrients in the watershed, agricultural management operations were developed based on common practices by local farmers in the watershed. A detail description of timing of tillage and type and amount of fertilizer applied is provided in the Giri et al. (2012a).

6.3.2.2 Sensitivity Analysis and Calibration

Model calibration is performed by adjusting the most sensitive model parameters, which are obtained through a process called as sensitivity analysis. This analysis provides a rank of the most influential parameters on model output. To evaluate the most influential parameters during sensitivity analysis, Latin-Hypercube One-factor-At-a-Time (LH-OAT) parameter sampling technique is used in the SWAT framework (van Griensven et al., 2006). After determining the sensitive parameters, calibration and validation was performed for stream flow, sediment, and nutrients on monthly time step with a two-year model warm-up period. A detail description of sensitivity analysis, calibration, and validation is described in Giri et al. (2012a).

6.3.2.3 Best Management Practices in SWAT

Five BMPs: stripcropping (SC), residue management (RM), conservation tillage (CT), native grass (NG), and no till (NT) were implemented separately on agricultural lands in the RW. The pre- and post- BMP implementation results were compared with each other to evaluate BMP effectiveness both at subbasin and watershed scales.

6.3.2.4 Spatial Targeting Methods

To optimize resource allocation for a BMP implementation plan, it is important to identify locations that contribute the most to overall pollution load either at the edge of a field or at the watershed outlet. These areas are known as CSAs. Four targeting methods; Concentration Impact Index (CII), Load Impact Index (LII), Load per Subbasin Area Index (LPSAI), and Load per Unit Area Index (LPUAI) were used to identify CSAs for sediment, total nitrogen, and total phosphorus. These four targeting methods were used to categorize the watershed into high, medium, and low priority areas. The categorization was performed based on the Jenks natural break optimization technique, where similar values of data form a group while maximizing the difference between groups (Jenks, 1967). The priority areas in CII targeting method is determined based on the pollutant concentration in the reach subbasin (Tuppad and Srinivasan, 2008) while LII targeting method categorized priority area based on cumulative pollutant load in the reach (Tuppad and Srinivasan, 2008, Giri et al., 2012a). The LPSAI targeting method classifies priority areas based on total pollutant load produced by each subbasin (Giri et al., 2012a) whereas the LPUAI targeting method determines priority areas based on the pollutant load per unit area of each subbasin (Tuppad and Srinivasan , 2008; Giri et al., 2012a). A detailed description of these targeting methods is provided in Giri et al. (2012a).

6.3.3 Environmental, Economic, and Social Aspects of BMP Implementation Plan

Before evaluating the overall impacts of BMP implementation plan using the AHP method, the environmental, economic, and social aspects of these implementation scenarios need to be assessed separately. The following sections describe the evaluation procedure.

6.3.3.1 Environmental Aspects of BMP Implementation Plan

The five BMPs were implemented one at a time based on the targeting scenarios (sediment, total nitrogen, and total phosphorus) by four targeting methods (CII, LII, LPSAI, and LPUAI). Overall, 180 different environmental scenarios (5 BMPs × 3 priority areas × 3 targeting scenarios × 4 targeting methods) were evaluated. The SWAT model outputs were aggregated/disaggregated to 56 m grids. The grid size is equal to the 2008 Cropland Data Layer land use resolution. The same resolution was used for the economic and social analyses to preserve spatial resolution consistency. The sediment, TN, and TP reduction for each BMP were then calculated at the field and watershed scales to determine BMP effectiveness.

6.3.3.2 Economic Aspects of BMP Implementation Plan

The BMPs used in this study were assumed to be implemented for five years (equal to the longest design life span among the BMPs – stripcropping and native grass). Therefore, the total BMP cost was calculated for a five-year period. Installation of BMPs is the one-time cost required (although this cost is multiplied by the five-year period if the lifespan is one year). The annual maintenance cost of BMP is the money spent to maintain effective pollution reduction throughout the year. Opportunity cost is the interest rate (3.9%) of BMP implementation cost if the life span of BMP is more than one year (NRCS, 2011). The total cost column in Table 6-1 is the summation of installation, annual maintenance, and opportunity costs. The BMP application area of each targeting scenario for each targeting method was multiplied with the respective total BMP cost to determine the total cost spent for that BMP. Then the total BMP cost was divided by the amount of pollution reduction (both at subbasin and watershed outlet), which provides dollar per mass of pollution reduction. The BMP cost and design lifespan presented in Table 6-1 are obtained from the United State Department of Agriculture - Natural Resources Conservation Service (NRCS, 2011). Overall, five different economic scenarios (five BMPs) were evaluated at 56 m resolution.

Table 6-1. Five-year itemized cost for different BMPs used in this study (NRCS, 2011).

BMPs*	Installation Cost (dollar/per hectare)	Annual Maintenance Cost (dollar/per hectare-year)	Opportunity cost (dollar/year)	Design lifespan(year)	Total five-year cost (dollar/per hectare
SC	64.22	0.64	2.5	5	79.95
RM	29.64	0.00	-	1	148.20
CT	49.40	0.00	-	1	247.00
NG	687.57	20.63	26.8	5	924.79
NT	67.26	0.00	-	1	336.29

6.3.3.3 Social Aspects of BMP Implementation Plan

The BMP application area is considered as the social component in this study. The preference of BMP selection by farmers depends on the BMP application area in the cropland. For example, BMPs that require a small implementation area are preferred by most of the farmers, whereas BMPs that need a large implementation area are preferred the least. Larger implementation areas require farmers to remove crops from production to accommodate the implementation. The BMP implementation area was obtained from local and national NRCS datasets (NRCS, 2008). Overall, five different social scenarios (five BMPs) were evaluated at 56 m resolution.

Table 6-2. The BMP allocation area and associated social preferences of different BMPs.

BMPs	Allocation area to BMP Implementation (%)	Social Preferences
SC	50	Moderate
RM	0	Most Favorable
CT	0	Most Favorable
NG	100	Least Favorable
NT	0	Most Favorable

6.3.4 Identify the best BMP type and implementation site using Analytic Hierarchy Process

The AHP method was introduced by Saaty in 1980 to solve complex decision making problems. It can be applied to a wide array of fields such as project management, strategic planning, and alternative selection processes. The AHP consists of four step processes: 1) construction of pairwise comparison matrix, 2) computation of priority vector, 3) calculation of consistency ratio, and 4) ranking of alternatives (Young et al., 2009).

1) Construction of pairwise comparison matrix: In this step, a pairwise matrix is constructed separately among the alternatives for each relevant criterion. An additional pairwise matrix is formed only among the relevant criteria. In each comparison matrix, each row entry (alternatives/criteria) is compared to each column entry (alternatives/criteria) by using a scale (1-9) of relative importance, where one is equally important and nine is absolutely more important.

2) Computation of priority vector: the priority vector of the pairwise comparison matrix (constructed in the previous step) is created by computing a normalized principal eigenvector (Saaty, 1980). To calculate the principal eigenvector, each column entry in the pairwise comparison matrix is divided by the sum of its respective column, generating a new entry for that column. The sum of the new column entry should equal one. Then the average of each row is calculated using the new entry in the matrix, which provides the priority vector.

3) Calculation of consistency ratio: Calculation confirms the consistency of importance of one entry over another in the matrix. The first step in calculating the consistency ratio is multiplying the original pairwise comparison matrix (step 1) with the priority vector calculated in step 2 to create a new matrix. Each entry of this new matrix is divided by the priority vector (step 2) to create another a new matrix. The average of all the entries in the new matrix provides the maximum eigenvalue ($\lambda_{\max}$). The closer the value of maximum eigenvalue is to the number of rows/columns in the pairwise comparison matrix the better the consistency among the entries. The consistency index is calculated by Saaty (1980) using the following equation:

$$Consistency\ Index(CI) = \frac{(\lambda_{\max} - n)}{(n-1)} \tag{6-1}$$

n is the number of rows/columns in the pairwise comparison matrix. The consistency ratio is calculated by using the following equation developed by Saaty (1980):

$$Consistency\ ratio = \frac{CI}{random\ index(RI)} \tag{6-2}$$

The random index varies based on n value and was obtained from Saaty (1980). If the consistency ratio is 0.1 or less, then the pairwise comparison matrix formed during first step is consistent. Otherwise, rearrangement of entries in the pairwise comparison matrix is performed to ensure the logic between the alternatives/criteria.

4) Ranking of alternatives: the priority vectors calculated among the alternatives for each criterion are extracted and placed into a new single matrix. The new matrix is multiplied by the priority vector obtained from relevant criteria which provides the rank of all the competing alternatives.

An AHP extension (ext_ahp.dll) in ArcGIS developed by Marinoni (2009) was used to calculate the BMP ranking considering environmental, social, and economic criteria. A flow chart representing the steps required during the application of AHP is provided in the Figure 6-2.

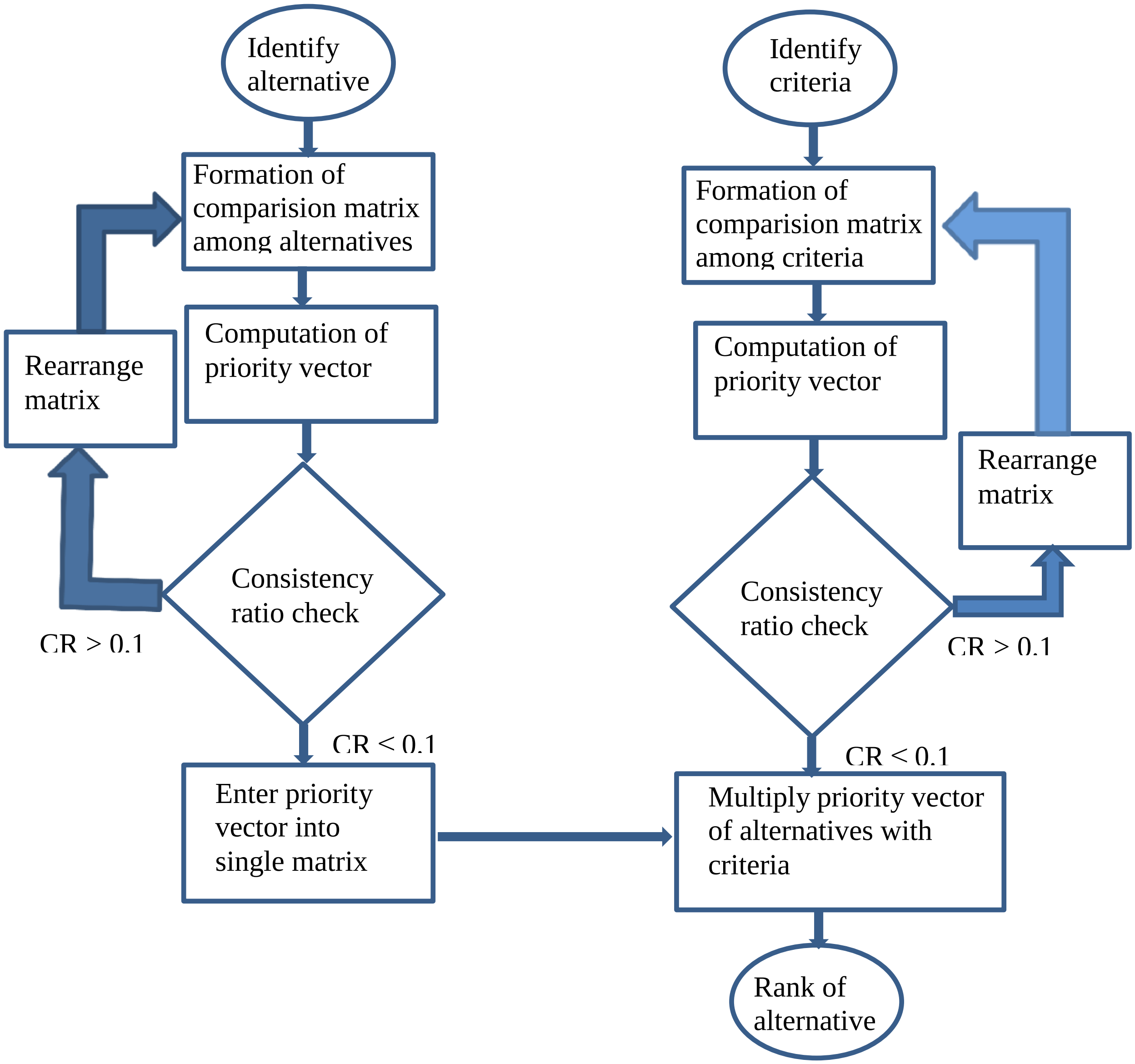

Figure 6-2. AHP flowchart to determine the rank of competing alternatives.

BMP implementation strategies can be developed based on pollution reduction at the subbasin or watershed level. Therefore, three scenarios were evaluated at each level to determine the applicability of AHP to optimize overall outcomes and compare the new approach in which environmental, economic, and social aspects are simultaneously considered (*Scenario 1*) versus more traditional approaches in which both environmental and economic aspects were considered

(*Scenario 2*) or only environmental aspects (sediment, TN, and TP) were considered (*Scenario 3*).

6.3.4.1 Scenario 1 -Using AHP to Optimize the Environmental, Economic, and Social Outcomes

BMPs are usually first implemented on agricultural fields within the high priority subwatersheds. However, regardless of targeting scenarios, no agricultural land was identified as high priority for the LII targeting method. Therefore, the comparisons were only performed on the high priority areas identified by for CII, LPSAI, and LPUAI methods for all targeting scenarios (sediment, TN, and TP). The following section describes the steps that were taken to develop the BMP implementation plan using AHP.

Step 1) Construction of pairwise comparison matrix: The BMP effectiveness was calculated based on the sediment, TN, and TP reductions at both subbasin and the watershed outlet. This was performed by calculating the total pollutants reduction before and after BMP implication. The process is presented here for one subbasin (43), which was identified as a high priority area by all targeting methods (CII, LPSAI, and LPUAI) (Figure B-1 in the Appendix). The pairwise comparison matrix are presented for sediment (Table 6-3), TN (Table 6-4), and TP (Table 6-5) reductions at the subbasin level. Similar tables for all subbasins were developed based on pollutions reductions at the watershed outlet that are presented in Tables B-2 through B-4 in the Appendix.

Table 6-3. Pairwise comparison matrix developed for subbasin 43 based on sediment reduction at the subbasin level.

BMPs	SC	RM	CT	NG	NT
SC	1.00	1.05	3.85	0.71	3.48
RM	0.95	1.00	3.68	0.68	3.32
CT	0.26	0.27	1.00	0.19	0.90
NG	1.40	1.47	5.40	1.00	4.88
NT	0.29	0.30	1.11	0.20	1.00

Table 6-4. Pairwise comparison matrix developed for subbasin 43 based on TN reduction at the subbasin level.

BMPs	SC	RM	CT	NG	NT
SC	1.00	2.00	9.00	0.56	9.00
RM	0.50	1.00	9.00	0.28	9.00
CT	0.11	0.11	1.00	0.11	1.12
NG	1.78	3.56	9.00	1.00	9.00
NT	0.11	0.11	0.89	0.11	1.00

Table 6-5. Pairwise comparison matrix developed for subbasin 43 based on TP reduction at the subbasin level.

BMPs	SC	RM	CT	NG	NT
SC	1.00	2.24	9.00	0.62	9.00
RM	0.45	1.00	9.00	0.28	9.00
CT	0.11	0.11	1.00	9.00	1.00
NG	1.60	3.59	9.00	1.00	9.00
NT	0.11	0.11	1.00	0.11	1.00

Steps 2) Computation of priority vector: After developing the pairwise comparison matrices, the weight vector was calculated by using the AHP extension (ext_ahp.dll) in ArcGIS developed by Marinoni (2009). The weight vector for sediment, TN, and TP reduction matrix at the subbasin level is presented in Table 6-6 and at the watershed outlet is presented in Table B-5.

Table 6-6. Weight vector calculation of BMPs for sediment, TN, and TP reduction for subbasin 43 at subbasin level.

BMPs	Sediment Weight	TN Weight	TP Weight
SC	0.2522	0.2942	0.3057
RM	0.2449	0.2033	0.1990
CT	0.0672	0.0333	0.0324
NG	0.3620	0.4377	0.4305
NT	0.0737	0.0316	0.0324

Step 3) Calculation of consistency ratio: The consistency ratios were calculated for subbasin (43) using the AHP extension (Marinoni, 2009). The consistency ratios for sediment, TN and TP at subbasin level are 0.0076, 0.0363, and 0.0302, and at watershed level are .0000, 0.0000, and 0.0000, respectively. All of the consistency ratios for all subbasins were acceptable as they were less than 0.1.

Similar to the pollutions (sediment, TN, and TP), total BMP cost (economic component) and BMP application area (social component) pairwise comparison matrices were prepared. However, contrary to the pollution pairwise comparison matrices, only one set was developed for all subbasins because BMP installation cost and farmer preference for applying those BMPs are consistent throughout the watershed. For this section, the consistency ratios and weight vectors were calculated using the AHP extension. The weight vector for total BMP implementation cost is provided in Table 6-7 and the weight vector for BMP application area is shown in Table 6-8.

Table 6-7. Weight vector calculation of BMPs for total BMP cost.

BMPs	Weight
SC	0.4440
RM	0.2513
CT	0.1511
NG	0.0424
NT	0.1112

Table 6-8. Weight vector calculation of BMP application area.

BMPs	Weight
SC	0.0770
RM	0.2984
CT	0.2984
NG	0.0278
NT	0.2984

Regarding the social component, the weight vector of conservation tillage, no-till, and residue management were the greatest (0.2984) whereas the weight vector of native grass was smallest (0.0278) (Table 6-8) which is justified, because the native grass takes 100% of agricultural land out of production, while this number is 0% in conservation tillage, no-till, and residue management (Table 6-2).

The weights for the criteria priority vector were divided equally among the three criteria (pollution reduction, total BMP cost, and BMP application area). The pollution reduction criterion priority vector was further divided into three equal weights as it consists of three components (sediment, TN, and TP). The weights of the criteria priority vector are presented in Table 6-9.

Table 6-9. Weight vector of criteria used in this study.

BMPs	Weight
Total BMP cost	0.33
Sediment reduction	0.11
TN reduction	0.11
TP reduction	0.11
BMP Application Area	0.33

Step 4) Ranking of alternatives: Finally, the weight vectors for each criterion among the BMPs were entered into a single matrix (Table 6-10 at the subbasin level and Table B-6 in the Appendix at watershed level) and this matrix was multiplied by the criteria priority vector (Table 6-9) to generate the final weight for individual BMPs. The final weight for individual BMP is presented in Table 6-11.

Table 6-10. Decision matrix of BMPs for all criteria developed for subbasin level analysis (subbasin 43).

BMPs	Total BMP cost	Sediment reduction	TN reduction	TP reduction	BMP Application Area
SC	0.4440	0.2522	0.2942	0.3057	0.0770
RM	0.2513	0.2449	0.2033	0.1990	0.2984
CT	0.1511	0.0672	0.0333	0.0324	0.2984
NG	0.0424	0.3620	0.4377	0.4305	0.0278
NT	0.1112	0.0737	0.0316	0.0324	0.2984

Table 6-11. Final weight vector of individual BMPs for subbasin 43.

BMPs	Weight (subbasin level)
SC	0.2657
RM	0.2526
CT	0.1630
NG	0.1585
NT	0.1503

Stripcropping and residue management are the most favorable BMPs, while native grass is most effective in reduction of sediment, TN, and TP (Tables 6-3 to 6-5). This result is due to the higher total BMP cost (Table 6-1) associated with higher BMP application area (Table 6-2) in the case of native grass compared to stripcropping and residue management. This result is only valid for the BMP ranking in subbasin 43 after simultaneously considering environmental, economic, and social factors. Similarly, the BMP ranking was calculated for all subbasins identified as high priority area by the three targeting methods (CII, LPSAI, and LPUAI) and all targeting scenarios (sediment, TN, and TP). The final ranking of BMPs for all subbasins identified as high priority area is presented in Table B-8 at the subbasin level and Table B-9 at the watershed level in the Appendix.

6.3.4.2 Scenario 2 -Using AHP Method to Optimize the Environmental and Economic Outcomes

The BMP selection was calculated based on sediment, TN, and TP reductions at the watershed outlet and total BMP cost. The pollution reductions were calculated for all BMPs for each subbasin in the previous scenario. The BMP cost for each subbasin was calculated by multiplying the total BMP cost (Table 6-1) for each BMP by the BMP application area in each subbasin. The weights for the criteria priority vector were divided equally among two criteria (pollution reduction and total BMP cost). The pollution reduction criterion priority vector is further divided into three equal weights (0.1667) as it consists of three components (sediment, TN, and TP). The BMP cost received the weight of 0.5. Similar procedures to *Scenario 1* were followed to produce the most favorable location for BMP placement for each targeting method. The final ranking of BMPs for all subbasins identified as high priority area is presented in Table B-10 at the subbasin level and Table B-11at the watershed level in the Appendix.

6.3.4.3 Scenario 3 -Using AHP Method to Optimize the Environmental Outcomes

The BMP selection was calculated based on the sediment, TN, and TP reduction. The amount of pollution generated by an individual subbasin was calculated after BMP application and this amount was subtracted from the pollution generated by the subbasin during the no BMP applied condition to determine the pollution reduction for each subbasin by individual BMP. Based on the amount of sediment reduction, a BMP rank was prepared for each subbasin. The weight for criteria priority vector was divided equally among three criteria in which each criterion received the weight of 0.3333. The final ranking of BMPs for all subbasin identified as high priority area is presented in Table B-12 at subbasin level and Table B-13 at watershed level in the Appendix.

6.4 RESULTS AND DISCUSSION

6.4.1 Determining the Cost of Pollution Reduction Associated with BMP Installation Both at Subbasin Level and the Watershed Outlet

The objective of this section was to determine the most effective BMPs by considering both pollutant reduction and total BMP cost. Pollutant reduction varies among the BMPs, priority areas and targeting methods. Figure 6-4 represents the sediment reduction in dollars per ton among BMPs, priority areas, and targeting methods. Overall, stripcropping and residue management were most effective compared to other BMPs both at the reach and subbasin levels (Figure 6-4) due to higher sediment reduction and lower BMP cost (Table 6-1). However, when BMP effectiveness is evaluated only based on environmental factors such as sediment reduction, native grass was the most effective, which agrees with Woznicki et al. (2011) and Giri et al.

(2012a). In this study, native grass demonstrated moderate effectiveness due to having the highest total BMP cost (Table 6-1). Conservation tillage and no-till are the least effective BMPs, both at the reach and subbasin levels, which is attributed to significantly lower sediment reduction compared to other BMPs.

The reduction cost per ton of sediment at the watershed outlet in the high priority areas ranges from $230 dollars to approximately $31,000, in the medium priority areas the cost ranges from $250 to nearly $11,000, and in the low priority areas the cost ranges from $390 to $15,000 (Figure 6-4a, 6-4b, and 6-4c). However, the sediment reduction cost at the subbasin level is lower in all priority areas compared to sediment reduction cost at the watershed outlet. The reduction cost per ton of sediment for subbasins in the high priority areas ranges from $50 to nearly $750, in the medium priority areas the cost ranges from $60 dollars to approximately $1150 dollars, and in the low priority areas the cost ranges from $50 to $1100 dollars (Figure 6-4d, 6-4e, and 6-4f). The sediment reduction cost of native grass is always less than the cost of conservation tillage and no-till at both the watershed outlet and the subbasins in all priority areas and targeting methods except for the low priority area at the subbasin level (Figure 6-4f). This result is due to combination of the highest total BMP cost of native grass (Table 6-1) and a slightly higher sediment reduction of native grass compared to conservation tillage and no-till on the low-priority area.

The effectiveness of targeting methods at the watershed outlet also varies among the priority areas. For example, the most cost effective method in the high priority areas is LPSAI (Figure 6-4a). However, this method is the least cost effective in the medium priority areas due to a smaller amount of available land for BMP implementation compared to other targeting methods (Table

6-12). Like the watershed outlet, the effectiveness of targeting methods also varies between the priority areas at the subbasin level. For example, the most effective method in the high priority areas is LPUAI (Figure 6-4d). However, this method is least cost-effective in the low priority areas due to less available land for BMP implementation, resulting in less sediment reduction compared to other targeting methods (Table 6-12).

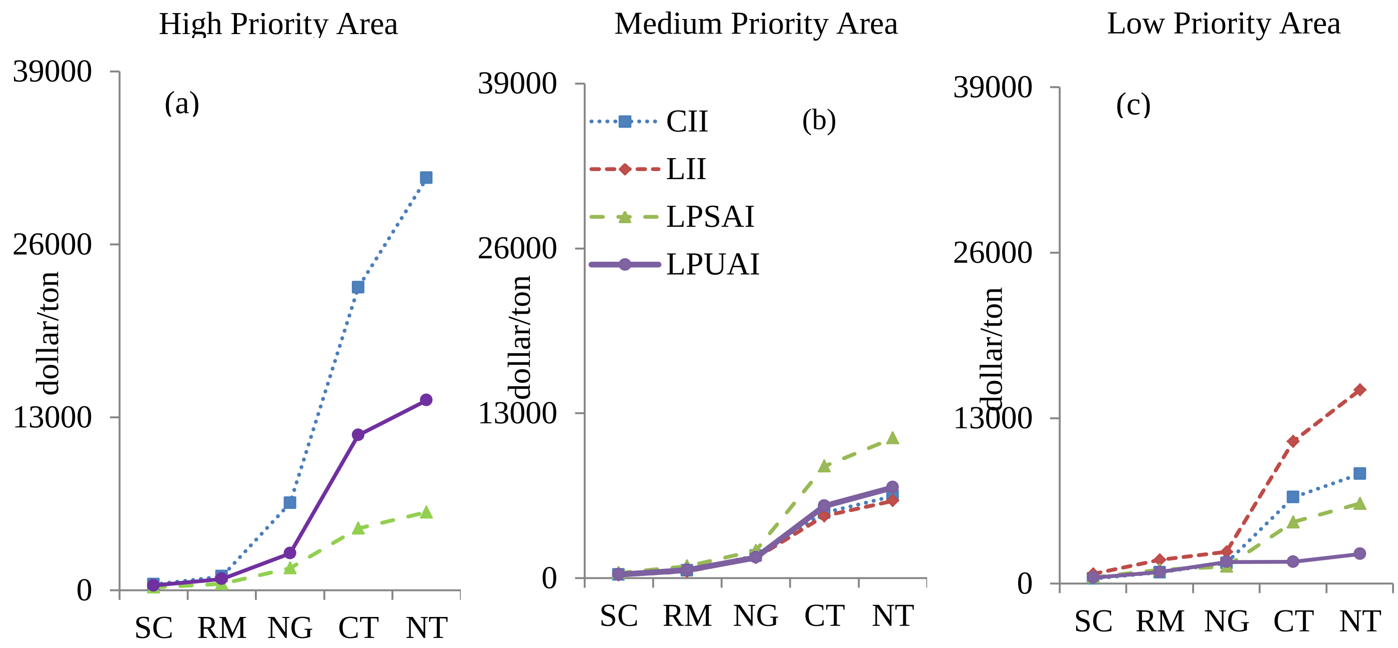

Figure 6-4. (a, b, and c) BMPs sediment reduction at the watershed outlet. by different targeting methods.

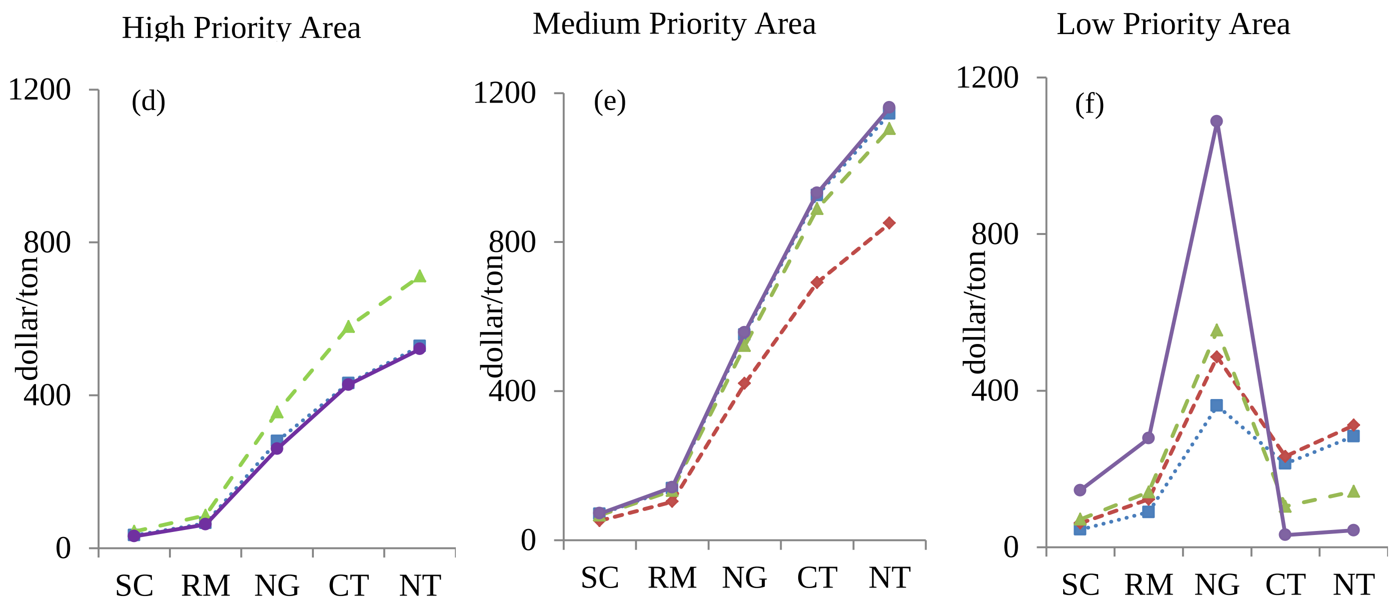

Figure 6-4. (d, e, and f) BMPs sediment reduction at the subbasin by different targeting methods.

Table 6-12. BMP implementation area for different priority area based on sediment targeting scenarios.

Targeting Method	Priority area	BMP implementation area (ha)
CII	H	27647.6
	M	202395.7
	L	115379.6
LII	H	0.0
	M	232351.0
	L	113071.9
LPSAI	H	143318.7
	M	160939.2
	L	41165.0
LPUAI	H	84977.4
	M	249368.0
	L	11077.5

In regard to other pollutants, a similar pattern was observed for TN and TP reduction by BMPs at the reach and subbasin levels (Figures 6-5 and 6-6). However, the overall cost per kilogram of pollutant is higher. In addition, residue management was identified as the least effective BMP on the low priority areas. Unlike sediment, an increase of TN and TP was observed for both conservation tillage and no-till at the reach and subbasin levels (Figures 6-5 and 6-6). This indicates that the project sponsor will lose money by implementing these BMPs to control nutrients generated by agricultural fields. The increased TN and TP may be due to an increase in organic matter content, which may be released into soil due to implementation of these practices (Giri et al., 2012a).

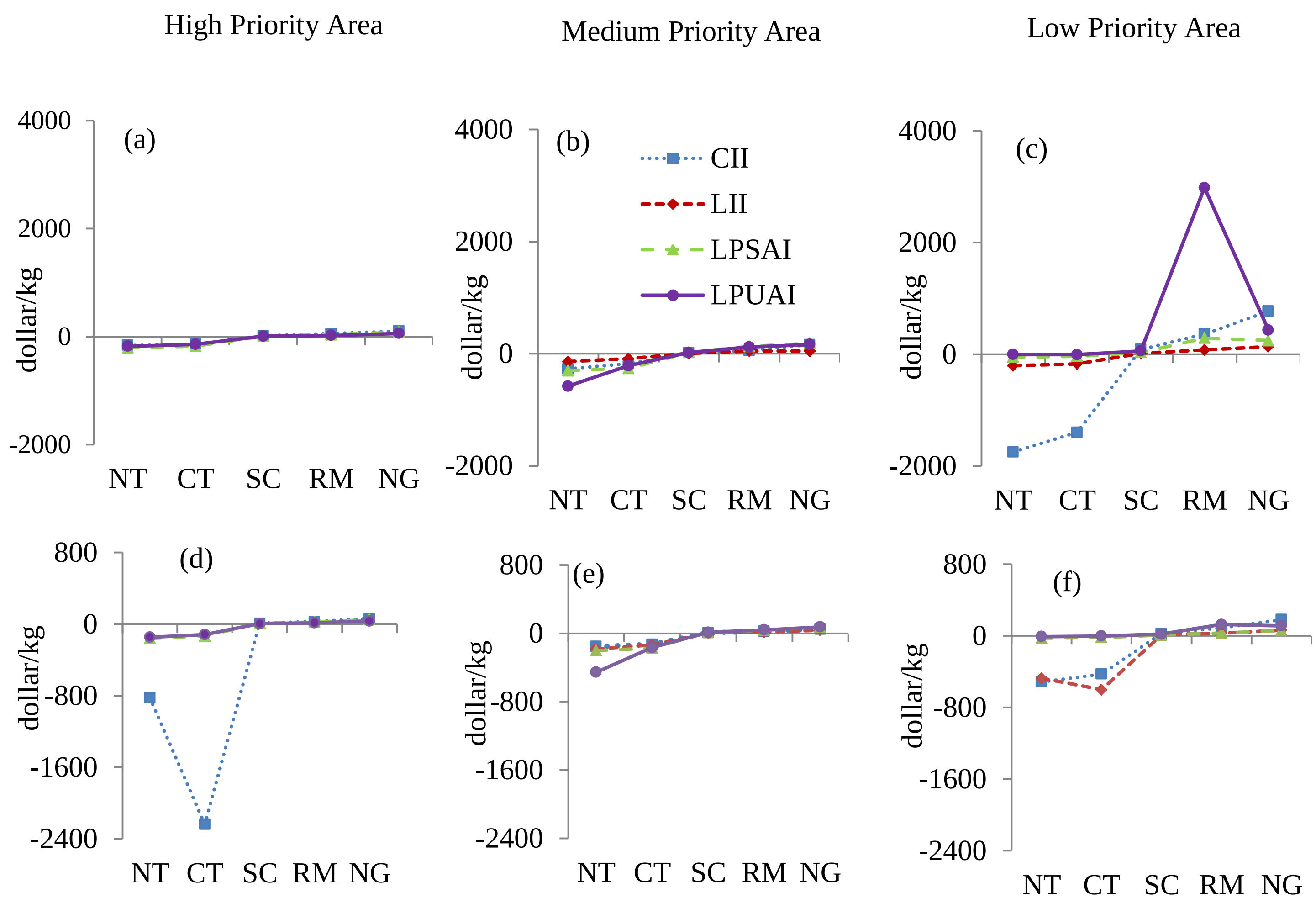

Figure 6-5. BMPs TN reduction at outlet (a, b, and c) and subbasin (d, e, and f) by different targeting methods.

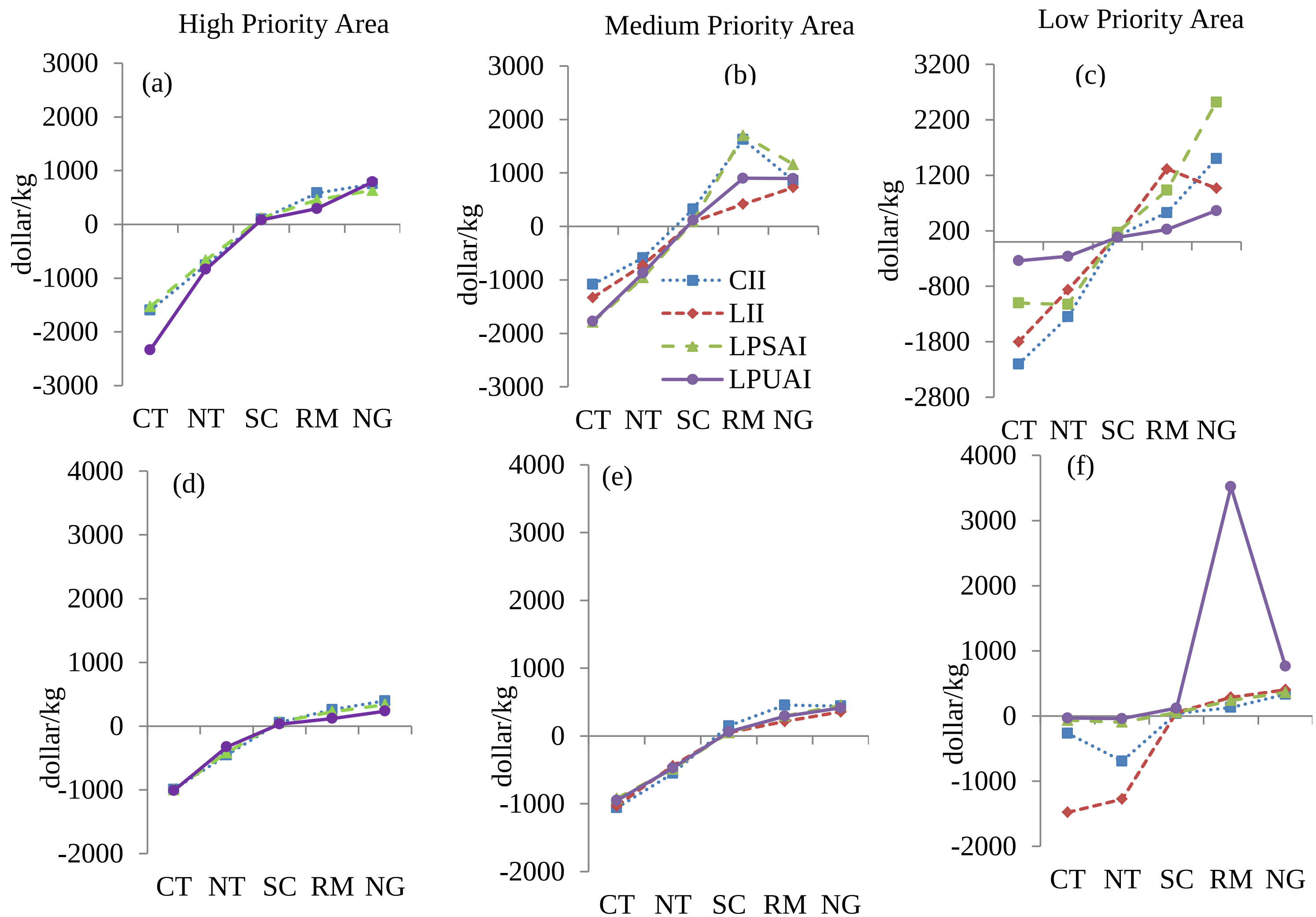

Figure 6-6. BMPs TP reduction at outlet (a, b, and c) and subbasin (d, e, and f) by different targeting methods.

6.4.2 Identify the Best BMP Type and Implementation Site Using Analytic Hierarchy Process

The objective of this section is to evaluate the rank and placement of BMPs based on different influential factors (environmental, economic, and social aspects) to achieve pollutant reduction. The findings of this section provide decision makers and stakeholders a wide array of solutions to improve water quality at the lowest cost and highest chance at being accepted by producers.

Figure 6-7 represents the placement of BMPs that ranked highest by different targeting methods at the subbasin level. In *Scenario 1*, where environmental, economic, and social factors have equal weights (33% each) considering equal importance of three pollutants, strip cropping was preferred in all identified CSAs by all targeting methods (Figure 6-7g, h, and i). This was due to the low BMP cost (Table 6-1) combined with high pollution reduction, and the moderate acceptance of this BMP by producers (Table 6-2). This finding suggests that policy makers and stakeholders should consider this BMP over the others during the BMP implementation strategy as it can satisfy the desires of both policy makers and stakeholders by reducing pollution in over a smaller BMP application area. The results were the same for *Scenario 2,* in which social impacts of BMP implementation were ignored even though environmental and economic impacts are considered. Stripcropping was preferred over all CSAs for all targeting methods. When *Scenario 2* was compared with *Scenario 3*, native grass (preferred BMP in *scenario 3*) was replaced by stripcropping in all CSAs (Figure 6-7 d, e and f). This result was due to the low cost of stripcropping ($80/hectare) compared to the high cost of native grass ($925/hectare) combined with a high pollution reduction capacity. When considering only pollutant reduction (*Scenario*

3), native grass was selected in all of the CSAs by all targeting methods (Figure 6-7a, b, and c). This result was due to greater pollution reduction capacity of native grass and the fact that the whole field is converted to grassland (Woznicki et al., 2011; Giri et al., 2012a). Overall, the percentage of BMP placement areas was the highest for the CII targeting method compared to LPSAI and LPUAI targeting methods as CII method is based on pollutant concentration (Giri et al., 2012a). One BMP (native grass- *Scenario 3*, stripcropping- *Scenario 2 and Scenario 3*) was preferred in all the subbasins if the BMP implementation strategy is focused at the subbasin. The lack of variation in preferred BMP for the CSAs may be due to the smaller distance between the BMP application area and measured effect at the subbasin level compared to the watershed outlet.

The placement of the highest ranked BMPs, dependent only on pollution reduction at the watershed outlet based on different scenarios and targeting methods, is provided in Figure 6-8. When the BMP selection criteria was based on combined environmental, economic, and social factors (*Scenario 1*); approximately, 59% of CSAs identified by the CII targeting method selected the moderately preferable BMP (stripcropping) and 41% selected the most favorable BMP (residue management) (Table 6-13). The replacement of some stripcropping from the CSAs in *scenario 2* with residue management (Figure 6-8 g) is due to producers' preference of residue management over stripcropping, as the BMP application area for stripcropping shall at least consist of 50% erosion resistant crops or sediment trapping cover (NRCS,2008). This suggests that selecting residue management saves 50% of the crop land that stripcropping would keep fallow for BMP application. When both environmental and economic factors are considered for BMP selection (*Scenario 2*), all native grass and some residue management (preferred BMP in *Scenario 3*) were eliminated by stripcropping (Figure 6-8d) due to its low total BMP cost (Table 6-1). Nearly 83% of CSAs selected stripcropping (Table 6-13) and the remaining 17% of CSAs selected residue management. Stripcropping was selected more compared to residue management because of the lower BMP cost of stripcropping compared to residue management (Table 6-1). For example, when only environmental factors are considered for BMP selection under the CII targeting method (*Scenario 3*); approximately 53% of CSAs preferred stripcropping, 24% of CSAs preferred native grass, and the remaining 23% of CSAs preferred residue management (Table 6-13). The number of preferred BMPs chosen for the CSAs increased from just native grass (based on pollution reduction at subbasin level) to stripcropping, native grass, and residue management (based on pollution reduction at watershed outlet). The change in preferred BMPs, based on pollution reduction at the watershed outlet, was due to in-stream processes and distance of individual BMP application areas to the watershed outlet. Similar BMPs were selected in the CSAs for different combinations of targeting methods and scenarios.

A summary of the AHP rank one BMPs' effectiveness, which includes social, environmental, and economic factors both for subbasin level and watershed outlet for different CSA targeting methods, is presented in Table 6-13. At the watershed outlet, the pollution reduction decreases from *Scenario 3* to *Scenario 1*, as BMPs that reduce less pollution are more preferable over BMPs reducing more pollution by stakeholders due to the less required area for BMP application and less expensive total implementation cost. Among the targeting methods at the watershed outlet, the LPUAI targeting method selected residue management (most favorable) BMP as having the lowest percentage of social acceptance compared to other targeting methods. This suggests that this method is less capable of identifying socially acceptable BMPs compared to other targeting methods. However, in the subbasin level, all targeting methods identified BMPs were categorized into same social acceptance level (Table 6-13) due to the selection of same type of BMP over all their respective CSAs.

Overall, the greater pollution reduction, higher expense, and least socially acceptable BMP (native grass) was eliminated in favor of the selection of the lesser pollution reduction, least expensive, and moderately socially acceptable stripcropping. Furthermore, some of the stripcropping-identified subbasins were replaced by the most socially acceptable BMP, residue management. More variety of BMPs is preferred in the CSAs based on pollution reduction at the watershed outlet than at the subbasin level due to stream morphology and in stream processes.

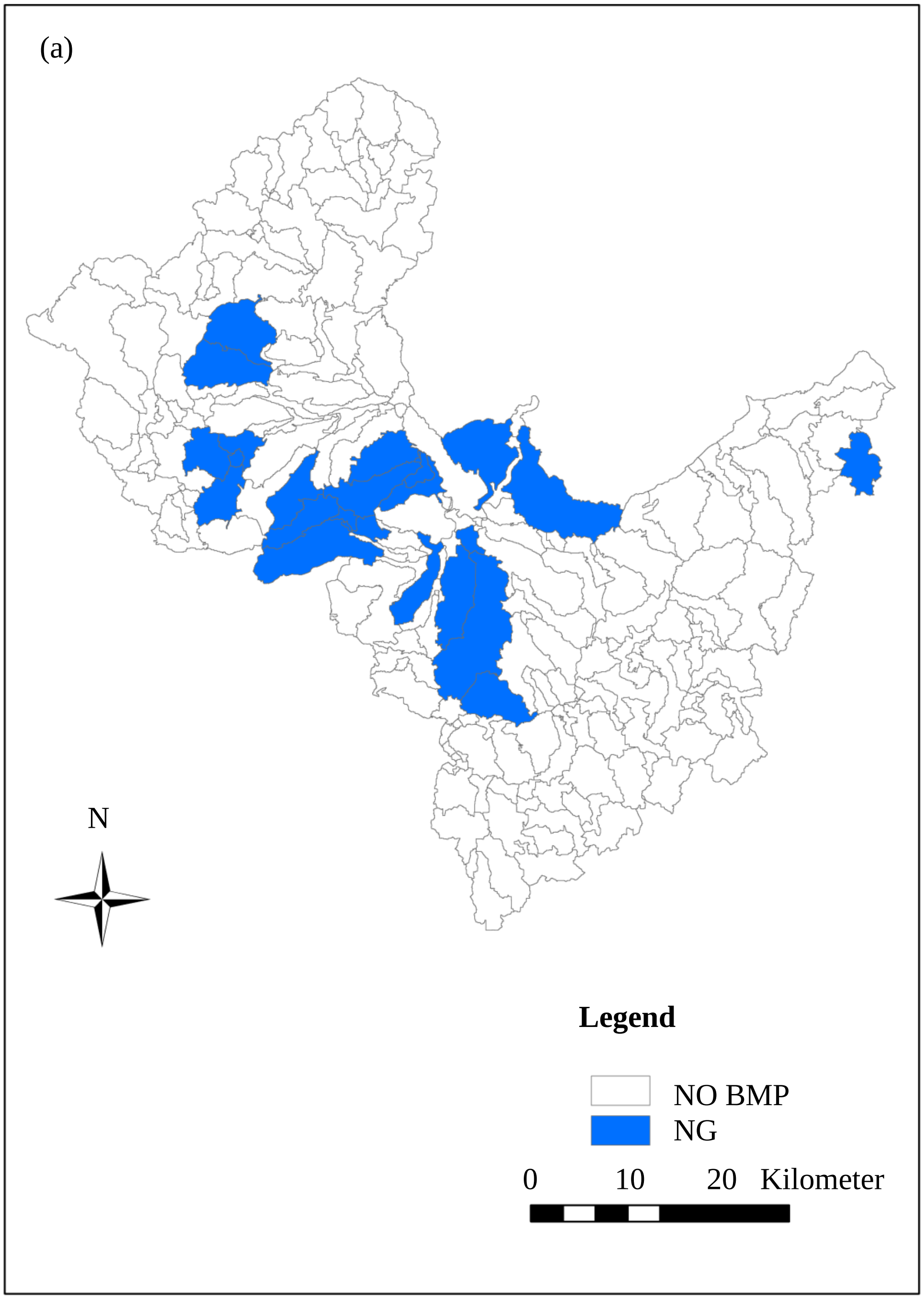

Figure 6-7. (a) Placement of BMP rank one in subbasin considering only environmental factor based on CII targeting methods.

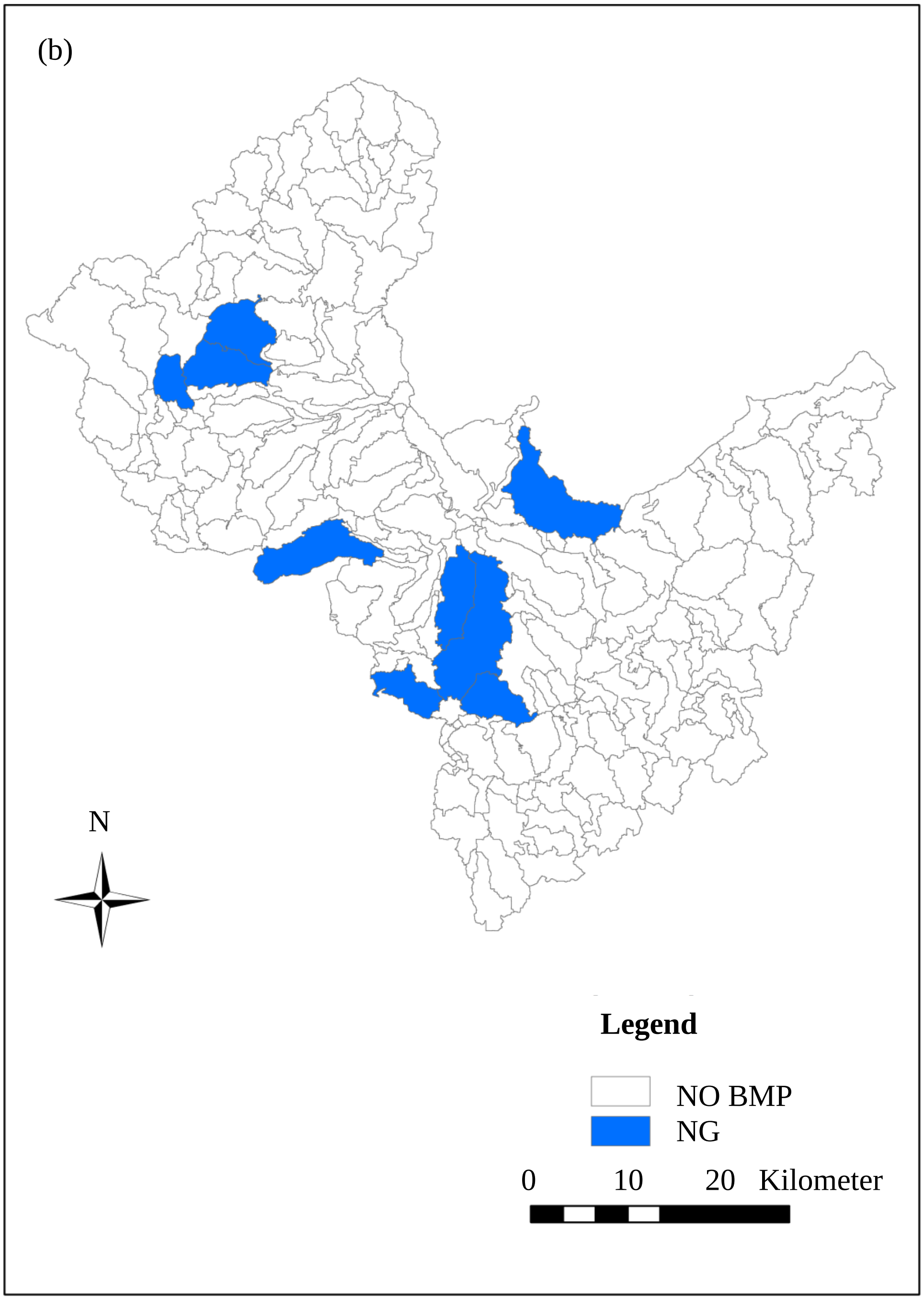

Figure 6-7. (b) Placement of BMP rank one in subbasin considering only environmental factor based on LPSAI targeting methods.

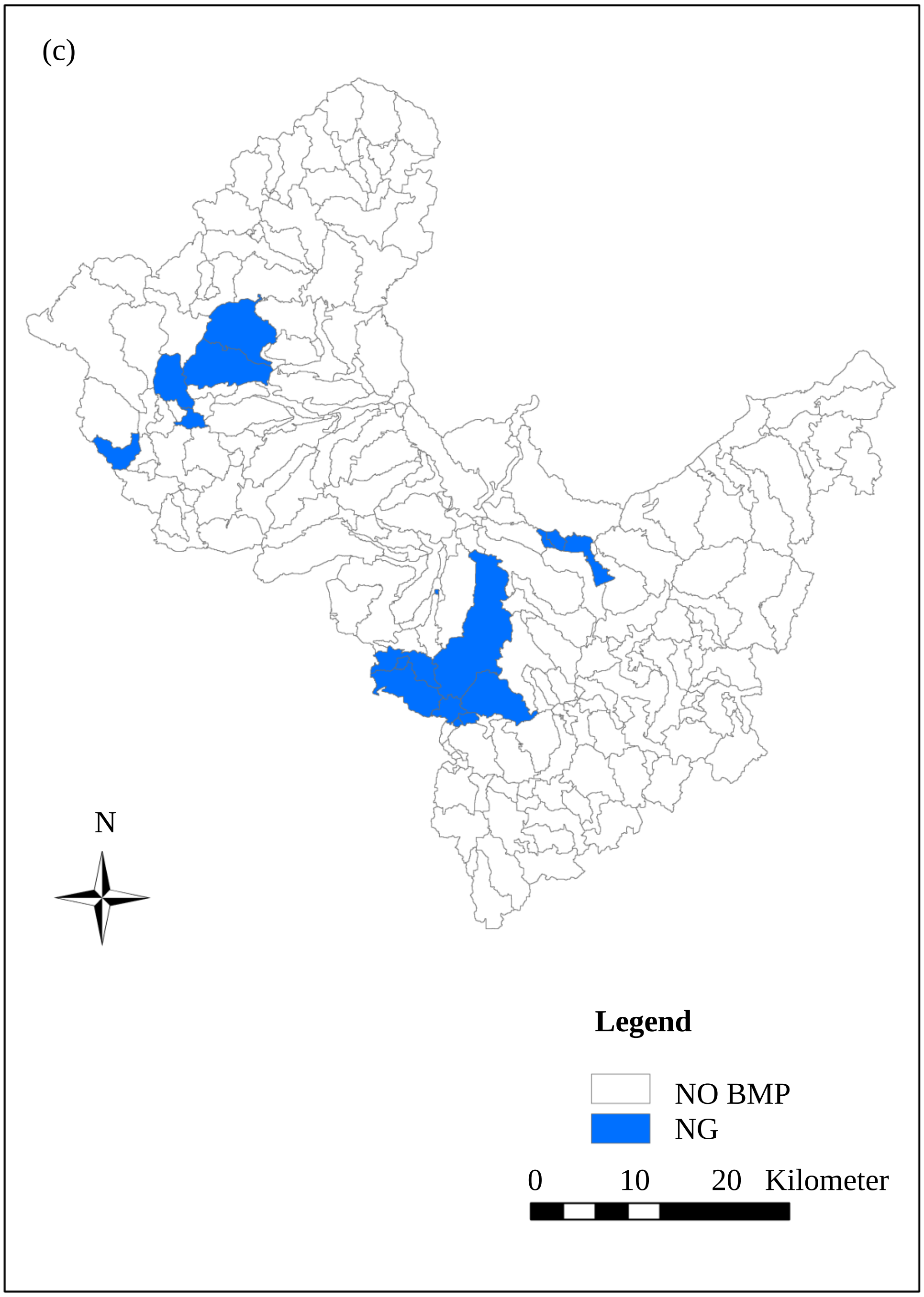

Figure 6-7. (c) Placement of BMP rank one in subbasin considering only environmental factor based on LPUAI targeting methods.

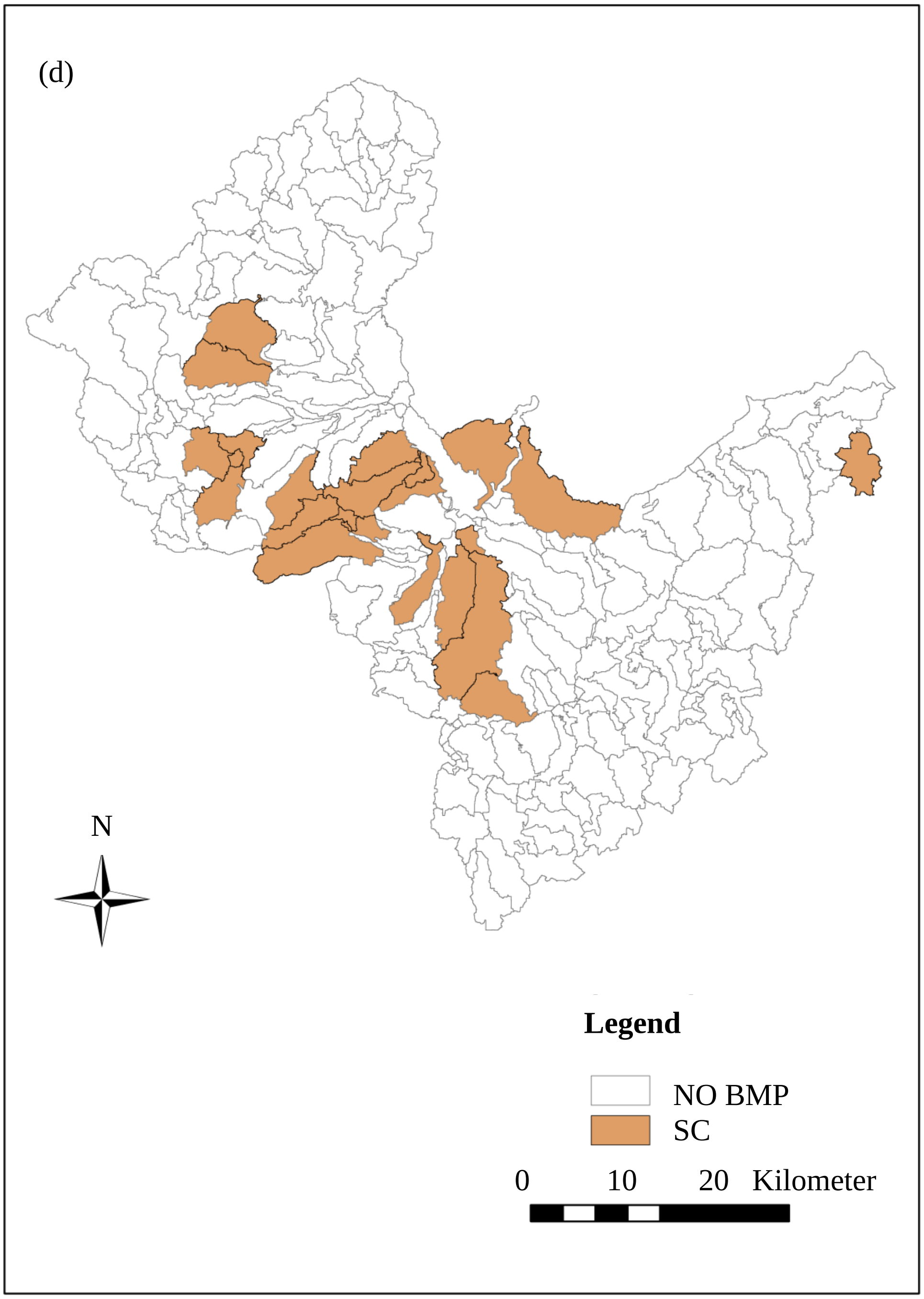

Figure 6-7. (d) Placement of BMP rank one in subbasin considering environmental-economic factors based on CII targeting methods.

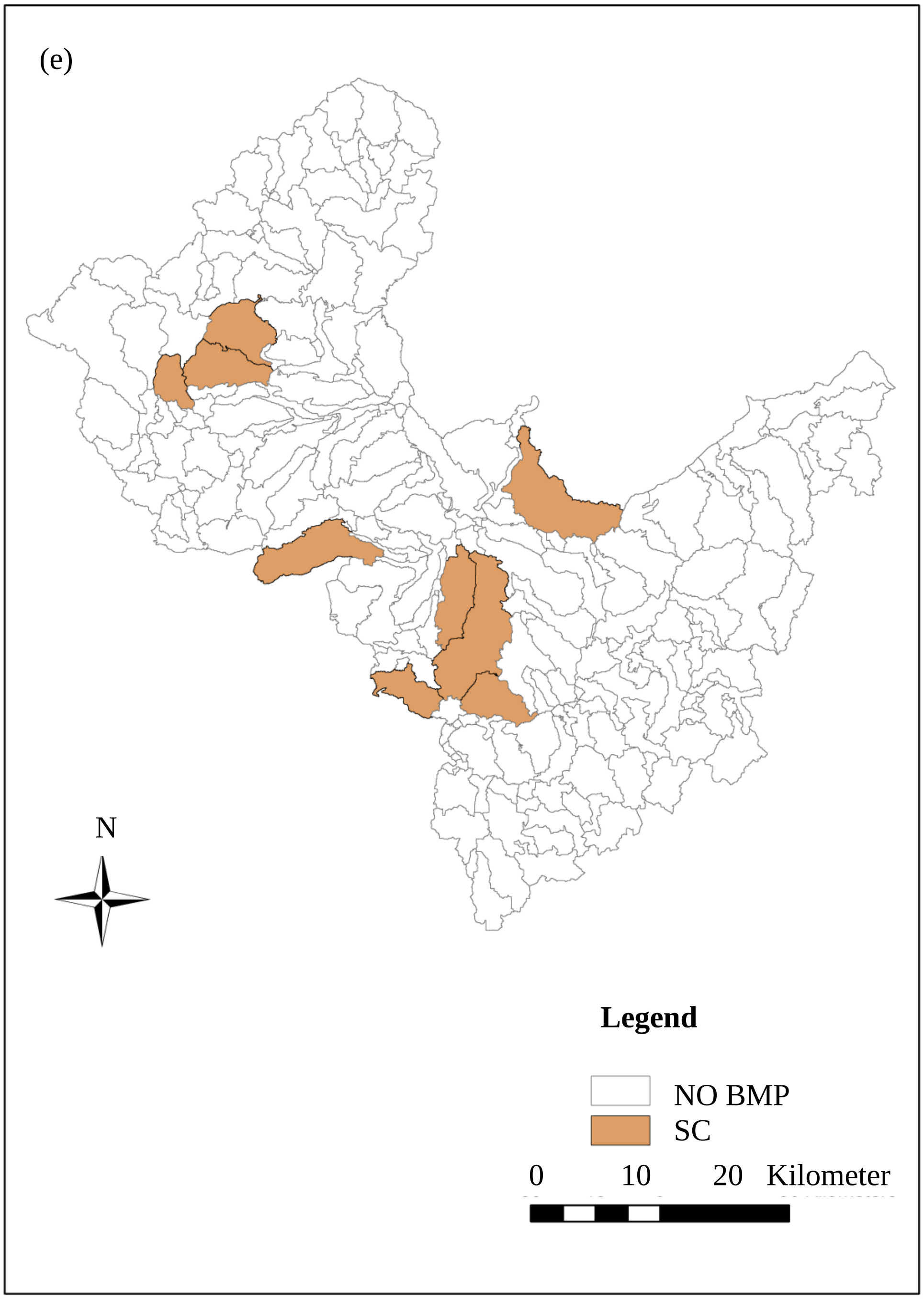

Figure 6-7. (e) Placement of BMP rank one in subbasin considering environmental-economic factors based on LPSAI targeting methods.

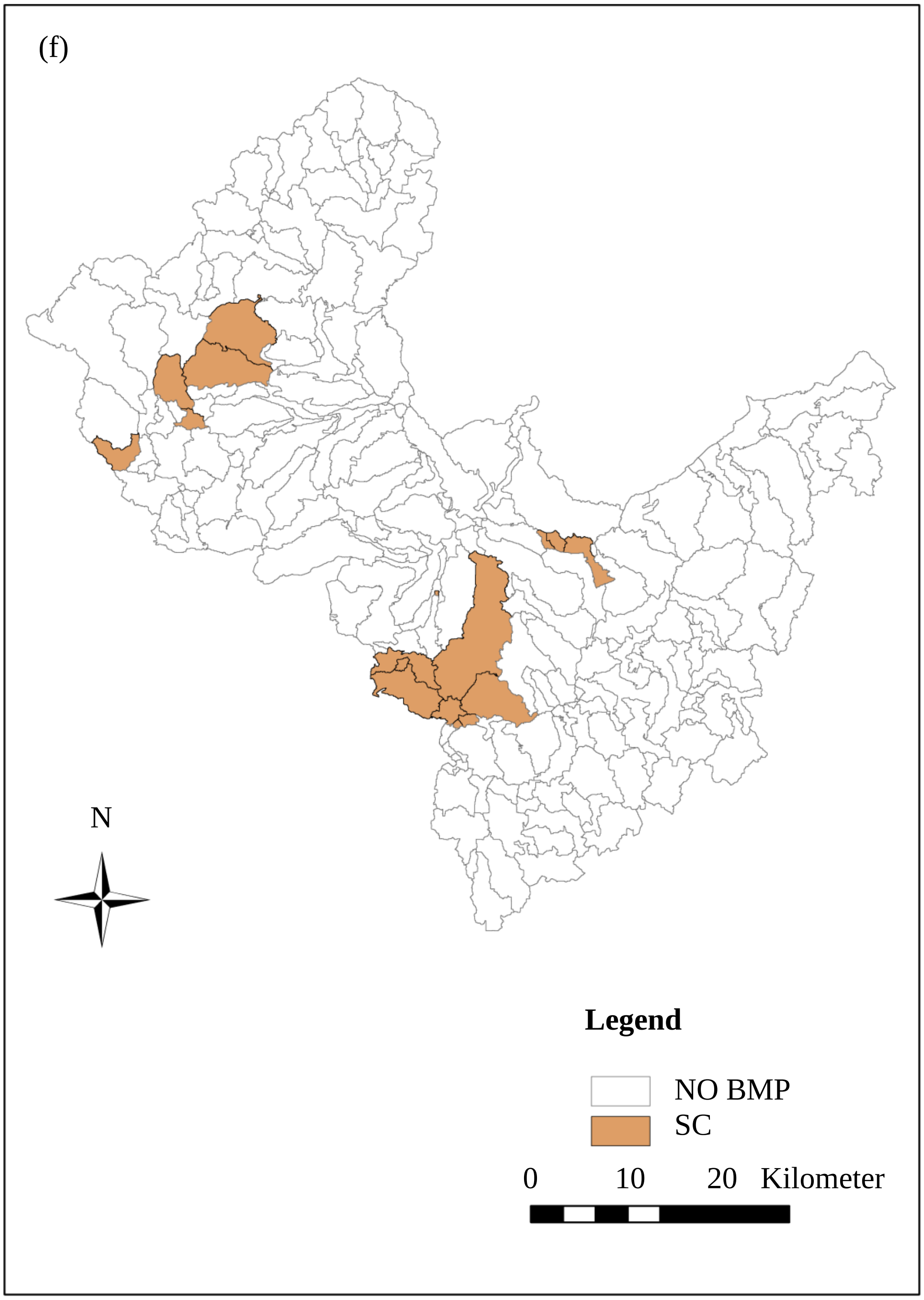

Figure 6-7. (f) Placement of BMP rank one in subbasin considering environmental-economic factors based on LPUAI targeting methods.

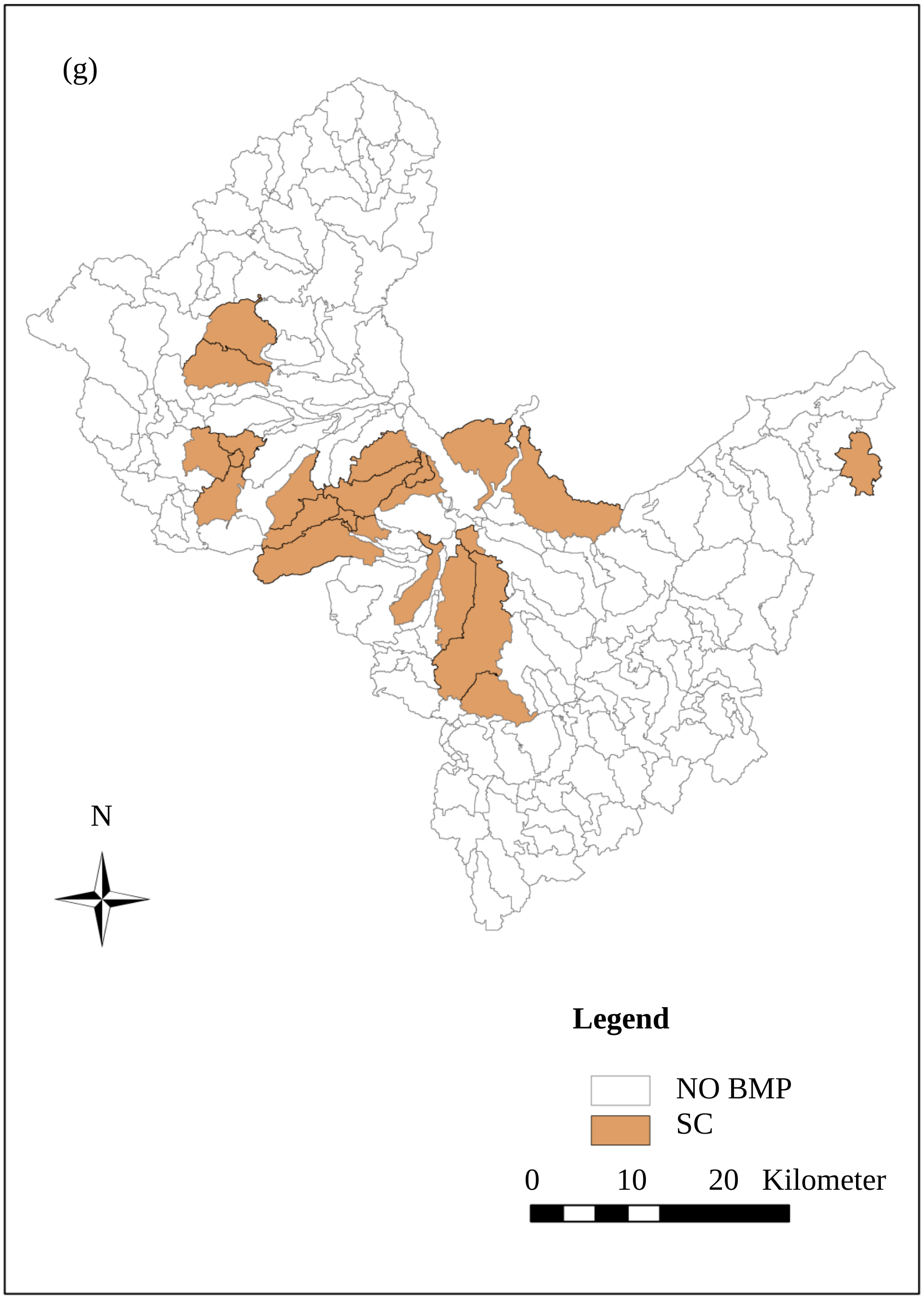

Figure 6-7. (g) Placement of BMP rank one in subbasin considering environmental-economic-social factors based on CII targeting methods.

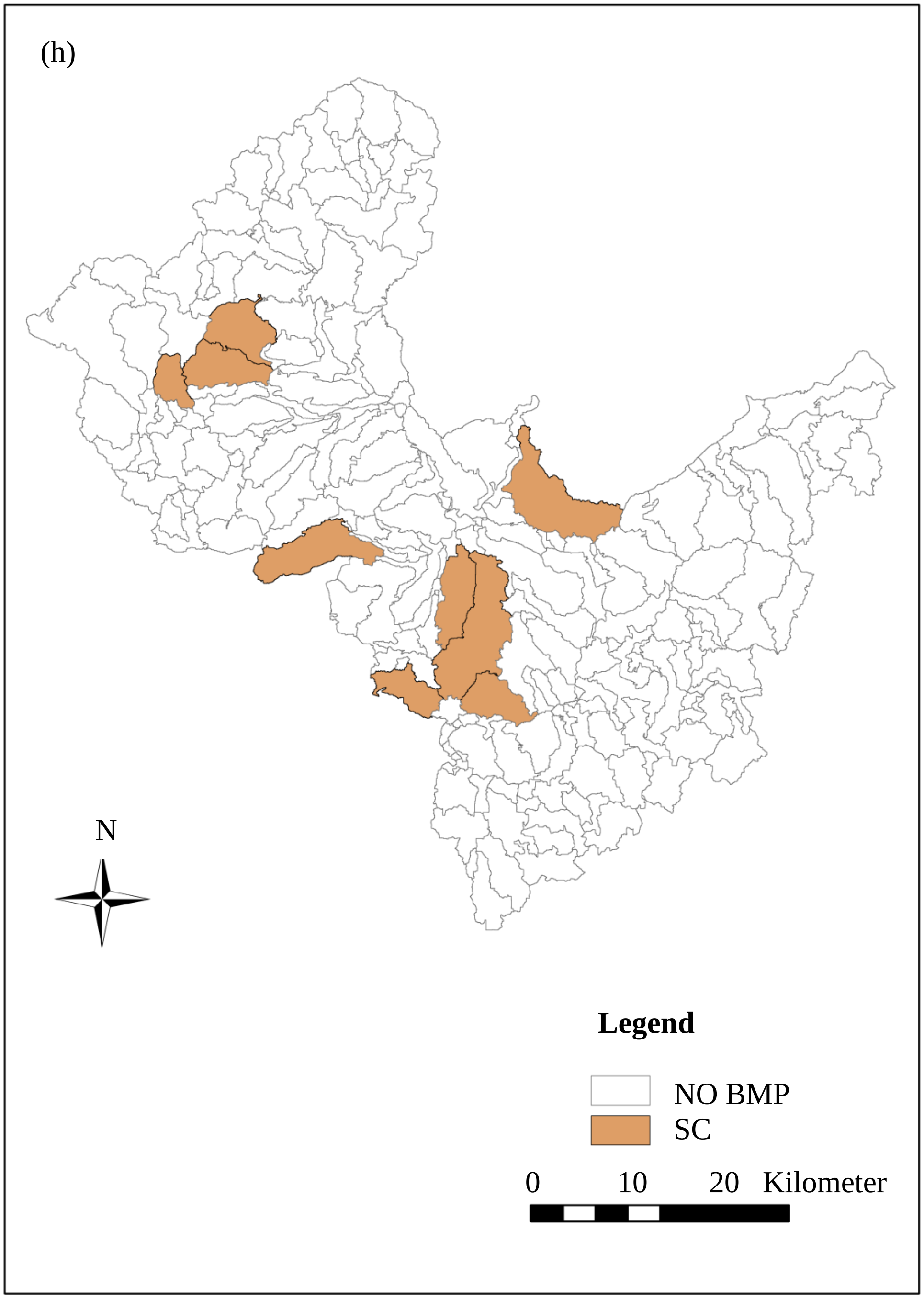

Figure 6-7. (h) Placement of BMP rank one in subbasin considering environmental-economic-social factors based on LPSAI targeting methods.

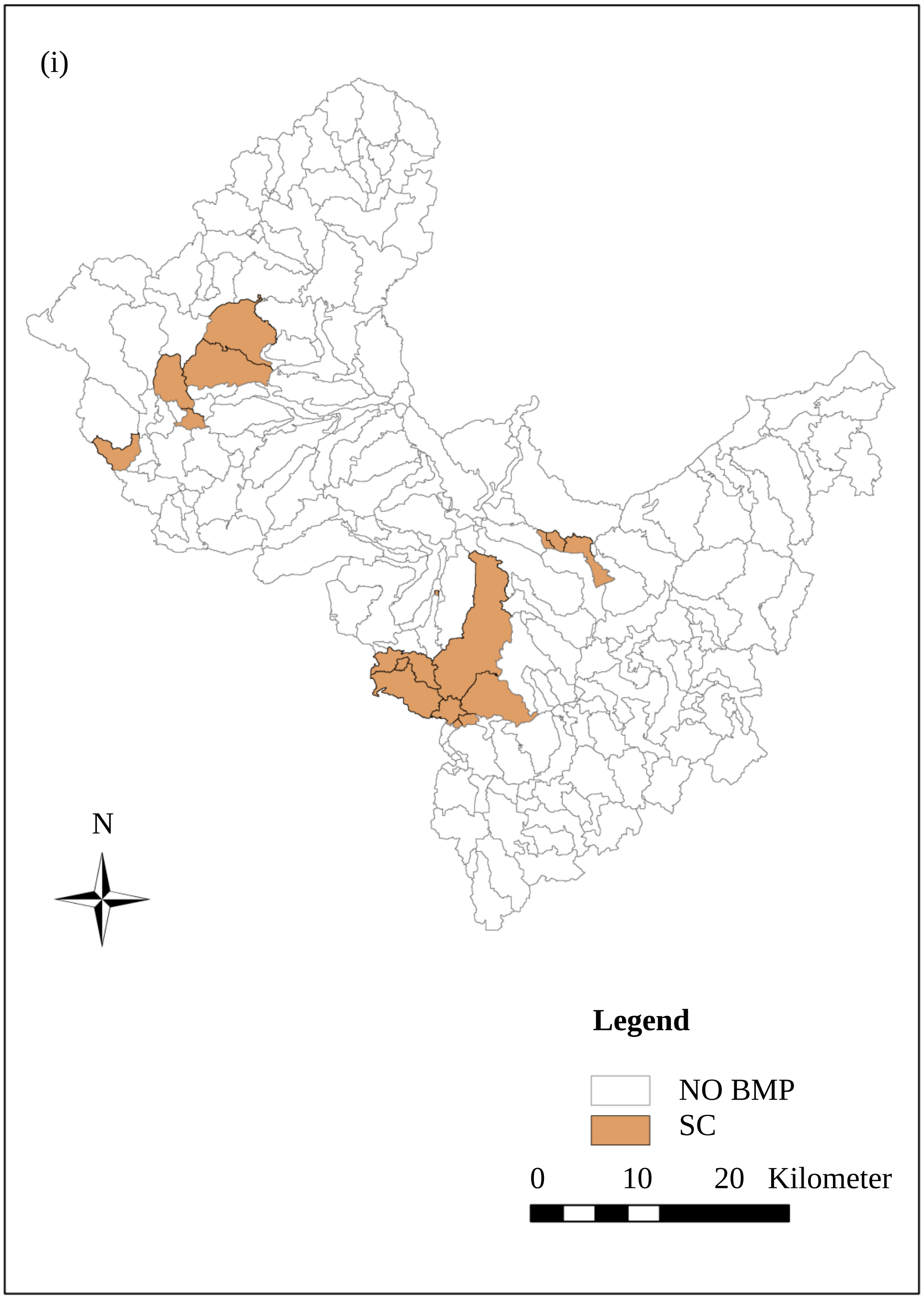

Figure 6-7. (i) Placement of BMP rank one in subbasin considering environmental-economic-social factors based on LPUAI targeting methods.

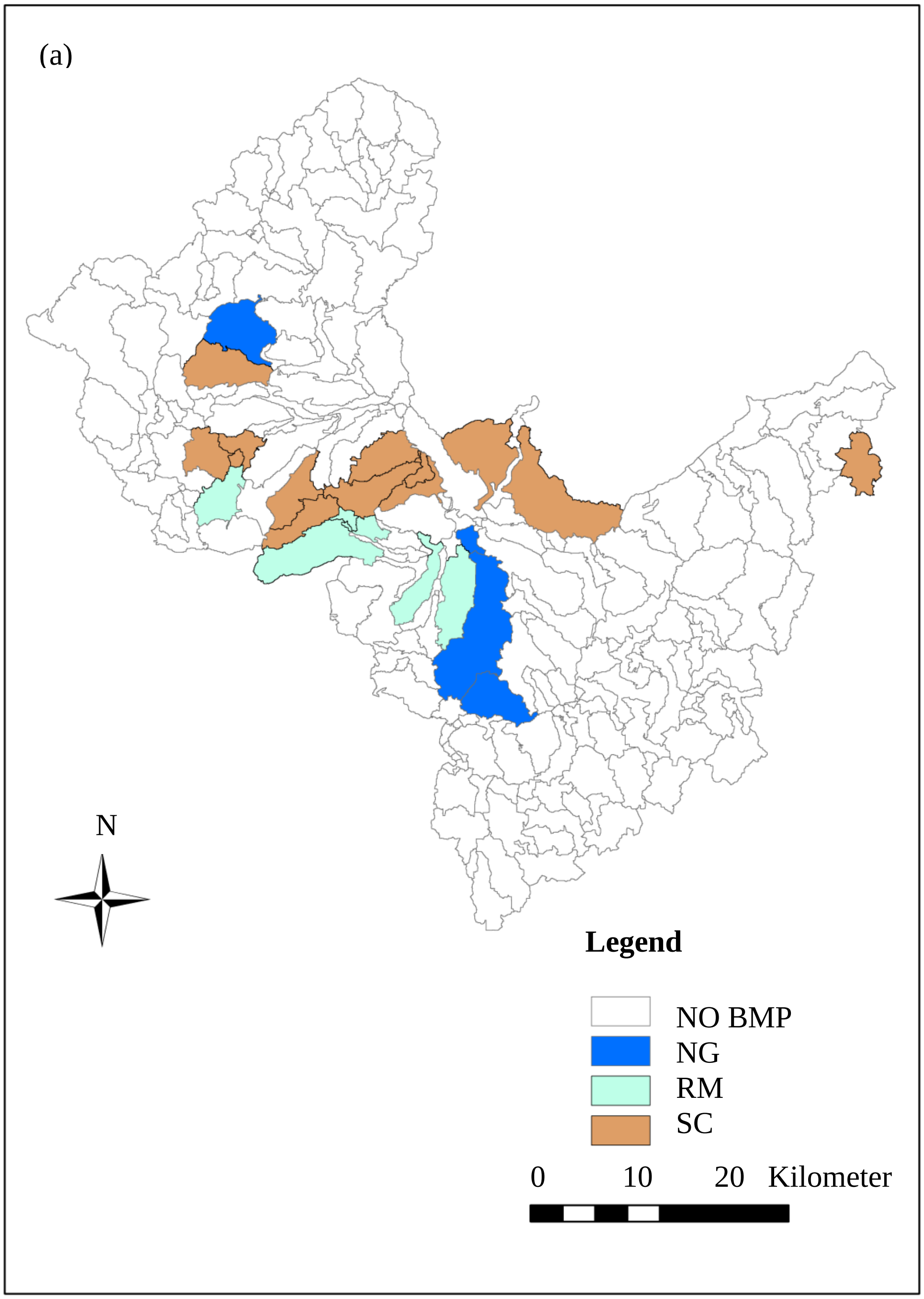

Figure 6-8. (a) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering only environmental factor by CII targeting method.

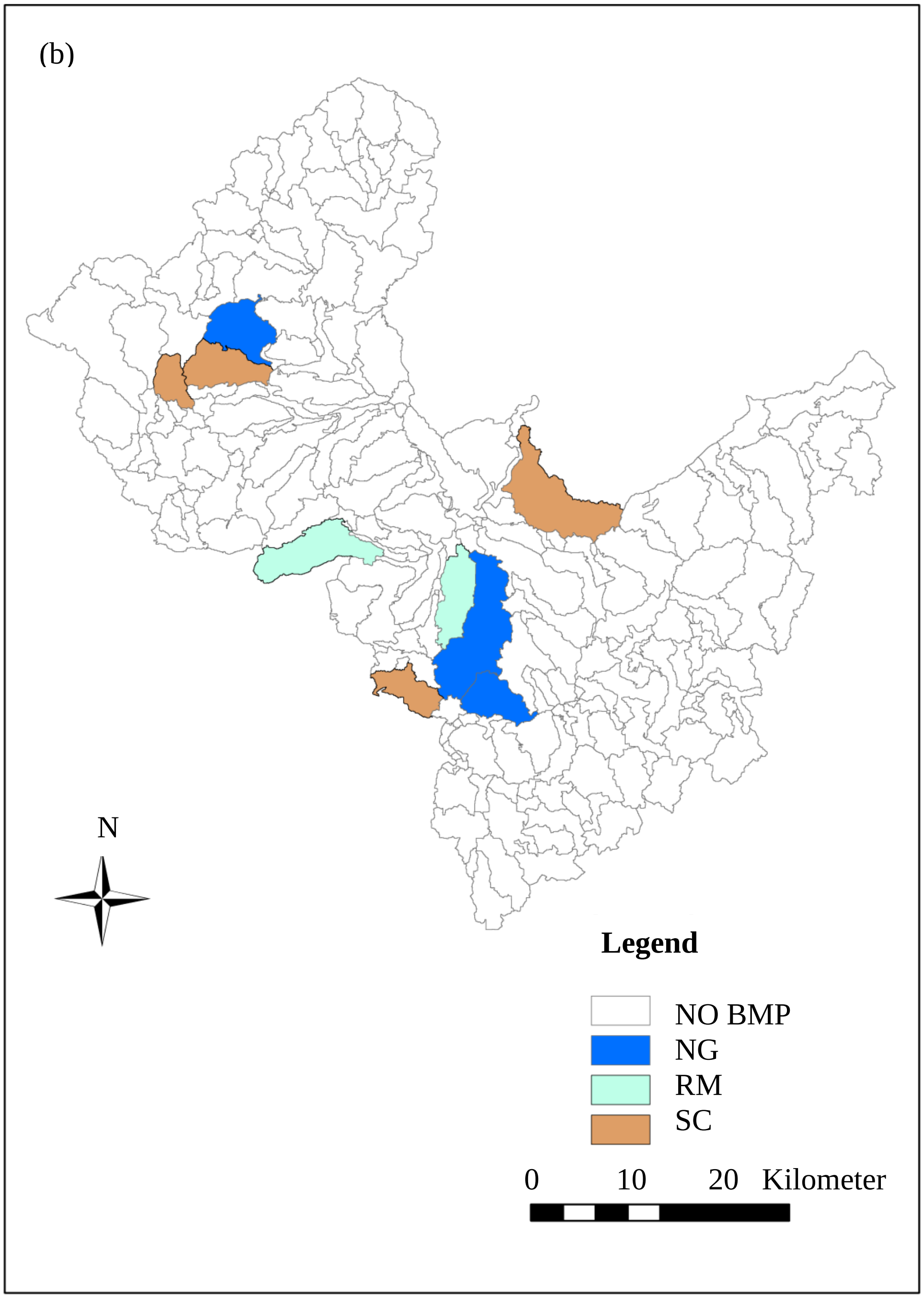

Figure 6-8. (b) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering only environmental factor by LPSAI targeting method.

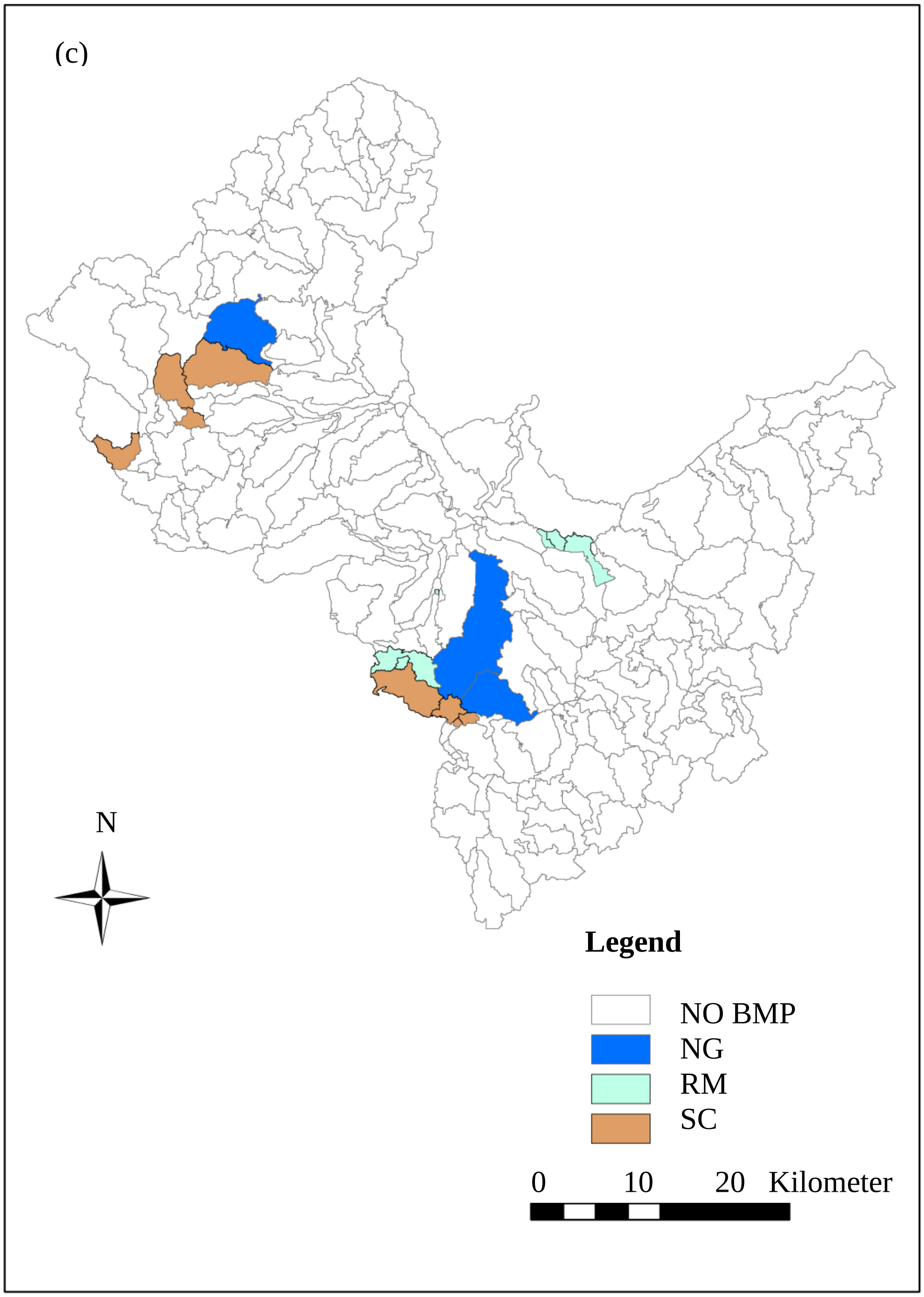

Figure 6-8. (c) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering only environmental factor by LPUAI targeting method.

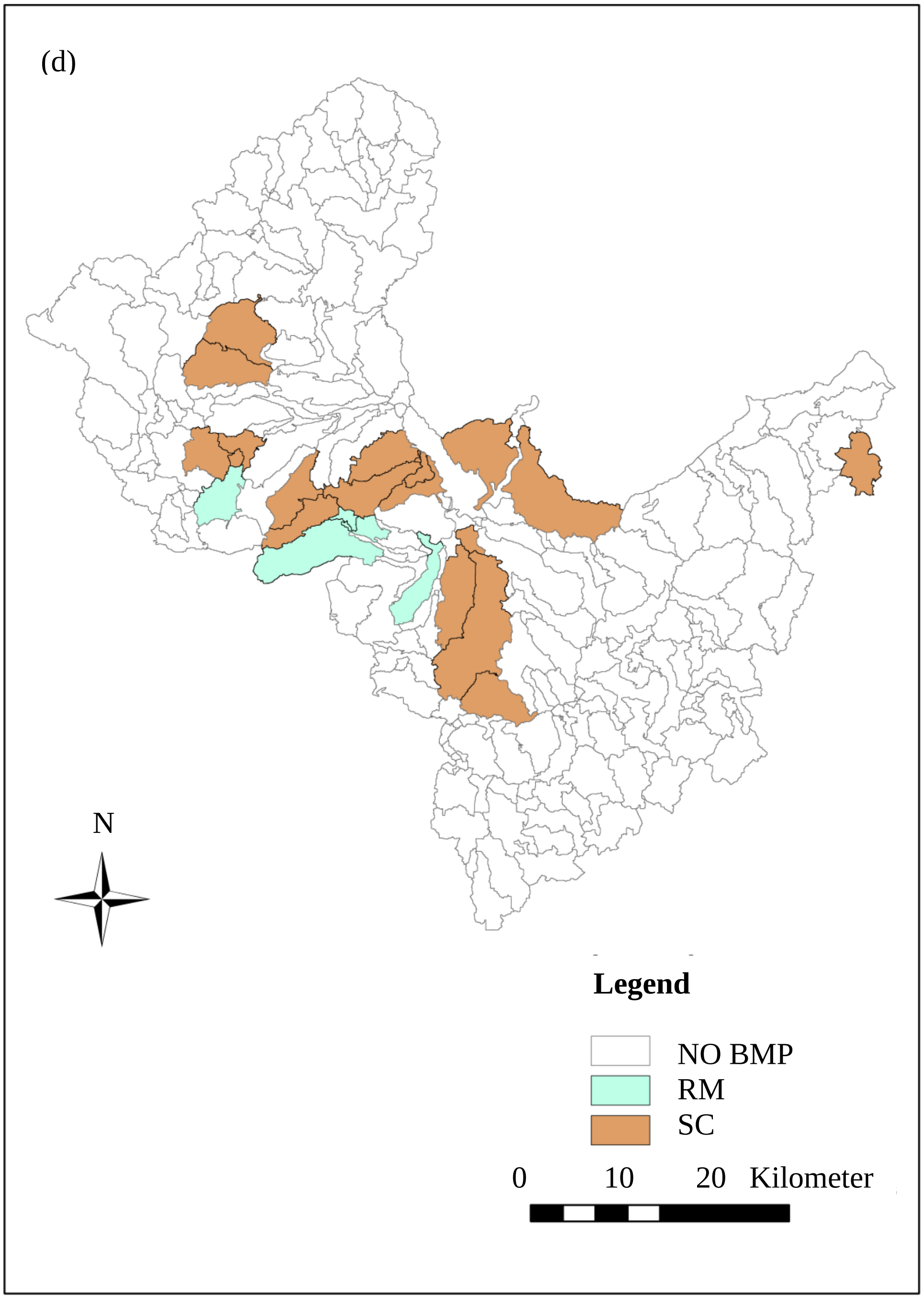

Figure 6-8. (d) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental- economic factors by CII targeting method.

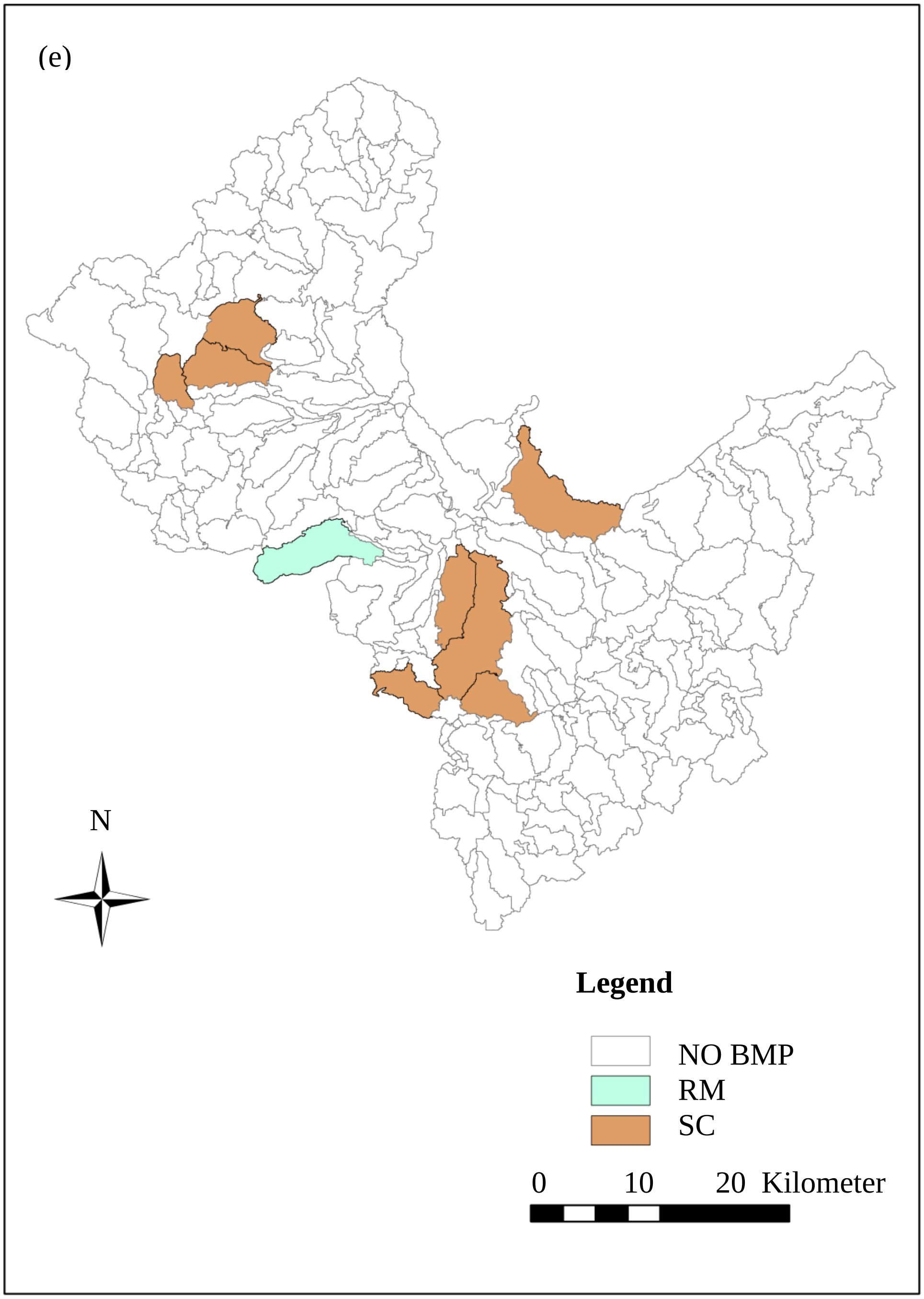

Figure 6-8. (e) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental- economic factors by LPSAI targeting method.

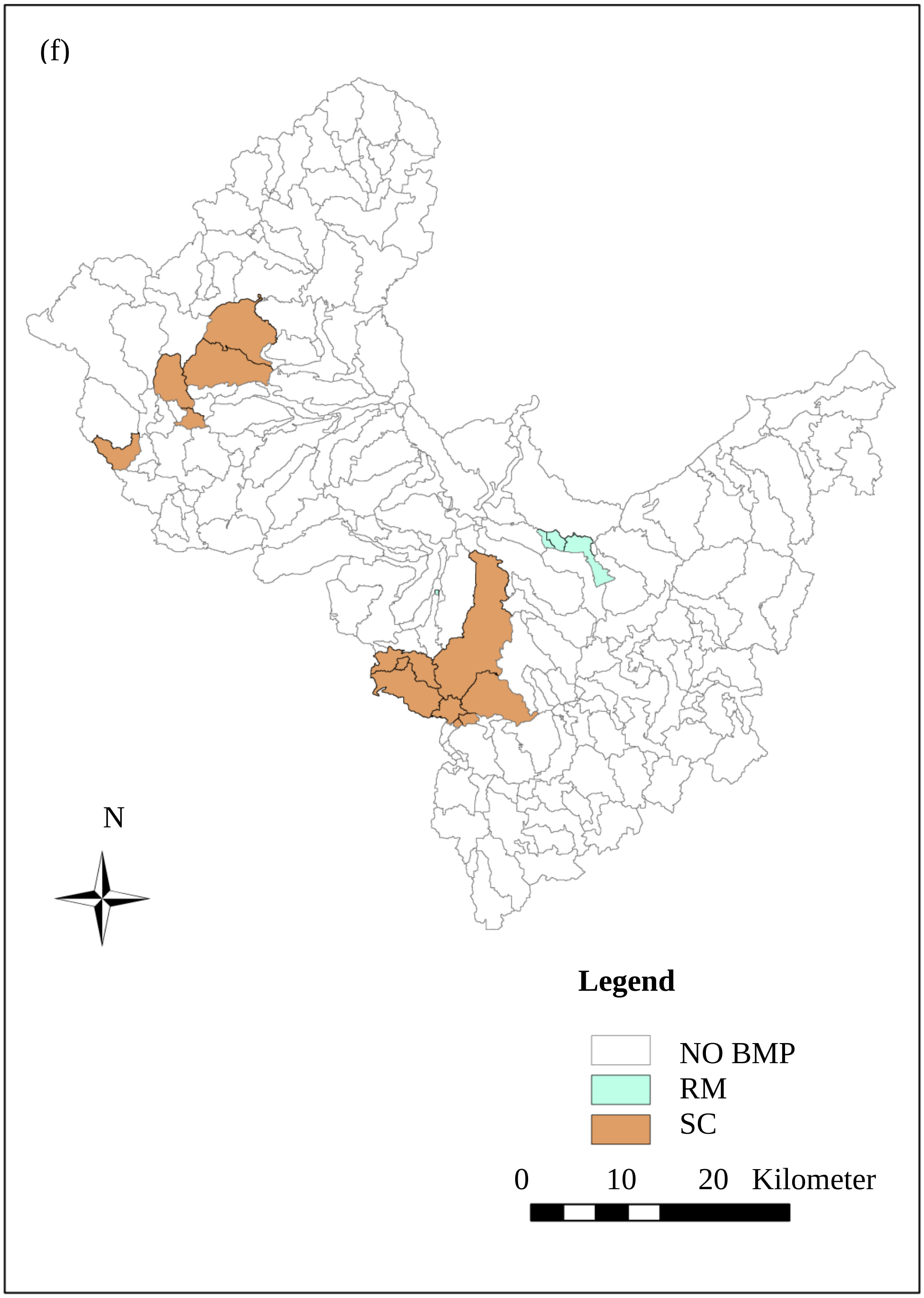

Figure 6-8. (f) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental- economic factors by LPUAI targeting method.

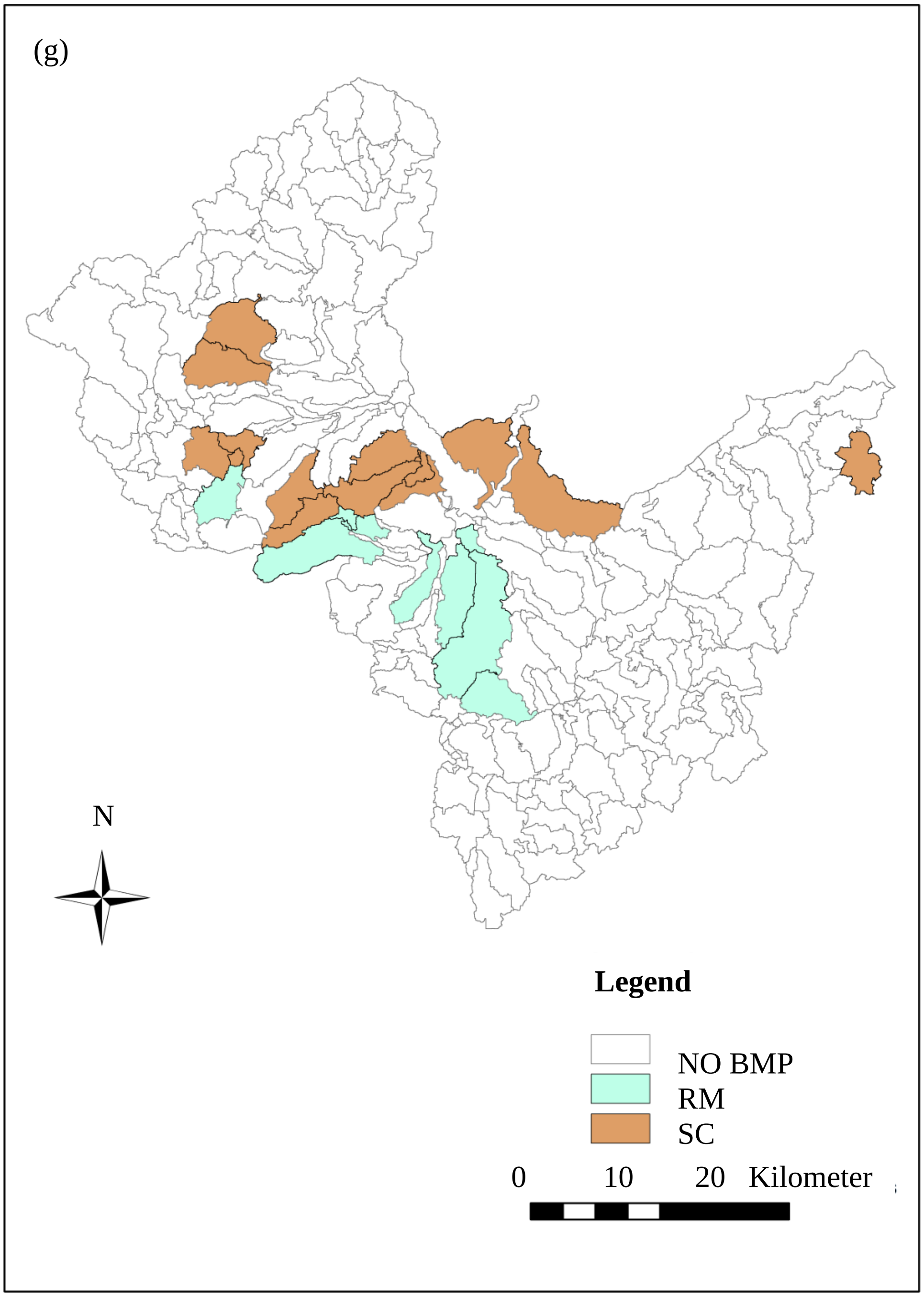

Figure 6-8. (g) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental-economic-social factors by CII targeting method.

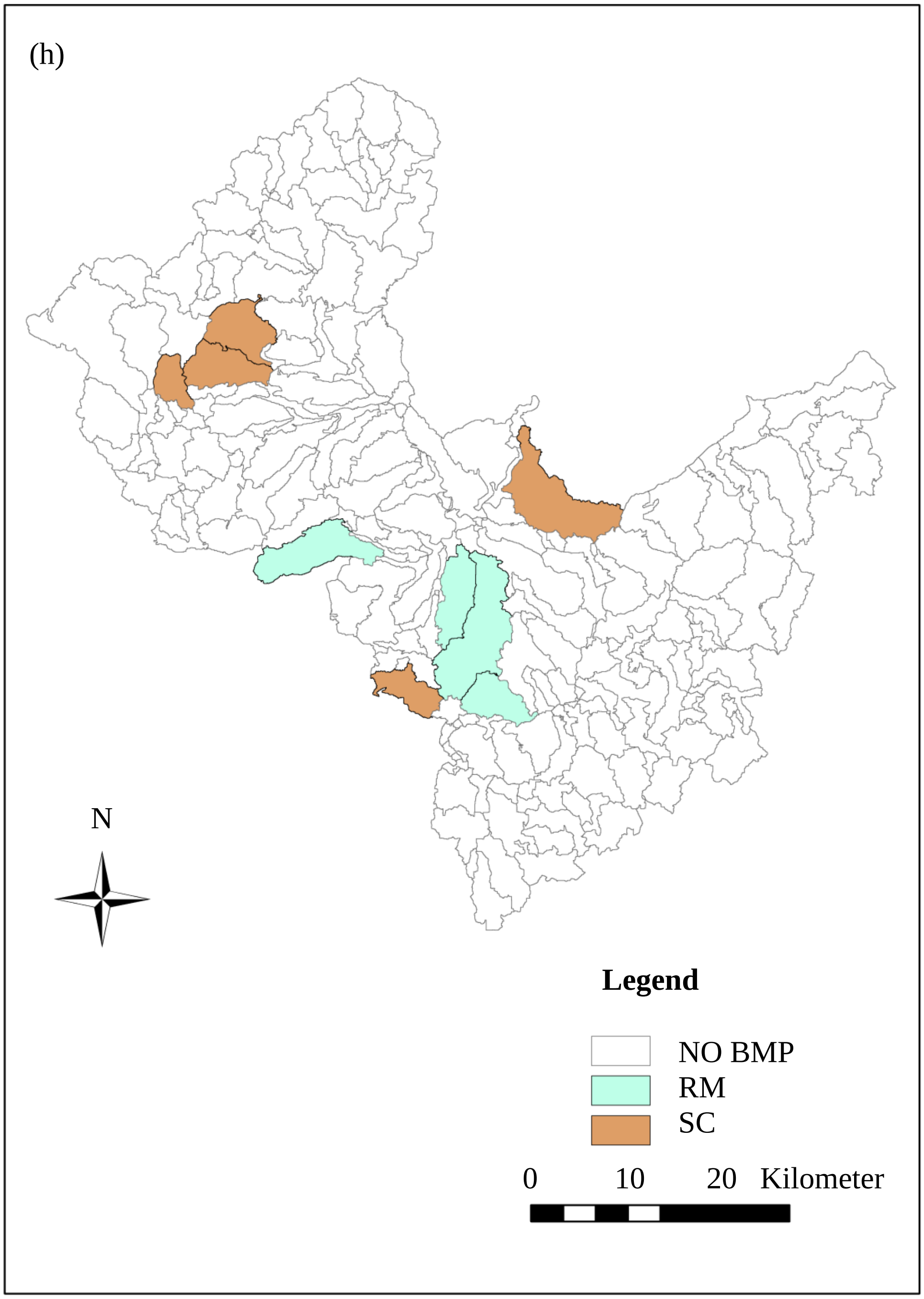

Figure 6-8. (h) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental-economic-social factors by LPSAI targeting method.

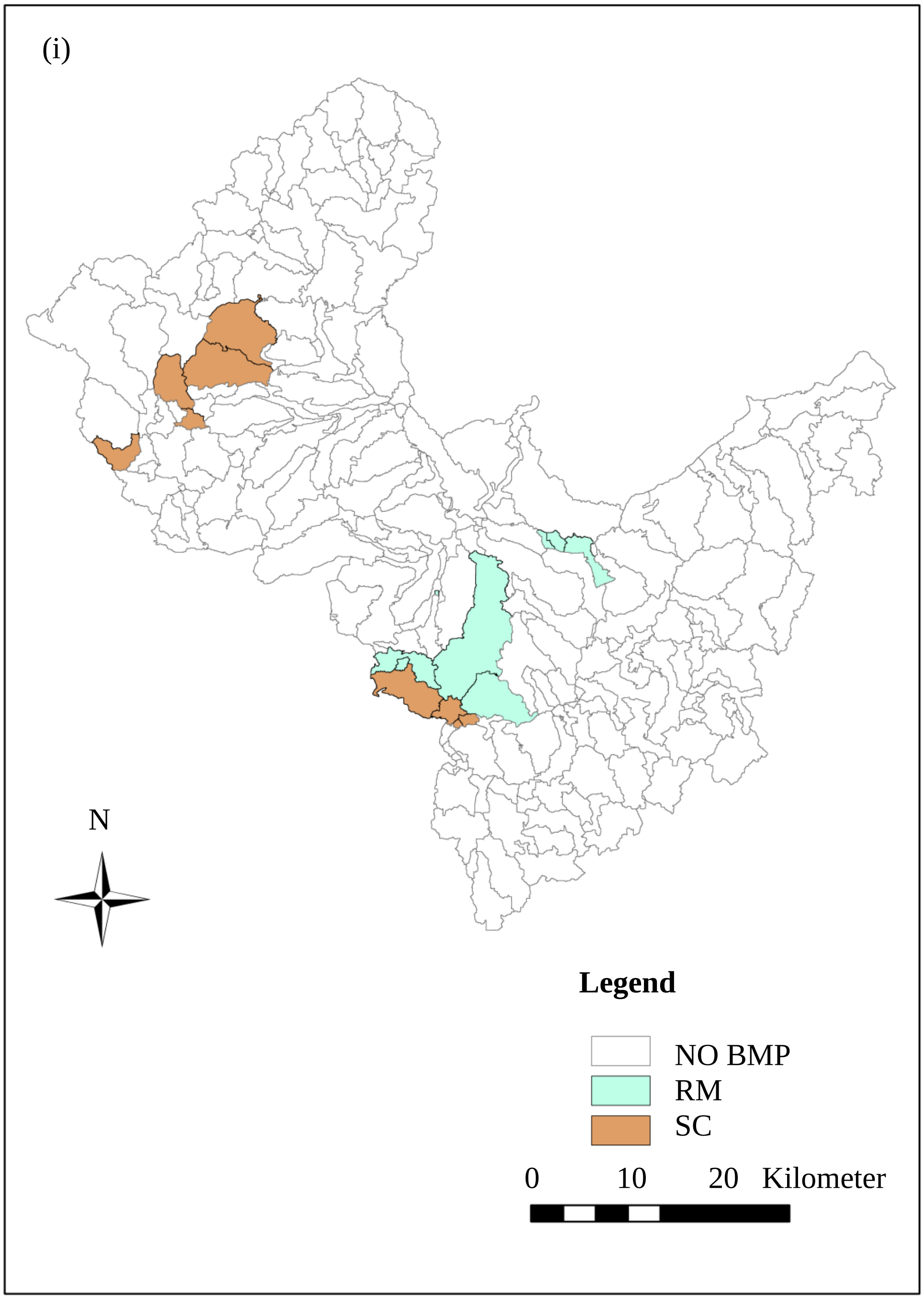

Figure 6-8. (i) Placement of BMP rank one in subbasin based on pollution reduction at watershed outlet considering environmental-economic-social factors by LPUAI targeting method.

Table 6-13. Summary of AHP identified rank one BMP effectiveness in all aspects (social, environmental, and economic) both subbasin level and watershed outlet.

AHP model	Parameter		CII	LPSAI	LPUAI
Environment	Social (% of total BMP application area)	Most favorable	23	23	12
		Moderate	53	39	37
		Least favorable	24	38	51
	Environmental (pollution reduction in ton)	Sediment	80,700	64,400	36,700
		TN	1650	1452	1382
		TP	214	170	155
	Economic (total BMP cost in dollar)		75,282,680	65,612,486	60,823,681
Environment - Economic	Social (% of total BMP application area)	Most favorable	17	13	5
		Moderate	83	87	95
		Least favorable	-	-	-
	Environmental (pollution reduction in ton)	Sediment	66,600	51,500	28,000
		TN	1337	1138	1024
		TP	186	141	118
	Economic (total BMP cost in dollar)		23,686,458	14,085,587	9,800,501
Environment-Economic-Social	Social (% of total BMP application area)	Most favorable	41	51	31
		Moderate	59	49	69
		Least favorable	-	-	-
	Environmental (pollution reduction in ton)	Sediment	63,400	48,200	24,900
		TN	1062	867	769
		TP	138	94	76

Table 6-13 (cont'd)

	Economic (total BMP cost in dollar)		27,771,921	18,101,727	11,816,275
Environment	Social (% of total BMP application area)	Most favorable	-	-	-
		Moderate	-	-	-
		Least favorable	100	100	100
	Environmental (pollution reduction in ton)	Sediment	470,533	394,623	384,232
		TN	3737	2999	2697
		TP	571	436	390
	Economic (total BMP cost in dollar)		238,604,221	146,099,773	108,365,621
Environment - Economic	Social (% of total BMP application area)	Most favorable	-	-	-
		Moderate	100	100	100
		Least favorable	-	-	-
	Environmental (pollution reduction in ton)	Sediment	323,841	279,725	276,471
		TN	2,229	1,812	1,653
		TP	346	272	247
	Economic (total BMP cost in dollar)		20,629,205	12,631,470	9,369,057
Environment-Economic-Social	Social (% of total BMP application area)	Most favorable	-	-	-
		Moderate	100	100	100
		Least favorable	-	-	-
	Environmental (pollution reduction in ton)	Sediment	323,841	279,725	276,471
		TN	2,229	1,812	1,653
		TP	346	272	247
	Economic (total BMP cost in dollar)		20,629,205	12,631,470	9,369,057

6.5 CONCLUSION

The objectives of this study were to (1) evaluate the cost of pollution reduction associated with BMP installation at both the subbasin level and the watershed outlet and (2) identify the best BMP and implementation site using AHP while considering social, economic, and environmental issues based on different spatial targeting methods. Four targeting methods were used to identify cost of pollution reduction both at subbasin level and watershed outlet whereas only three targeting methods were used to identify best BMP and implementation site using AHP, as the LII targeting method identified no agricultural land in its CSAs. The targeting methods were used to identify CSAs of sediment, TN, and TP and five BMPs (SC, RM, CT, NG, and NT) were implemented in the identified CSAs to evaluate BMP effectiveness. The AHP method was used to rank the BMPs for three different scenarios, which were based on different combinations of environmental, environmental-economic, and environmental-economic-social factors. The environmental factor consisted of sediment, TN, and TP reduction, the economic factor consisted of total BMP cost, and the social factor consisted of farmer preference in BMP implementation. In *Scenario 1* environmental, economic, and social factors had equal weight (0.33). *Scenario 2* was based on both environmental and economic factors where an equal weight. S*cenario 3* was only based on environmental factors where an equal weight of 0.33 was assigned to each component (reduction of sediment, TN, and TP) during the ranking of BMPs.

The BMP effectiveness was compared among targeting methods and priority area by considering both pollution reduction and BMP cost. Results suggest that stripcropping and residue management were the most cost-effective BMPs having lesser pollution reduction cost both at the subbasin level and watershed outlet, whereas conservation tillage and no-till were the least cost-effective. Increases of TN and TP associated with increased organic matter content were observed for conservation tillage and no-till at the watershed scale. Meanwhile, native grass demonstrated a moderate pollution reduction cost even though having the highest total cost among all the BMPs.

Among the five BMPs native grass, stripcropping, and residue management were selected as rank one by AHP for various combinations of targeting methods (CII, LPSAI, and LPUAI) and scenarios. In *Scenario 1*, at the subbasin level, stripcropping was placed all over the CSAs in all targeting methods, suggesting that it can satisfy from both a pollution reduction stand point (policy makers objective), BMP implementation cost, and social acceptance (from stakeholders objective). However, at watershed outlet, some of the stripcropping was replaced by the socially most acceptable BMP (residue management). In *Scenario* 2 and at subbasin level, stripcropping was selected for all CSAs by all targeting methods due to higher pollution reduction capacity and the lowest total BMP cost. Meanwhile, more residue management was selected at the watershed outlet in *Scenario 2* compared to *Scenario 1*. At the subbasin level, *Scenario 3*, the least socially preferable BMP (native grass) was selected at the subbasin level due to a greater pollution reduction capacity of native grass compared to other BMPs. In fact, at the subbasin level all CSAs selected native grass for all targeting methods. However, in the case of pollution reduction at watershed outlet, the percentage of placement of native grass in CSAs varied from 24 to 51% between the targeting methods.

Overall, no single BMP can satisfy all environmental, economic, and social issues. The results from different scenarios provide a wide variety of solution for different conditions and should be selected based on the watershed management plan requirements. The result of this study can help policy makers and stakeholders determine the placement of suitable BMPs in suitable locations for strengthening science-based decision making.

7.CONCLUSIONS

BMP pollutant reduction efficiency depends on several parameters such as type, placement, implementation plan, design procedure, and maintenance frequency. This study primarily focuses on the placement, selection, and implementation plan of BMPs. The findings help create a useful BMP implementation strategy, which can fulfill the objectives of both policy makers and stakeholders with the intent of improving water quality on a watershed scale. In this study, four targeting methods, concentration impact index (CII), load impact index (LII), load per subbasin area index (LPSAI), and load per unit area index (LPUAI), were used to identify the critical source areas based on sediment, TN, and TP in the watershed using Soil and Water Assessment Tool (SWAT) resulting following conclusions.

- When sediment control is the objective, LPSAI should be considered (Figure 7-1). Similarly, when TN and TP control is the goal, the pollutant CII should be considered (Figure 7-1).

- The LPSAI targeting method identifies the maximum amount of agricultural lands in the high priority areas based on sediment targeting (Figure 7-1) whereas CII targeting method identifies the maximum amount of agricultural lands in the high priority area based on TN and TP targeting scenarios (Figure 7-1).

- The LII targeting method, based on pollutant load in the stream, was incapable of identifying agricultural lands in its high priority areas, indicating this method should not be used to identifying suitable BMP placement location.

- A strong agreement was found between LPSAI and LPUAI for the categorization of priority areas based on sediment and TN targeting scenarios (Figure 7-2). This provides insight to the method of categorization for priority areas by targeting methods.

After understanding the different targeting methods, 10 BMPs namely: contour farming, terraces, recharge structures, conservation tillage, no-till, native grass, residue management (0 kg/ha), residue management (1000 kg/ha), residue management (2000 kg/ha), and strip cropping were modeled in the agricultural lands of SEW based on the priority areas identified by each targeting method. A modified paired t-test was used to evaluate BMP pollutant reduction effectiveness and the conclusions are provided below:

- All the BMPs, except conservation tillage and no-till, showed some significant pollutant reduction (targeted and non-targeted) for all targeting methods (Figure 7-3).

- An insignificant pollution reduction was observed by BMPs when the BMP implementation areas went from high plus medium priority areas to high plus medium plus low priority areas; indicating that BMP implementation in high plus medium priority areas is sufficient at achieving significant pollution reduction.

In the previous study, BMPs were evaluated based on the pollution reduction only. In this study, AHP was used to determine the best BMP type using environmental (reduction of sediment, TN, and TP), economic (total BMP implementation cost), and social factors (preference of BMP by stakeholders) simultaneously. The conclusion of this study is provided below.

- When only environmental factors are considered for BMP selection, native grass is preferred in all the CSAs to achieve maximum pollution reduction at the subbasin level (Figure 7-4).

- When both environmental and economic factors are considered for BMP selection, strip cropping is preferred in all CSAs to achieve maximum pollution reduction at the subbasin level (Figure 7-4).

- Strip cropping was also preferred in all CSAs (to attain maximum pollution reduction at the subbasin level) when the BMP selection criteria was based on environmental, economic, and social factors (Figure 7-4).

- Using environmental factors as BMP selection criteria, strip cropping, residue management, and native grass was selected in the CSAs to obtain maximum pollution reduction at the watershed outlet (Figure 7-4).

- When the BMP selection was based on environmental and economic factors, only strip cropping and residue management were selected in the CSAs to achieve maximum pollution reduction at the watershed outlet (Figure 7-4).

- Strip cropping and residue management were also selected when the BMP selection criteria was based on environmental, economic, and social factors to attain maximum pollution reduction at the watershed outlet (Figure 7-4).

Understanding the spatiotemporal variability of critical source areas is important for constructing a successful BMP implementation plan. In this study, native grass and contour farming was selected as to examine the variability of priority areas, these BMPs were chosen because they showed the highest and lowest significant pollution reduction among all BMPs respectively. These BMPs were implemented only in the high priority areas of the watershed for two consecutive years for all targeting pollutants (sediment, TN, and TP). The conclusions of this study are provided below.

- A distinct change in high priority areas was observed by the end of the second year in the case of native grass due to higher pollution reduction efficiency of native grass compared to contour farming.

- A minimal change in high priority areas was observed for contour farming by the end of second year due to lesser pollution reduction capacity compared to native grass.

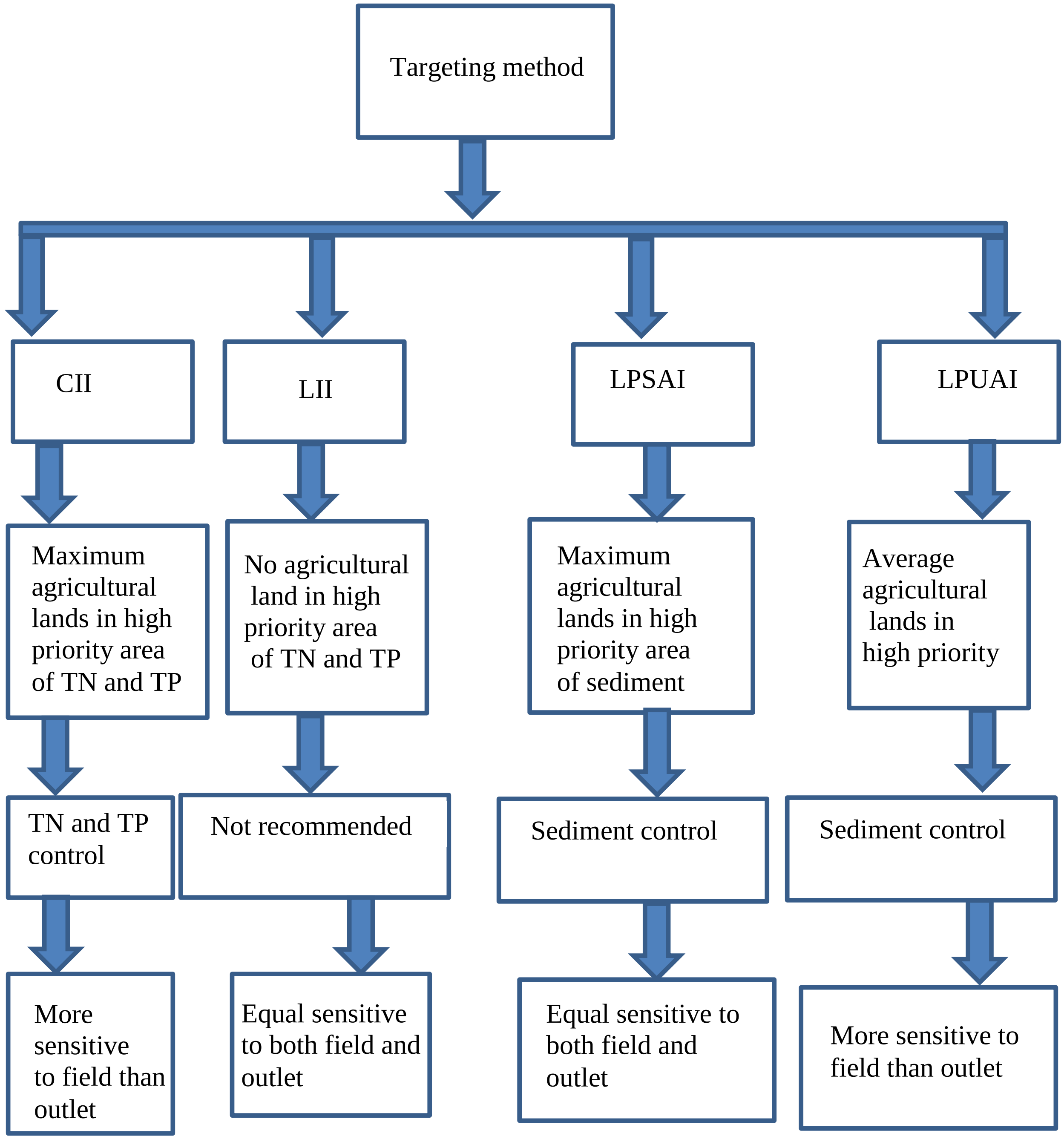

Figure 7-1. Targeting methods recommendation for different pollutants.

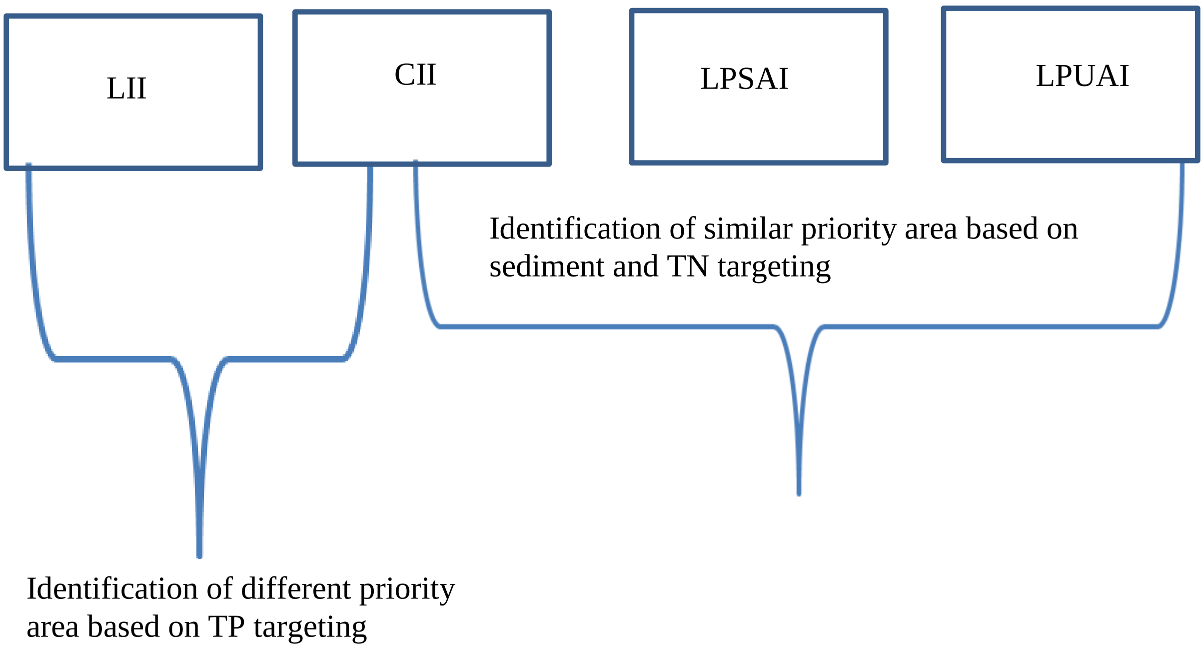

Figure 7-2. Spatial correlation between targeting methods in identifying priority areas.

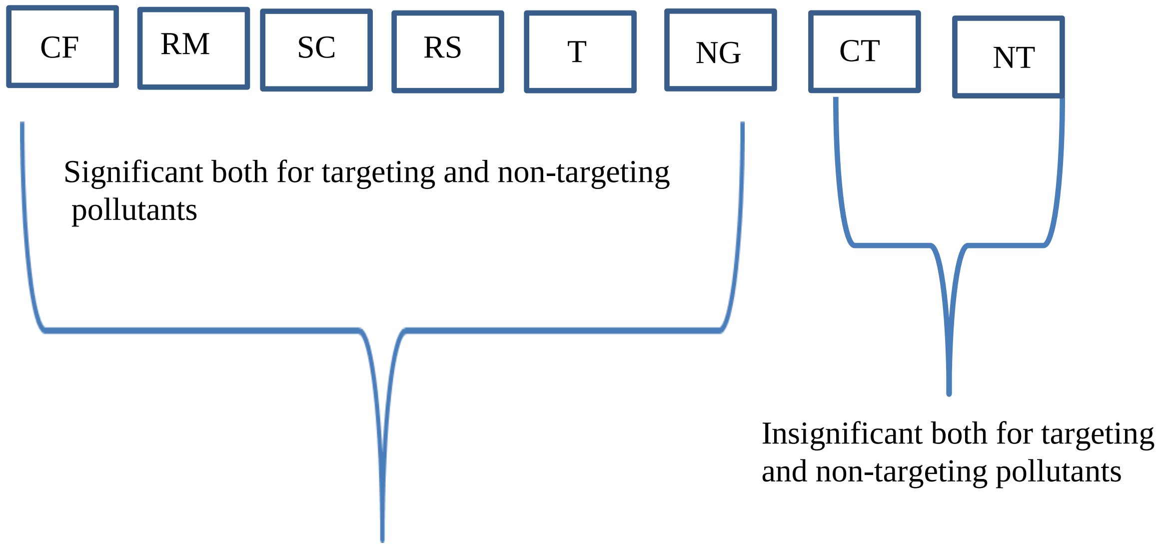

Figure 7-3. Effectiveness of different BMPs in this study.

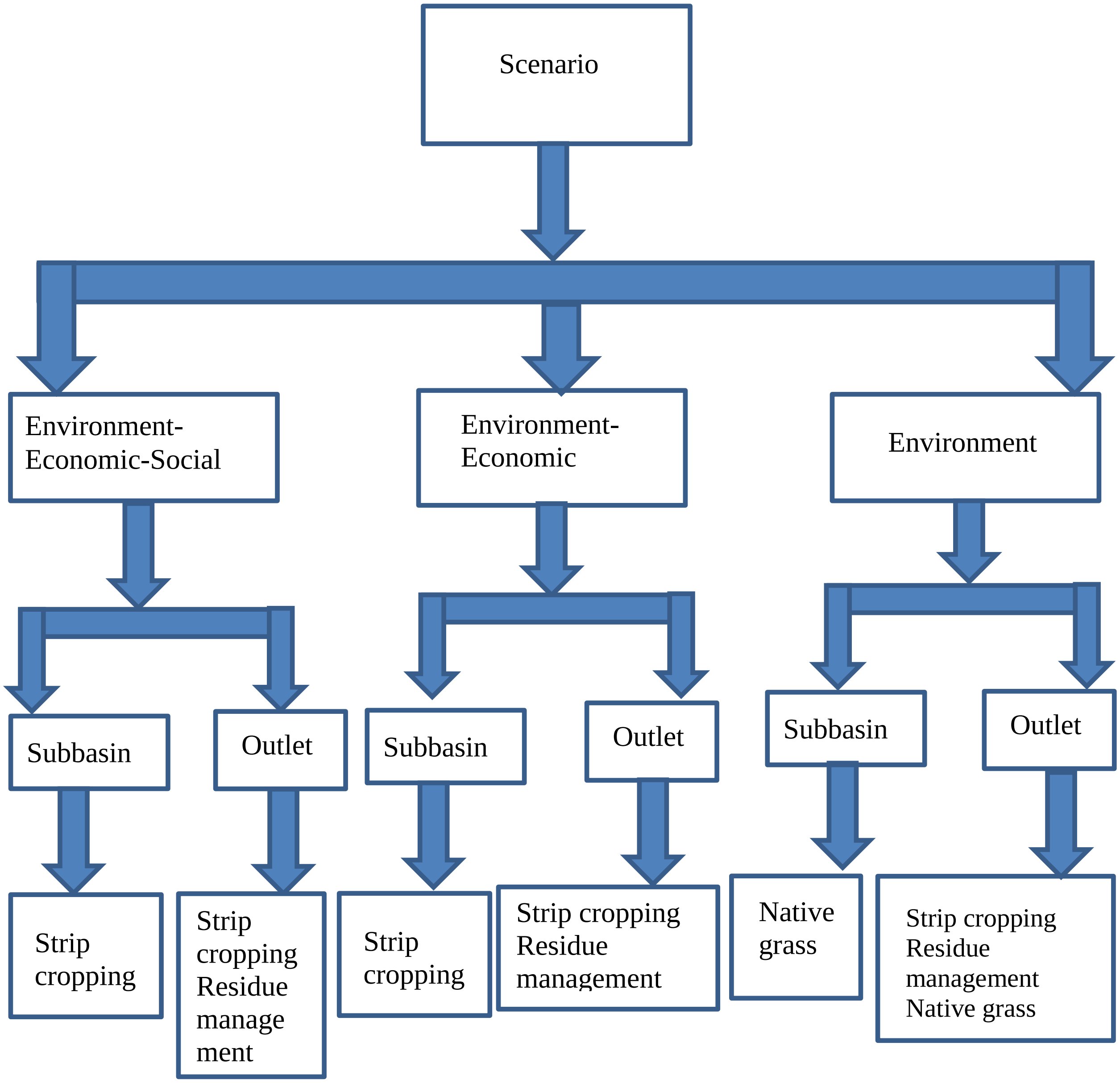

Figure 7-4. Most effective BMPs in CSAs both for subbasin and outlet for all scenarios.

8. RECOMMENDATION FOR FUTURE RESEARCH

Based on the finding of this study, the following future studies are recommended.

- Targeting methods were used to categorized priority area into high, medium, and low based on individual pollutants (sediment, TN, and TP). The next step of this study would be combining the priority area of sediment, TN, and TP simultaneously to obtain the overall priority area for all pollutants and targeting methods using geographical information system.

- The BMP selection criteria in AHP were based on only three factors environmental, economic, and social. However, other factors such as BMPs serving as habitat to wildlife, frequency of maintenance, efficiency in removing pathogen and bacteria, aesthetic value of BMP, and ability of BMPs to make a value added product can be added as BMP selection criteria during construction of pairwise comparison matrix.

- During BMP selection process in AHP, weights are assigned to individual factors and AHP tries to meet the criteria while satisfying the given weights for individual factors. However, in the attempt to satisfy all the criteria, some criteria may not reach the optimal values resulting in a non-ideal solution. Therefore, more than one technique should be used during the decision making process just like the BMP selection process.

- During the spatiotemporal variability analysis of priority areas, only one BMP from the highest pollution reduction category and one from the lowest pollution reduction category were used for the study. However, more BMPs (such as strip cropping and conservation tillage) should be used from each category (highest and lowest pollution reduction) to reinforce the results found in this study.

- Spatiotemporal variability of the selected BMPs was studied only in the high priority areas of the watershed. However, it would be interesting to incorporate these BMPs in the medium and low priority areas as well to determine the spatiotemporal variability of the BMPs in medium and low priority areas.

APPENDICES

(APPENDIX A – ADDITIONAL MATERIAL TO SECTION 5 TITTLED "ANALYSIS OF BEST MANAGEMENT PRACTICE EFFECTIVENESS AND SPATIOTEMPORAL VARIABILITY BASED ON DIFFERENT TARGETING STRATEGIES")

APPENDIX A

Table A-1. P-values for BMPs based on AR (1) model for different targeting methods based on TN targeting(Sediment).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM 2000	RS	T	NG
CII Targeting Method										
B vs. H	1.32E-01	2.36E-01	6.37E-02	4.48E-04	2.56E-05	5.87E-07	7.81E-07	1.21E-09	4.43E-12	2.22E-16
B vs. H+M	1.12E-01	1.40E-01	2.90E-02	1.85E-05	3.67E-07	8.02E-10	1.98E-09	1.74E-13	0.00E+00	0.00E+00
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	2.26E-01	1.43E-01	1.29E-01	2.68E-02	1.98E-02	3.47E-03	7.31E-03	6.92E-04	7.48E-07	9.82E-13
H+M vs. H+M+L	2.70E-01	2.06E-01	2.38E-01	1.55E-01	1.78E-01	1.16E-01	1.51E-01	2.85E-01	2.40E-02	6.26E-05
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	2.31E-01	2.31E-01	1.36E-01	9.45E-02	9.48E-02	7.40E-02	8.17E-02	5.27E-02	4.47E-02	8.58E-02
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	1.16E-01	1.11E-01	5.71E-02	8.48E-05	1.88E-06	6.39E-09	1.36E-08	3.74E-11	0.00E+00	0.00E+00
LPSAI Targeting Method										
B vs. H	1.63E-01	1.61E-01	6.32E-02	1.93E-03	4.85E-04	5.08E-05	7.53E-05	1.18E-05	1.06E-07	2.85E-09
B vs. H+M	1.23E-01	1.19E-01	3.27E-02	3.14E-05	8.83E-07	3.02E-09	8.12E-09	5.44E-11	0.00E+00	0.00E+00
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	1.96E-01	1.99E-01	1.38E-01	1.39E-02	4.58E-03	4.31E-04	8.09E-04	7.56E-05	3.07E-08	1.22E-11

Table A-1 (cont'd)

H+M vs. H+M+L	2.41E-01	2.51E-01	2.11E-01	5.37E-02	6.04E-01	5.37E-02	7.21E-02	1.82E-02	1.04E-03	1.44E-10
LPUAI Targeting Method										
B vs. H	2.13E-01	2.11E-01	5.63E-02	1.88E-02	1.88E-02	8.45E-03	1.21E-02	6.14E-03	1.65E-03	2.23E-03
B vs. H+M	1.17E-01	1.92E-01	4.61E-02	4.23E-04	2.33E-07	1.01E-09	1.01E-09	1.06E-11	0.00E+00	0.00E+00
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	8.05E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	1.37E-01	2.23E-01	1.35E-01	1.70E-02	4.15E-05	7.65E-07	7.65E-07	2.26E-08	5.55E-15	0.00E+00
H+M vs. H+M+L	2.53E-01	1.41E-01	2.50E-01	2.72E-02	2.20E-01	2.06E-01	2.06E-01	7.31E-02	6.55E-02	3.64E-02

Cell having darker color are significantly different at p<0.05 level of significance based on AR(1) model.

Table A-2. P-values for BMPs based on AR (1) model for different targeting methods based on TN targeting (TN).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM2000	RS	T	NG
CII Targeting Method										
B vs. H	7.47E-01	7.85E-01	4.56E-02	4.52E-04	5.89E-03	1.51E-05	3.70E-03	3.01E-03	1.11E-03	4.47E-09
B vs. H+M	8.47E-01	8.78E-01	3.84E-02	5.28E-08	7.69E-04	7.15E-08	4.92E-04	7.97E-04	2.97E-06	0.00E+00
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	1.99E-06	0.00E+00
H vs. H+M	3.10E-01	2.72E-01	1.64E-01	3.42E-02	1.21E-01	4.37E-02	1.34E-01	3.78E-02	3.40E-01	3.64E-02
H+M vs. H+M+L	2.47E-01	1.10E-01	2.62E-01	2.89E-01	4.97E-01	3.07E-01	5.36E-01	3.62E-02	3.30E-01	3.59E-01
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-		
B vs. H+M	3.65E-01	3.57E-01	1.52E-01	5.76E-02	8.86E-02	4.13E-02	7.98E-02	1.04E-01	2.38E-02	1.56E-02
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08
H vs. H+M	-	-	-	-	-	-	-	-		
H+M vs. H+M+L	7.02E-01	7.32E-01	5.89E-02	6.13E-05	3.60E-03	3.43E-06	8.00E-04	1.02E-03	2.44E-09	1.89E-06
LPSAI Targeting Method										
B vs. H	4.97E-01	5.16E-01	5.97E-02	6.06E-04	6.23E-03	1.10E-04	4.32E-03	1.62E-02	1.83E-06	6.58E-07
B vs. H+M	6.65E-01	6.88E-01	1.32E-02	8.74E-08	8.22E-04	1.31E-07	5.60E-04	1.54E-03	1.23E-11	5.14E-11
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08

Table A-2 (cont'd)

H vs. H+M	3.91E-01	3.66E-01	1.63E-01	1.10E-02	7.98E-02	9.18E-03	8.60E-02	6.86E-02	3.39E-04	4.56E-03
H+M vs. H+M+L	3.86E-01	3.29E-01	2.38E-01	2.41E-01	4.37E-01	2.26E-01	2.81E-01	4.12E-02	2.83E-01	2.47E-01
LPUAI Targeting Method										
B vs. H	4.08E-01	4.16E-01	3.96E-02	2.40E-03	1.36E-02	1.22E-03	1.20E-02	8.70E-02	1.35E-04	5.75E-05
B vs. H+M	6.96E-01	5.48E-01	3.54E-02	1.32E-04	6.61E-04	4.71E-08	4.20E-04	1.32E-03	2.99E-12	0.00E+00
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	0.00E+00
H vs. H+M	4.97E-01	3.56E-01	1.27E-01	7.34E-02	1.97E-02	5.38E-04	1.70E-02	1.20E-02	2.30E-06	1.70E-04
H+M vs. H+M+L	3.57E-01	2.84E-01	2.70E-01	1.43E-01	5.16E-01	3.45E-01	5.57E-01	5.05E-02	4.85E-01	3.96E-01

Cell having darker color are significantly different at $p<0.05$ level of significance based on AR(1) model

Table A-3. P-values for BMPs based on AR (1) model for different targeting methods based on TN targeting (TP).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM2000	RS	T	NG
CII Targeting Method										
B vs. H	2.50E-01	9.35E-01	8.85E-01	1.48E-06	1.26E-03	3.86E-10	8.19E-05	6.02E-12	4.44E-16	7.77E-15
B vs. H+M	3.42E-01	6.50E-01	9.09E-01	2.78E-08	3.17E-04	3.06E-14	1.12E-05	2.22E-16	0.00E+00	0.00E+00
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	2.84E-04	1.82E-14	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	6.96E-02	1.04E-01	1.05E-01	2.49E-02	7.94E-02	4.08E-03	5.75E-02	1.03E-03	3.66E-05	4.01E-04
H+M vs. H+M+L	5.50E-02	5.77E-02	2.26E-01	1.35E-01	2.04E-01	1.29E-01	2.11E-01	8.80E-03	1.46E-04	3.32E-01
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	8.83E-02	8.41E-02	1.33E-01	1.06E-02	2.19E-02	4.09E-03	1.38E-02	2.30E-03	1.69E-03	1.27E-03
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	1.16E-02	2.84E-04	0.00E+00	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	2.55E-01	7.77E-01	9.20E-01	4.03E-07	8.10E-04	0.00E+00	6.39E-05	6.66E-16	0.00E+00	1.33E-15
LPSAI Targeting Method										
B vs. H	1.82E-01	7.11E-01	6.02E-01	1.04E-05	1.40E-03	1.47E-07	1.74E-04	1.11E-07	8.30E-11	3.90E-11
B vs. H+M	3.42E-01	6.73E-01	9.77E-01	4.94E-08	1.01E-04	1.10E-13	1.52E-05	3.18E-13	0.00E+00	0.00E+00
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	2.84E-04	1.82E-14	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	1.25E-01	2.67E-01	2.78E-01	6.81E-03	1.42E-02	1.40E-04	6.33E-03	7.15E-05	3.12E-08	4.71E-08

Table A-3 (cont'd)

H+M vs. H+M+L	6.04E-02	6.54E-02	2.28E-01	9.63E-02	1.58E-01	5.97E-02	1.54E-01	3.76E-04	2.05E-02	1.01E-01
					LPUAI Targeting Method					
B vs. H	1.02E-01	3.16E-01	1.55E-01	2.67E-03	4.87E-03	8.47E-05	2.02E-03	1.75E-04	8.15E-06	9.02E-06
B vs. H+M	3.77E-01	6.93E-01	9.00E-01	1.57E-06	1.19E-03	1.91E-14	9.93E-06	1.01E-13	0.00E+00	0.00E+00
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	9.37E-04	1.82E-14	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	2.30E-01	1.73E-01	8.67E-01	1.64E-03	4.60E-03	1.05E-08	7.27E-04	7.55E-08	0.00E+00	8.08E-13
H+M vs. H+M+L	7.38E-02	2.50E-01	2.22E-01	3.48E-02	2.10E-01	1.53E-01	2.22E-01	1.00E-03	1.30E-01	4.04E-01

Cell having darker color are significantly different at $p<0.05$ level of significance based on AR(1) model

Table A-4. P-values for BMPs based on AR (1) model for different targeting methods based on TP targeting (sediment).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM2000	RS	T	NG
					CII Targeting Method					
B vs. H	1.64E-01	1.62E-01	6.77E-02	2.17E-03	5.35E-04	4.91E-05	7.77E-05	8.52E-06	4.45E-08	4.16E-10
B vs. H+M	1.37E-01	1.34E-01	5.57E-02	2.66E-04	1.55E-05	3.21E-06	1.34E-06	5.88E-09	0.00E+00	4.16E-10
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	2.13E-01	2.20E-01	2.04E-01	5.50E-02	3.05E-02	4.55E-02	1.36E-02	3.93E-03	2.69E-04	1.78E-01
H+M vs. H+M+L	2.09E-01	2.16E-01	1.40E-01	2.76E-02	1.79E-02	5.24E-04	5.55E-03	5.97E-04	2.00E-07	0.00E+00
					LII Targeting Method					
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	1.56E-01	1.52E-01	8.12E-02	2.92E-03	5.41E-04	8.26E-05	9.25E-05	2.79E-05	5.63E-07	1.50E-06
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	1.87E-01	1.91E-01	1.08E-01	6.10E-03	1.94E-03	7.71E-05	1.90E-04	1.18E-06	1.34E-11	0.00E+00
					LPSAI Targeting Method					
B vs. H	1.62E-01	1.59E-01	5.20E-02	1.41E-03	3.90E-04	7.49E-03	5.21E-05	8.52E-06	3.91E-08	7.52E-10
B vs. H+M	1.23E-01	1.19E-01	3.27E-02	3.14E-05	8.83E-07	2.96E-09	8.12E-09	1.11E-09	0.00E+00	0.00E+00
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	3.12E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	1.97E-01	2.01E-01	1.63E-01	1.79E-02	5.55E-03	1.74E-06	1.13E-03	1.15E-04	8.33E-08	7.10E-12
H+M vs.	2.41E-	2.51E-	2.11E-	1.11E-	1.08E-01	5.41E-	7.21E-	1.69E-	1.04E-	4.49E-

Table A-4 (cont'd)

H+M+L	01	01	01	01		02	02	02	03	10
LPUAI Targeting Method										
B vs. H	2.22E-01	2.20E-01	1.18E-01	6.98E-02	7.09E-02	5.02E-02	6.24E-02	7.12E-02	2.88E-02	4.77E-02
B vs. H+M	1.21E-01	1.17E-01	2.78E-02	1.52E-05	3.48E-07	6.81E-10	1.91E-09	2.73E-11	0.00E+00	0.00E+00
B vs. H+M+L	1.10E-01	1.05E-01	2.80E-02	1.24E-05	2.02E-07	8.05E-10	8.05E-10	1.11E-12	0.00E+00	0.00E+00
H vs. H+M	1.33E-01	1.30E-01	6.87E-02	1.68E-04	5.50E-06	2.82E-08	5.38E-08	5.45E-10	0.00E+00	0.00E+00
H+M vs. H+M+L	2.48E-01	2.59E-01	2.51E-01	1.73E-01	1.83E-01	1.28E-01	1.56E-01	4.07E-02	2.54E-02	1.89E-03

Cell having darker color are significantly different at $p<0.05$ level of significance based on AR(1) model

Table A-5. P-values for BMPs based on AR (1) model for different targeting methods based on TP targeting (TN).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM2000	RS	T	NG
CII Targeting Method										
B vs. H	5.26E-01	5.45E-01	1.07E-01	5.26E-01	9.51E-03	9.32E-05	6.38E-03	5.74E-03	9.92E-07	1.74E-06
B vs. H+M	6.08E-01	6.26E-01	3.85E-02	6.08E-01	4.53E-03	3.81E-08	2.85E-03	1.40E-03	1.13E-08	2.41E-09
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	2.95E-01	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08
H vs. H+M	3.26E-01	2.93E-01	2.95E-01	3.26E-01	2.63E-01	1.93E-01	2.67E-01	1.58E-01	5.48E-02	1.14E-01
H+M vs. H+M+L	4.29E-01	3.71E-01	1.77E-01	4.29E-01	1.34E-01	3.66E-02	1.46E-01	5.92E-02	1.20E-02	3.46E-02
LII Targeting Method										
B vs. H	-	-	-	-	-	-	-	-	-	-
B vs. H+M	4.71E-01	4.63E-01	7.05E-02	2.95E-04	1.62E-02	1.41E-03	1.32E-02	4.33E-02	6.12E-12	2.27E-04
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08
H vs. H+M	-	-	-	-	-	-	-	-	-	-
H+M vs. H+M+L	5.63E-01	5.49E-01	5.29E-02	8.02E-04	1.95E-02	2.97E-04	1.86E-02	3.66E-03	2.76E-06	1.47E-04
LPSAI Targeting Method										
B vs. H	5.01E-01	5.20E-01	4.68E-02	4.13E-04	5.30E-03	8.54E-02	3.49E-03	1.60E-02	5.69E-07	3.87E-07
B vs. H+M	6.65E-01	6.88E-01	1.32E-02	8.74E-08	8.22E-04	1.24E-07	5.60E-04	1.61E-03	1.23E-11	4.43E-11
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08
H vs. H+M	3.86E-01	3.65E-01	2.01E-01	4.48E-02	9.37E-02	4.68E-07	1.04E-01	7.71E-02	6.39E-04	5.72E-03
H+M vs.	3.86E-	3.29E-	2.38E-	2.41E-	4.37E-01	2.32E-	2.81E-	8.76E-	2.83E-	2.60E-

Table A-5(cont'd)

H+M+L	01	01	01	01		01	01	02	01	01
LPUAI Targeting Method										
B vs. H	3.52E-01	3.51E-01	1.15E-01	4.33E-02	8.30E-02	3.62E-02	8.32E-02	1.75E-01	1.94E-02	2.52E-02
B vs. H+M	6.43E-01	6.61E-01	3.12E-02	8.70E-08	6.21E-04	1.33E-07	3.87E-04	2.34E-03	2.34E-11	7.22E-10
B vs. H+M+L	8.44E-01	8.72E-01	3.39E-02	3.16E-08	6.18E-04	3.81E-10	3.94E-04	1.11E-04	6.12E-12	1.21E-08
H vs. H+M	5.46E-01	5.58E-01	1.04E-01	2.14E-04	6.14E-03	1.37E-05	4.34E-03	6.37E-03	1.39E-08	8.47E-08
H+M vs. H+M+L	4.00E-01	3.47E-01	4.81E-01	4.26E-01	5.18E-01	2.61E-01	5.57E-01	3.23E-02	3.18E-01	1.88E-01

Cell having darker color are significantly different at p <0.05 level of significance based on AR (1) model.

Table A-6. P-values for BMPs based on AR (1) model for different targeting methods based on TP targeting (TP).

p-value	CT	NT	RM 0	CF	RM 1000	SC	RM2000	RS	T	NG
					CII Targeting Method					
B vs. H	2.15E-01	8.58E-01	8.24E-01	4.85E-06	1.38E-03	9.36E-07	1.35E-04	3.36E-09	1.62E-14	4.86E-13
B vs. H+M	2.88E-01	8.68E-01	8.89E-01	7.33E-07	9.34E-04	1.41E-10	5.63E-05	1.15E-11	0.00E+00	2.22E-15
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	2.84E-04	1.82E-14	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	8.57E-02	1.29E-01	1.59E-01	5.98E-02	1.48E-01	4.67E-02	1.14E-01	6.84E-03	2.15E-05	1.65E-03
H+M vs. H+M+L	7.40E-02	1.05E-01	3.17E-01	3.43E-02	1.01E-01	1.92E-03	7.54E-02	4.63E-05	1.46E-04	6.68E-04
					LII Targeting Method					
B vs. H	-	-	-	-	-		-	-	-	-
B vs. H+M	1.62E-01	4.75E-01	3.73E-01	6.38E-04	4.93E-03	2.40E-05	1.45E-03	1.52E-05	5.35E-07	1.25E-06
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	2.84E-04	0.00E+00	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	-	-	-	-	-		-	-	-	-
H+M vs. H+M+L	1.62E-01	4.79E-01	4.95E-01	7.23E-05	4.93E-03	8.01E-02	1.10E-03	3.11E-10	3.35E-01	4.49E-11
					LPSAI Targeting Method					
B vs. H	1.85E-01	7.32E-01	5.35E-01	6.63E-06	1.62E-03	8.56E-05	1.31E-04	7.46E-08	3.06E-12	1.55E-11
B vs. H+M	3.42E-01	6.73E-01	9.77E-01	4.94E-08	1.01E-04	8.10E-14	1.52E-05	4.06E-13	0.00E+00	0.00E+00
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	2.84E-04	1.82E-14	9.75E-06	0.00E+00	0.00E+00	0.00E+00
H vs. H+M	1.27E-01	2.67E-01	3.36E-01	1.03E-02	1.54E-02	2.68E-09	9.21E-03	1.44E-04	9.15E-08	8.32E-09

Table A-6 (cont'd)

H+M vs. H+M+L	6.04E-02	6.54E-02	2.28E-01	9.63E-02	1.58E-01	6.57 E-02	1.54E-01	3.59E-04	2.05E-02	1.16E-01
LPUAI Targeting Method										
B vs. H	6.97E-02	1.28E-01	6.95E-02	6.40E-03	1.36E-02	3.19 E-03	9.87E-03	4.45E-03	1.46E-03	2.76E-03
B vs. H+M	3.26E-01	7.19E-01	9.43E-01	3.67E-08	1.89E-04	8.79 E-14	6.76E-06	8.75E-14	0.00E +00	0.00E +00
B vs. H+M+L	3.46E-01	6.33E-01	8.94E-01	2.06E-08	9.37E-04	1.82 E-14	9.75E-06	0.00E+00	0.00E +00	0.00E +00
H vs. H+M	2.66E-01	9.57E-01	9.17E-01	5.75E-06	1.12E-03	1.53 E-10	8.40E-05	7.13E-11	0.00E +00	1.40E-14
H+M vs. H+M+L	7.39E-02	9.01E-02	3.32E-01	1.17E-01	2.36E-01	7.98 E-02	2.34E-01	2.40E-04	3.23E-02	1.40E-14

Cell having darker color are significantly different at p <0.05 level of significance based on AR (1) model.

Table A-7. Spatial correlation among the targeting methods for different targeting scenarios.

Parameter	Kappa (95% CI)	Weighted Kappa (95% CI)	G^2 (df=2)	β (p-value)	δ (p-value)	τ
CII vs. LII	0.24 (0.09,0.38)	0.20 (0.05,0.35)	2.60	-0.15 (0.77)	1.24 (0.00)	10.20
CII vs. LPSAI	0.50 (0.33,0.67)	0.56 (0.36,0.76)	9.65	0.79 (0.09)	1.41 (0.00)	36.91
CII vs. LPUAI	0.37 (0.22,0.51)	0.30 (0.14,0.46)	0.26	-0.12 (0.76)	1.99 (0.00)	47.39
LII vs. LPSAI	0.32 (0.18,0.45)	0.37 (0.22,0.52)	14.89	0.48 (0.20)	0.91 (0.01)	9.90
LII vs. LPUAI	0.27 (0.15,0.39)	0.31 (0.17,0.44)	16.80	0.47 (0.12)	0.61 (0.04)	5.42
LPSAI vs. LPUAI	0.56 (0.43,0.68)	0.63 (0.49,0.77)	12.78	1.10 (0.02)	1.57 (0.00)	69.61
CII vs. LII	0.15 (0.08,0.23)	0.10 (0.04,0.17)	12.13	-0.42 (0.28)	1.75 (0.00)	21.79
CII vs. LPSAI	0.29 (0.19,0.38)	0.39 (0.27,0.51)	0.33	1.26 (0.00)	0.53 (0.06)	10.09
CII vs. LPUAI	0.29 (0.20,0.38)	0.48 (0.39,0.58)	28.39	1.58 (0.00)	-0.02 (0.94)	4.65
LII vs. LPSAI	-0.06 (-0.10,-0.02)	-0.05 (-0.14,0.04)	2.20	6.42 (1.00)	-13.13(1.00)	0.00
LII vs. LPUAI	-0.02 (-0.09,0.06)	-0.03 (-0.12,0.06)	2.55	-0.34 (0.63)	0.12 (0.85)	0.90
LPSAI vs. LPUAI	0.51 (0.39,0.63)	0.59 (0.45,0.72)	6.74	0.89 (0.03)	1.08 (0.00)	21.19
		TP targeting scenario				
CII vs. LII	-0.08 (-0.13,-0.02)	-0.07 (-0.16,0.03)	1.53	6.53 (1.00)	-13.45(1.00)	0.00
CII vs. LPSAI	-0.10 (-0.13,-0.08)	-0.13 (-0.16,-0.09)	0.00	-7.28 (1.00)	-8.72 (1.00)	0.00
CII vs. LPUAI	0.24 (0.15,0.33)	0.43 (0.30,0.55)	29.05	1.13 (0.00)	-0.21 (0.65)	2.05
LII vs. LPSAI	0.70 (0.58,0.82)	0.81 (0.72,0.90)	0.00	8.94 (1.00)	9.99 (1.00)	3.6E+1
LII vs. LPUAI	-0.14 (-0.21,-0.07)	-0.17 (-0.23,-0.11)	0.00	-15.49 (1.00)	7.00 (1.00)	0.22
LPSAI vs. LPUAI	-0.13 (-0.17,-0.10)	-0.15 (-0.19,-0.11)	0.00	-7.07 (1.00)	-9.87 (1.00)	0.00

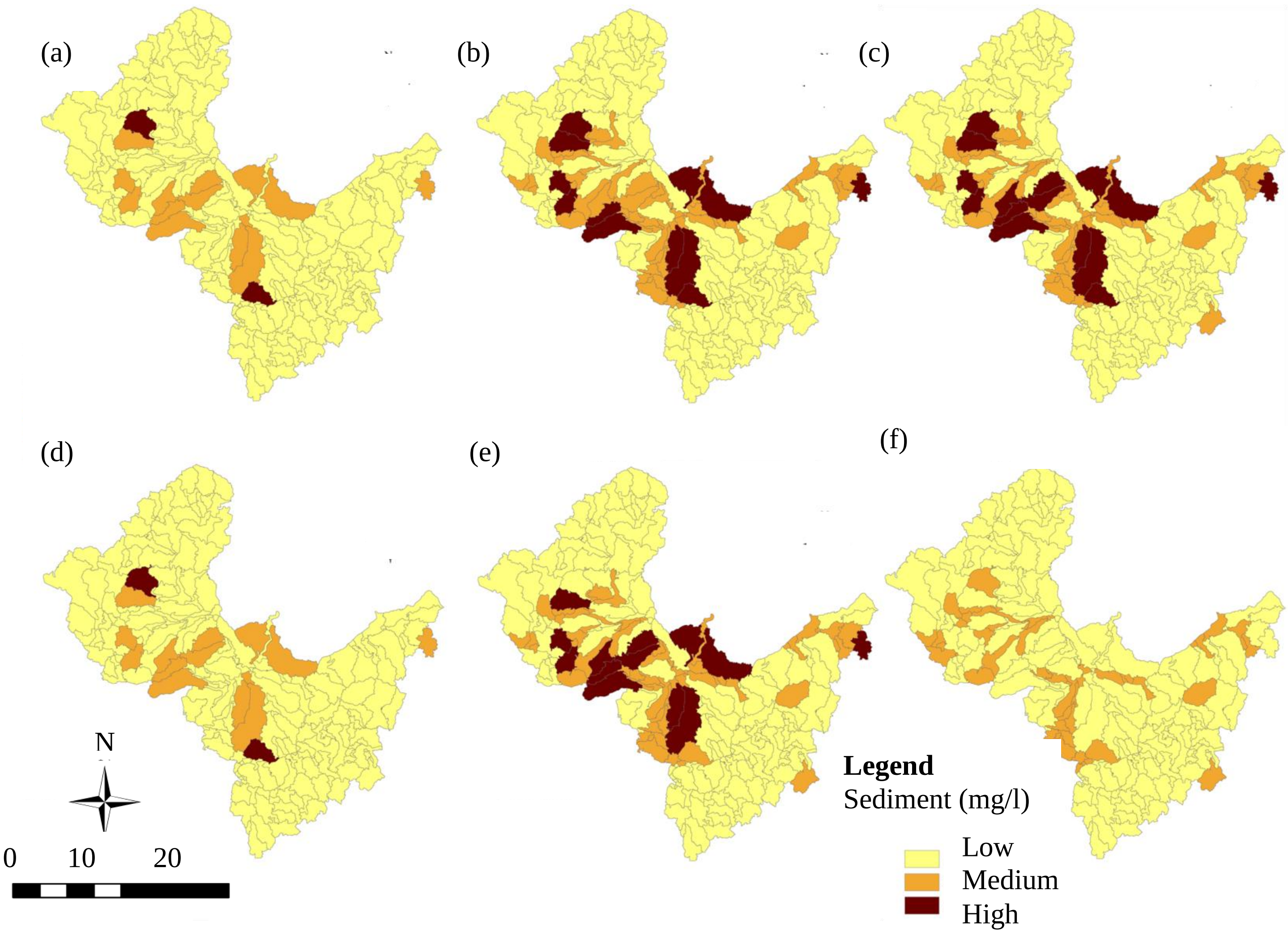

Figure A-8. CII priority areas – sediment targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

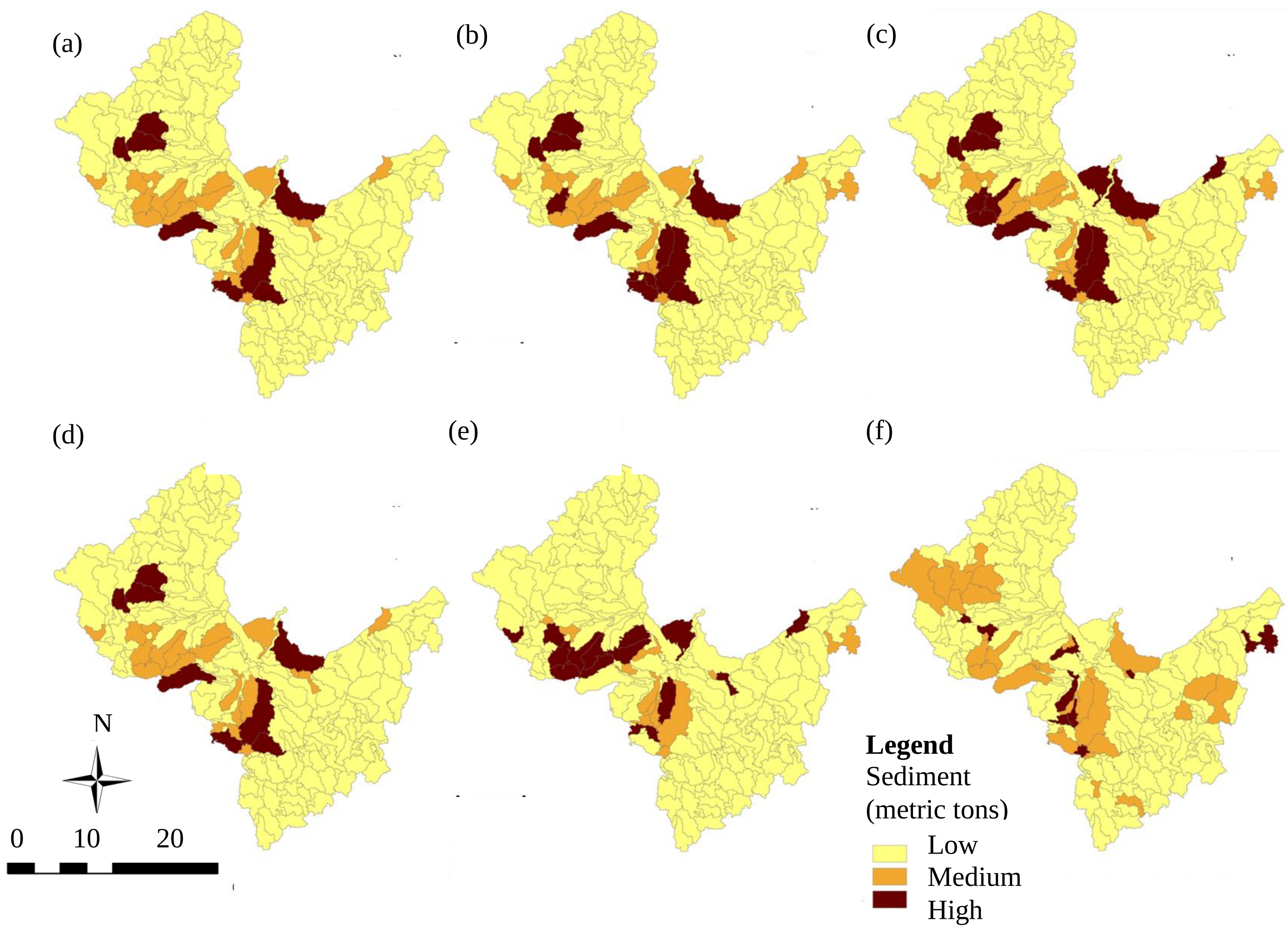

Figure A-9. LPSAI priority areas – sediment targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

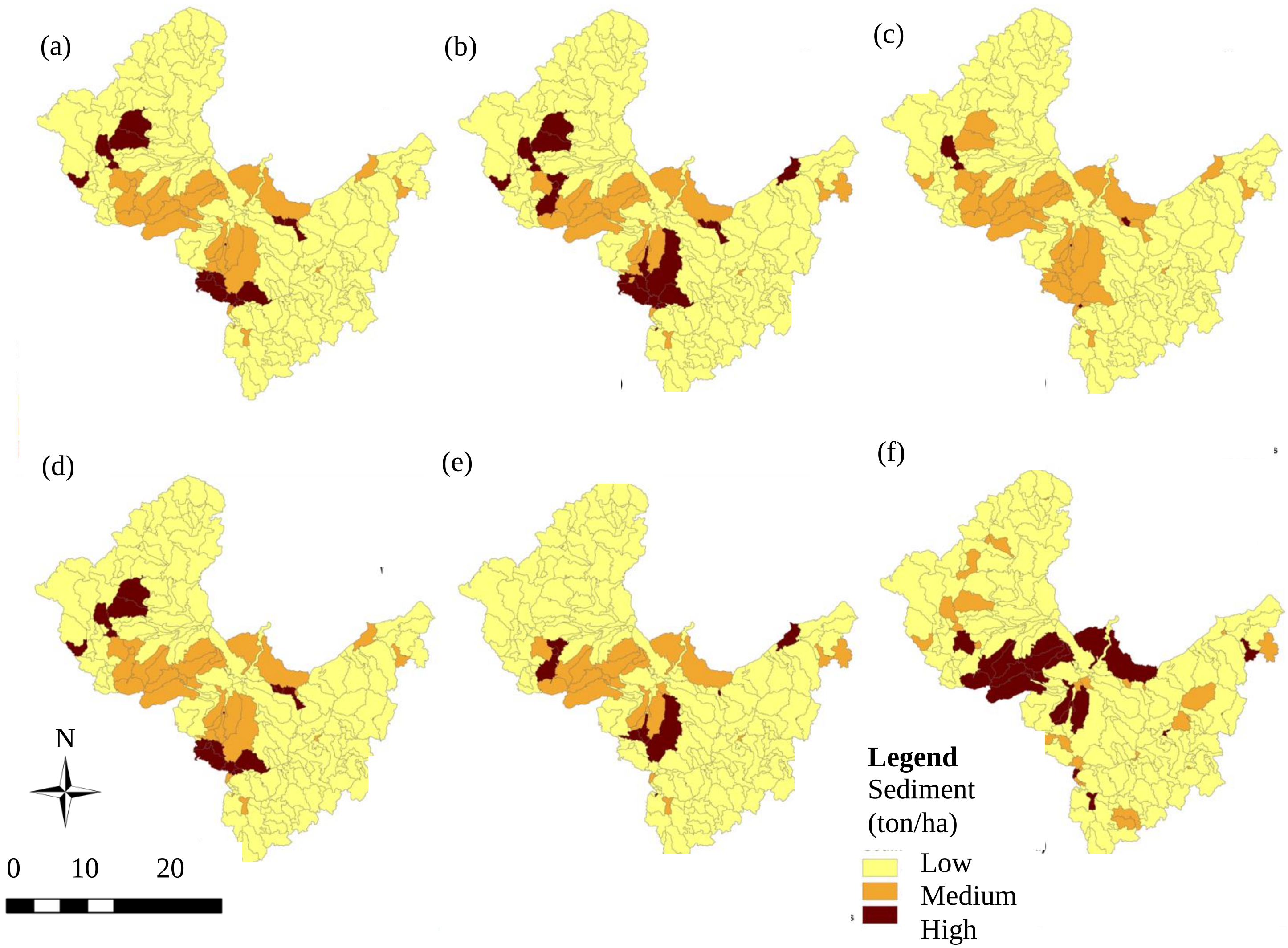

Figure A-10. LPUAI priority areas – sediment targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

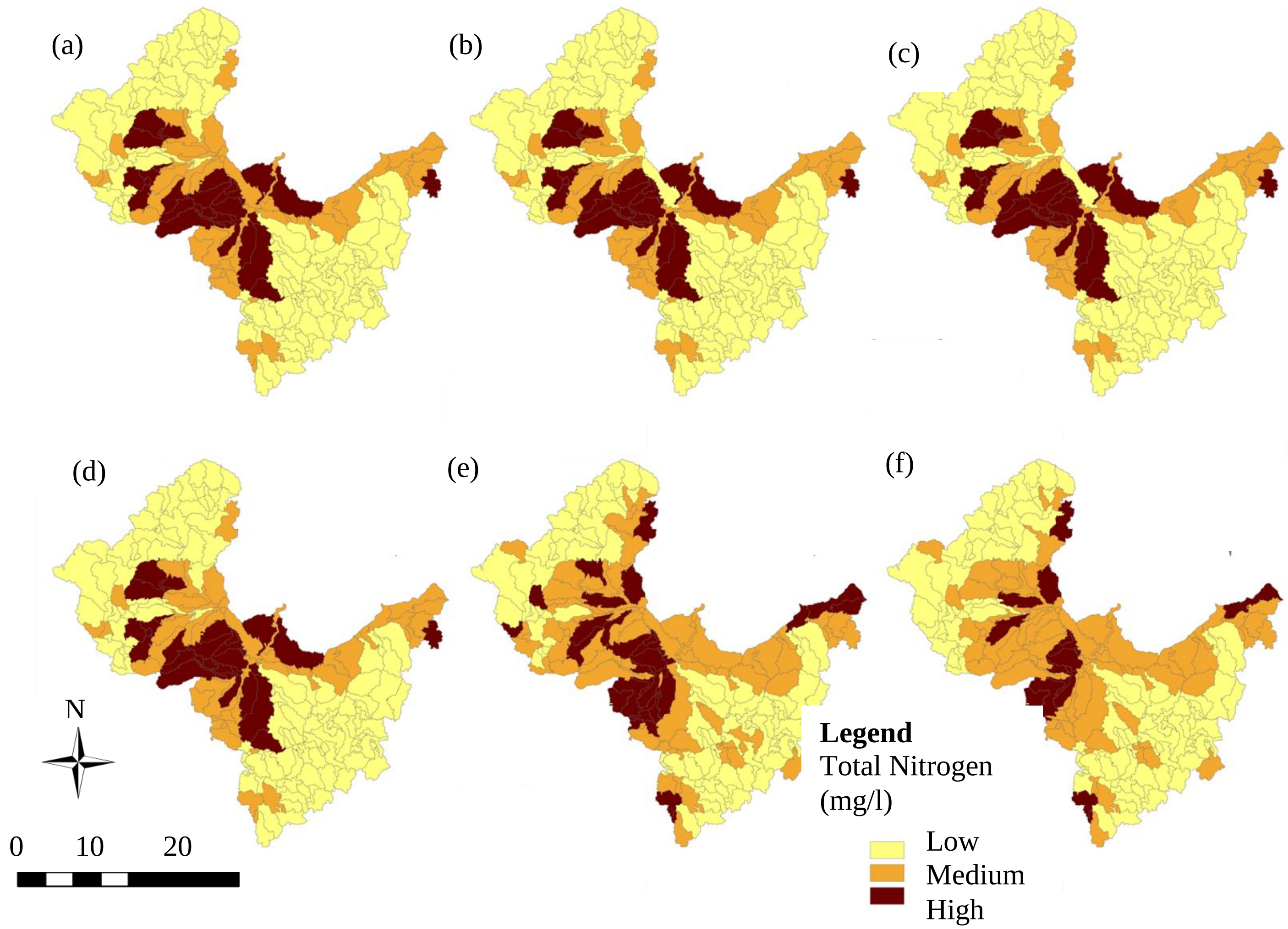

Figure A-11. CII priority areas – TN targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

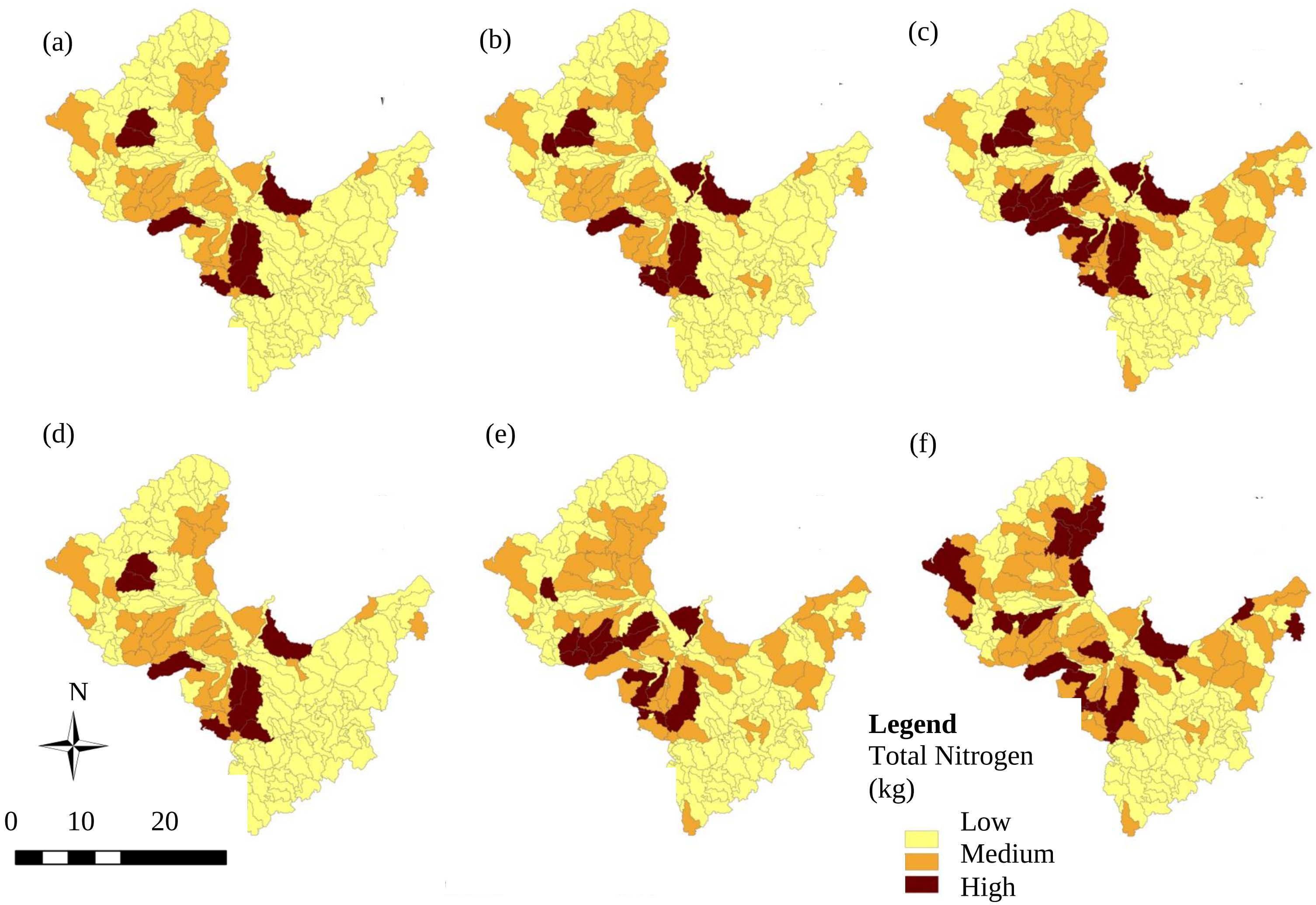

Figure A-12. LPSAI priority areas – TN targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

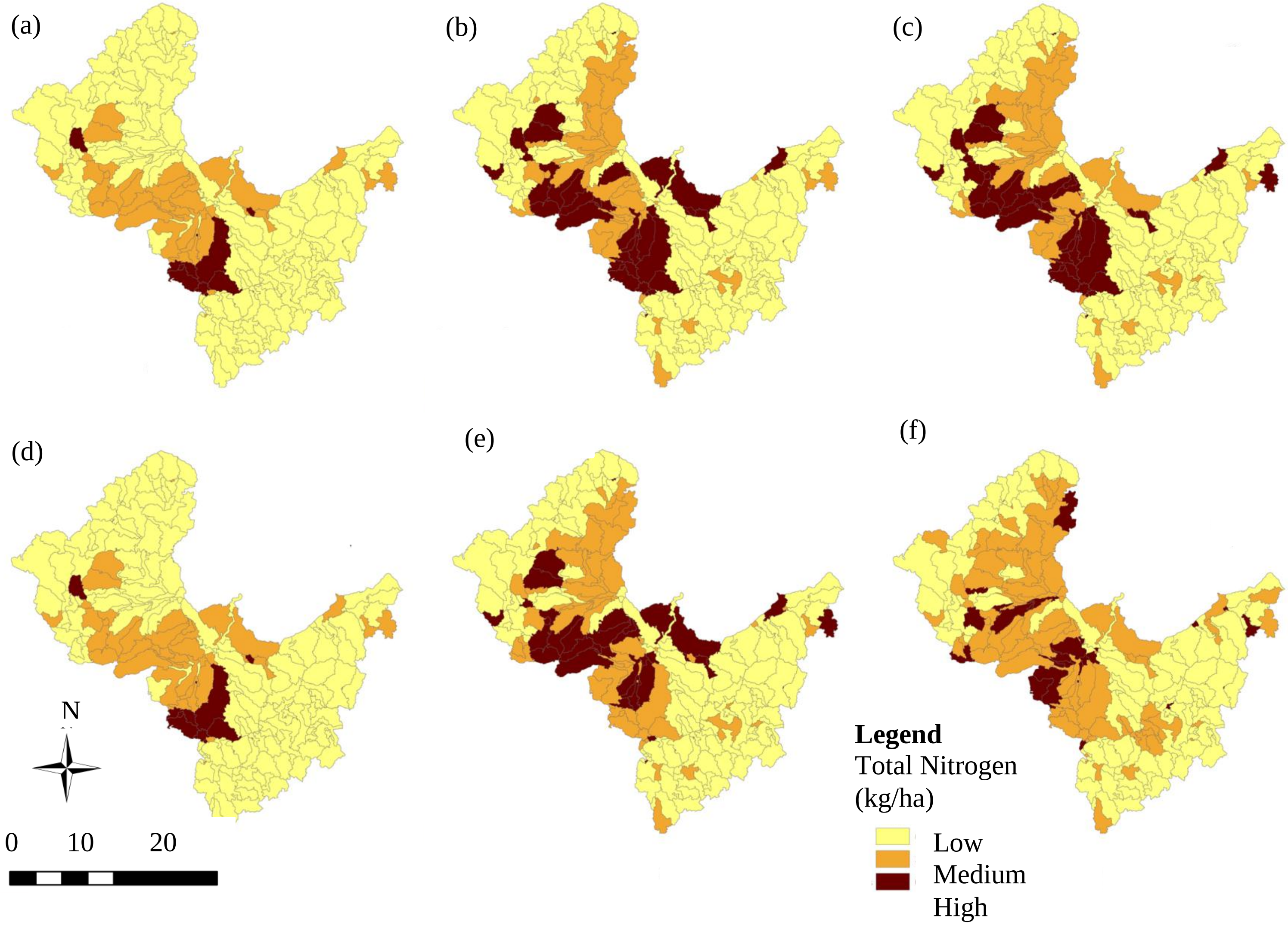

Figure A-13. LPUAI priority areas – TN targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

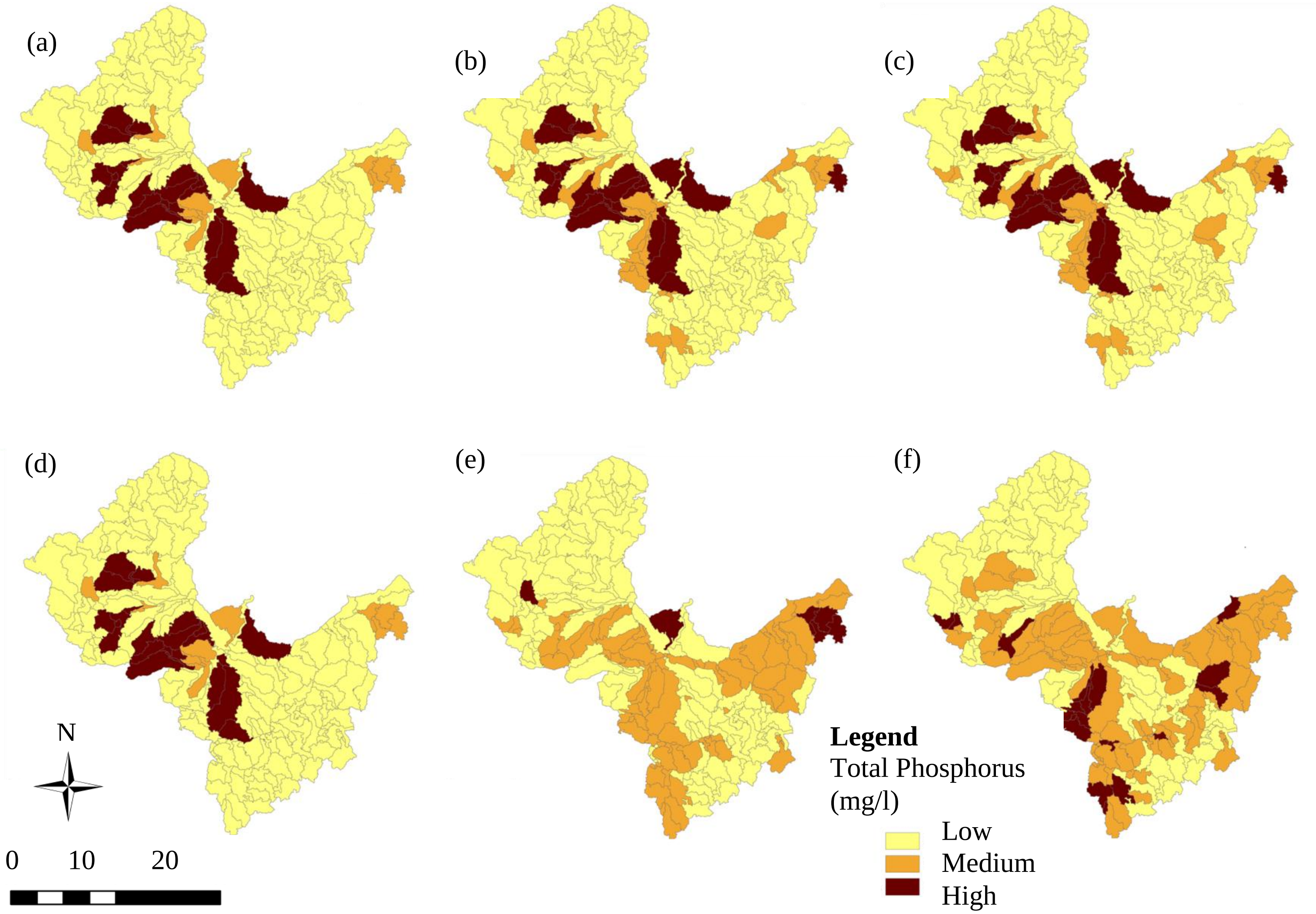

Figure A-14. CII priority areas – TP targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

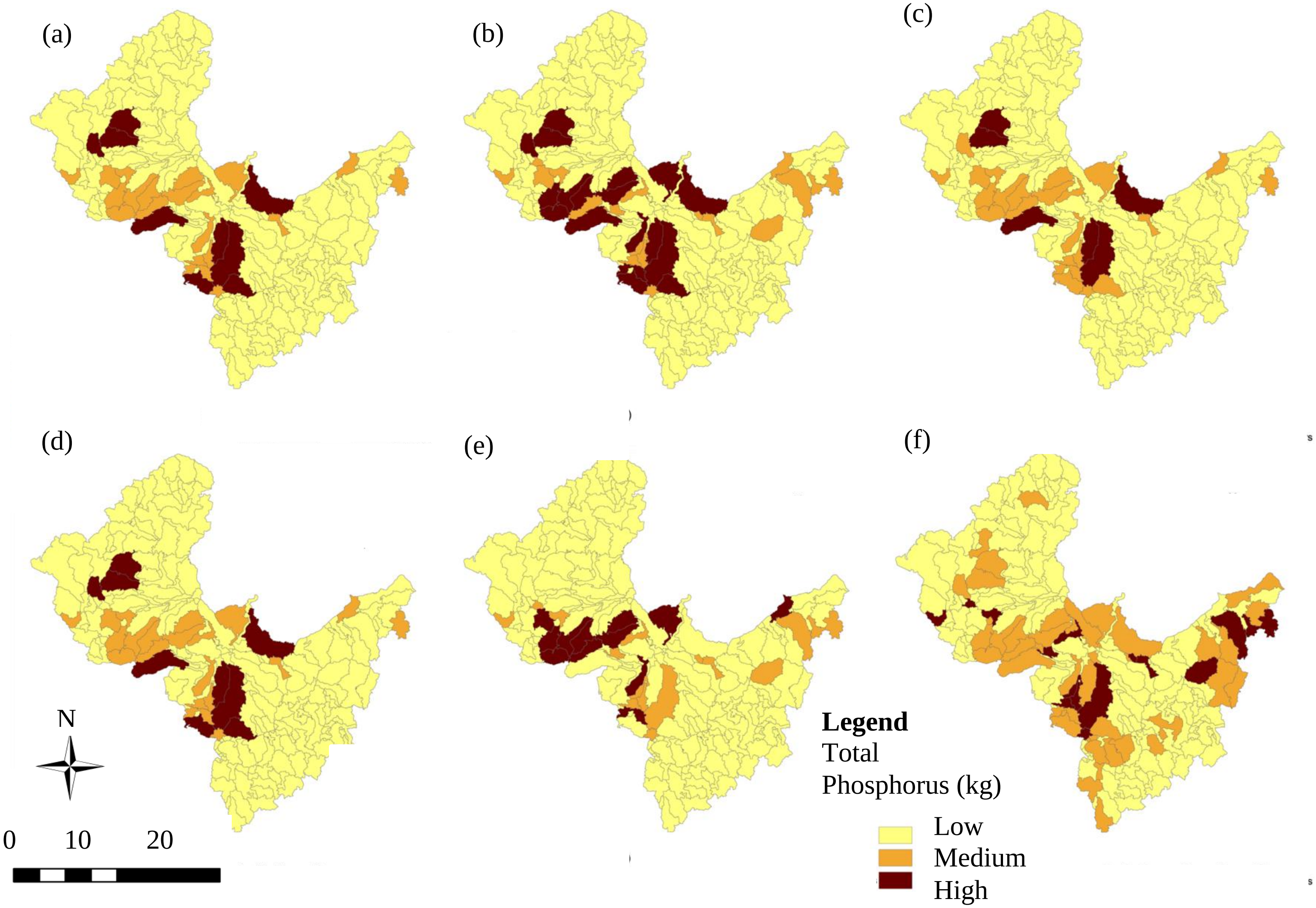

Figure A-15. LPSAI priority areas – TP targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

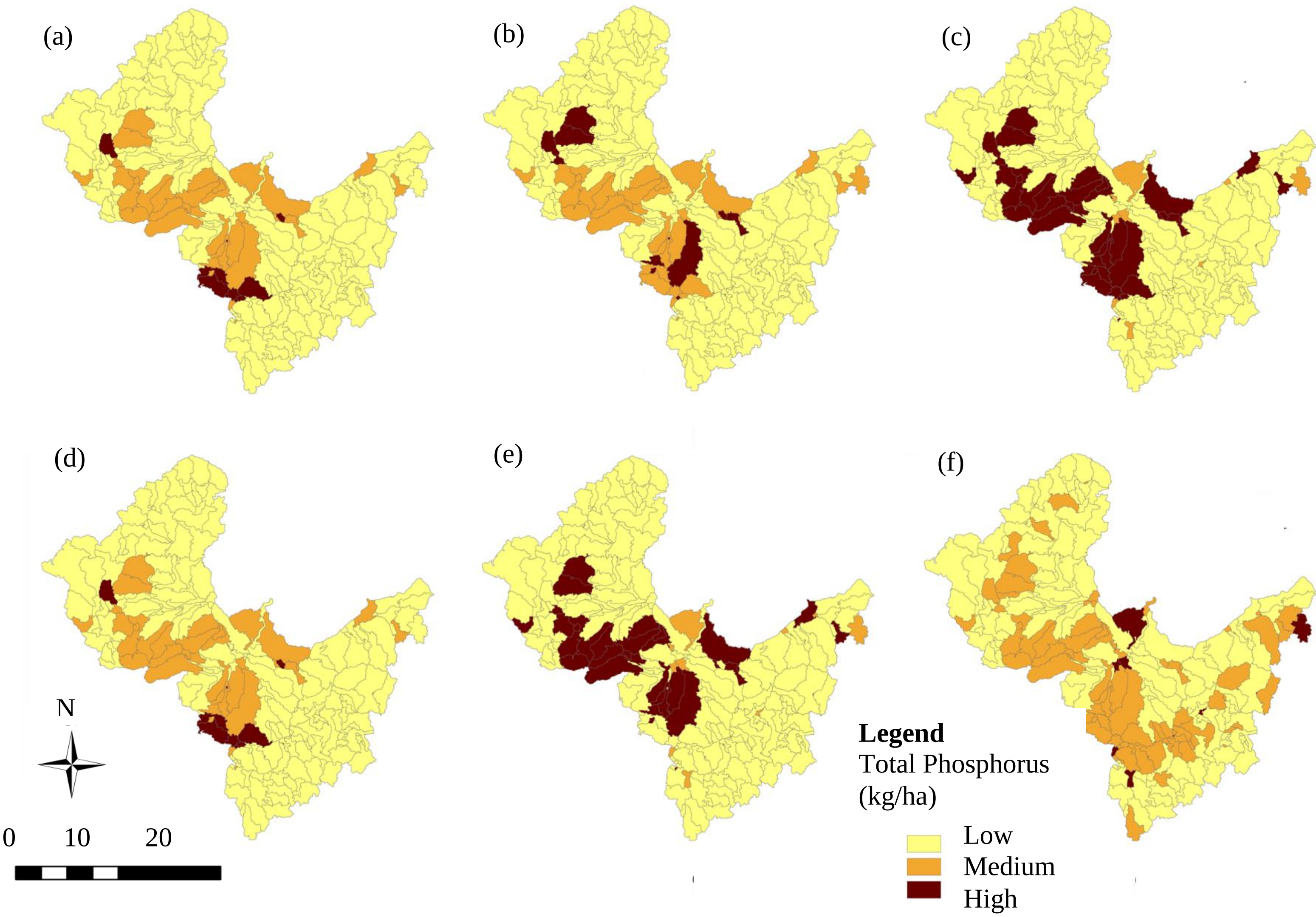

Figure A-16. LPUAI priority areas – TP targeting scenario. (a) base scenario, (b) year one contour farming, (c) year two contour farming, (d) base scenario, (e) year one native grass, (f) year two native grass.

(APPENDIX B – ADDITIONAL MATERIAL TO SECTION 6 TITTLED "APPLICATION OF ANALYTICAL HIERARCHY PROCESS FOR EFFECTIVE SELECTION OF AGRICULTURAL BEST MANAGEMENT PRACTICES.")

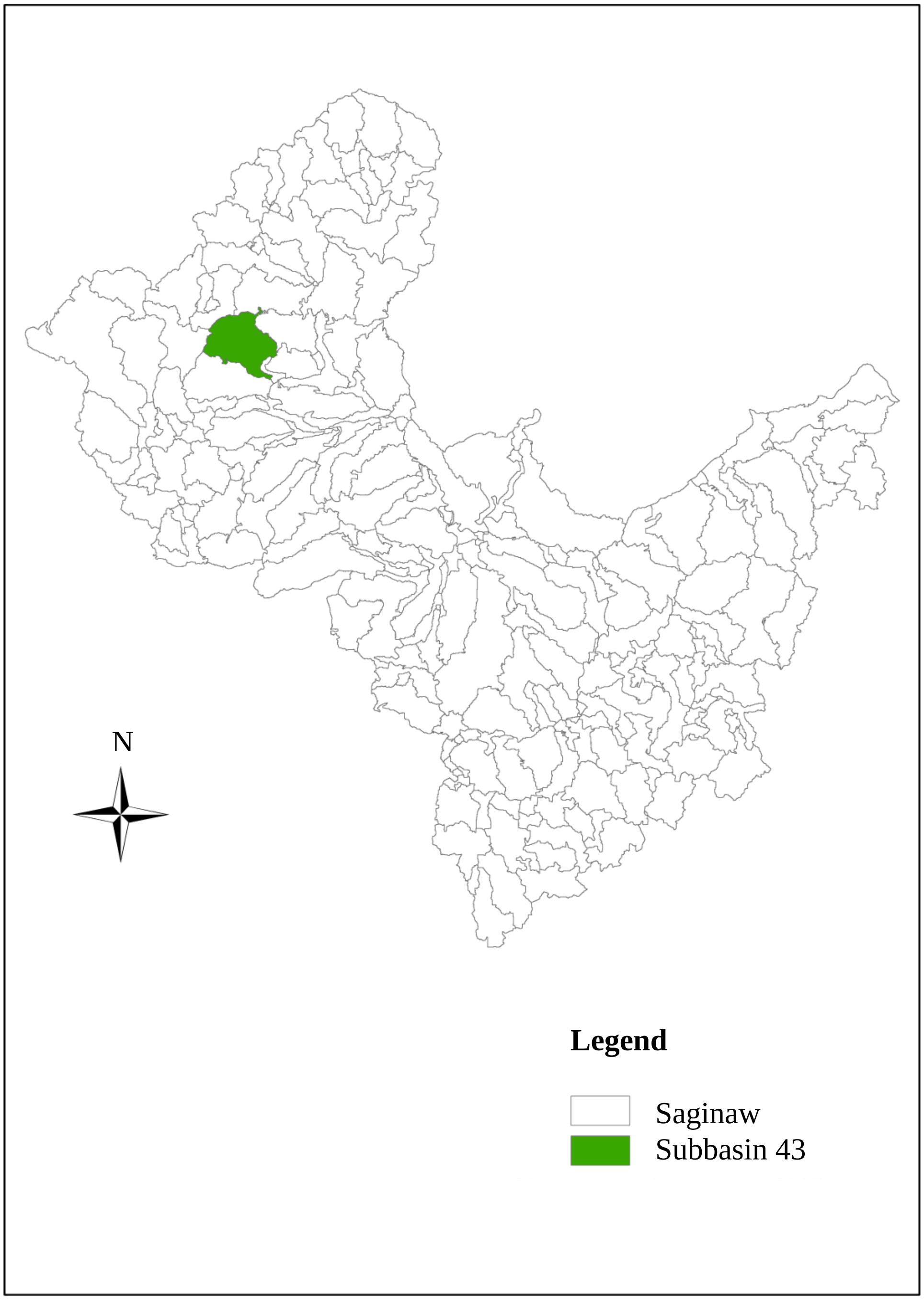

Figure B-1. Subbasins boundaries within the Saginaw River Watershed.

Table B-2. Pairwise comparison matrix developed for subbasin 43 based on sediment reduction at the watershed outlet.

BMPs	SC	RM	CT	NG	NT
SC	1.00	1.13	1.05	1.05	1.09
RM	0.88	1.00	0.93	0.93	0.96
CT	0.95	1.08	1.00	1.00	1.04
NG	0.95	1.08	1.00	1.00	1.03
NT	0.92	1.04	0.96	0.97	1.00

Table B-3. Pairwise comparison matrix developed for subbasin 43 based on TN reduction at the watershed outlet.

BMs	SC	RM	CT	NG	NT
SC	1.00	1.43	1.61	0.72	2.31
RM	0.70	1.00	1.13	0.50	1.61
CT	0.62	0.89	1.00	0.45	1.43
NG	1.39	2.00	2.25	1.00	3.22
NT	0.43	0.62	0.70	0.31	1.00

Table B-4. Pairwise comparison matrix developed for subbasin 43 based on TP reduction at the watershed outlet.

BMs	SC	RM	CT	NG	NT
SC	1.00	1.26	1.63	0.66	2.13
RM	0.79	1.00	1.29	0.52	1.69
CT	0.61	0.77	1.00	0.41	1.30
NG	1.51	1.91	2.47	1.00	3.22
NT	0.47	0.59	0.77	0.31	1.00

Table B-5. Weight vector calculation of BMPs for sediment, TN, and TP reduction for subbasin 43 at the watershed level.

BMPs	Sediment-Weight	TN-Weight	TP-Weight
SC	0.2117	0.2405	0.2271
RM	0.1875	0.1681	0.1801
CT	0.2028	0.1493	0.1394
NG	0.2020	0.3377	0.3461
NT	0.1961	0.1045	0.1073

Table B-6. Decision matrix of BMPs for all criteria developed for watershed level analysis.

BMPs	Total BMP cost	Sediment reduction	TN reduction	TP reduction	BMP Application Area
SC	0.4440	0.2117	0.2405	0.2271	0.0770
RM	0.2513	0.1875	0.1681	0.1801	0.2984
CT	0.1511	0.2028	0.1493	0.1394	0.2984
NG	0.0424	0.2020	0.3377	0.3461	0.0278
NT	0.1112	0.1961	0.1045	0.1073	0.2984

Table B-7. Final weight vector of individual BMPs for subbasin 43.

BMPs	Weight (watershed outlet)
SC	0.2467
RM	0.2403
CT	0.2024
NG	0.1206
NT	0.1800

Table B-8. BMP ranking at subbasin level based on environmental, economic, and social factors.

Subbasin	SC	RM	CT	NG	NT
43	1	2	3	4	5
46	1	2	3	4	5
59	1	2	3	4	5
62	1	2	4	3	5
83	1	2	4	3	5
86	1	2	4	3	5
88	1	2	4	3	5
89	1	2	4	3	5
90	1	2	3	4	5
91	1	2	3	5	4
94	1	2	3	4	5
95	1	2	3	4	5
96	1	2	3	5	4
99	1	2	3	5	4
103	1	2	3	5	4
106	1	2	4	3	5
109	1	2	3	5	4
115	1	2	3	4	5
116	1	2	3	4	5
127	1	2	3	4	5
129	1	2	3	4	5
135	1	2	3	4	5
136	1	2	3	4	5
140	1	2	3	4	5
142	1	2	3	5	4
147	1	2	3	4	5
148	1	2	4	3	5
152	1	2	3	4	5
159	1	2	3	4	5
181	1	2	3	4	5
184	1	2	3	4	5
187	1	2	3	4	5
188	1	2	3	4	5
205	1	2	3	4	5
214	1	2	3	4	5
215	1	2	3	4	5
219	1	2	3	5	4

Table B-9. BMP ranking at watershed level based on environmental, economic, and social factors.

Subbasin	SC	RM	CT	NT	NG
43	1	2	3	4	5
46	1	2	3	4	5
59	1	2	3	4	5
62	1	2	3	4	5
83	1	2	3	4	5
86	1	2	3	4	5
88	1	2	3	4	5
89	1	2	3	4	5
90	1	2	3	4	5
91	1	2	3	4	5
94	1	2	3	4	5
95	1	2	3	4	5
96	1	2	3	4	5
99	1	2	3	4	5
103	1	2	3	4	5
106	1	2	3	4	5
109	1	2	3	4	5
115	1	2	3	4	5
116	4	1	3	2	5
127	4	1	3	2	5
129	4	1	3	2	5
135	4	1	3	2	5
136	4	1	3	2	5
140	4	1	3	2	5
142	4	1	3	2	5
147	4	1	3	2	5
148	3	1	4	2	5
152	3	1	4	2	5
159	3	1	4	2	5
181	3	1	4	2	5
184	3	1	4	2	5
187	2	1	4	3	5
188	2	1	4	3	5
205	1	2	4	3	5
214	1	2	4	3	5
215	1	2	4	3	5
219	1	2	4	3	5

Table B-10. BMP ranking at subbasin level based on environmental and economic factors.

Subbasin	SC	RM	NG	CT	NT
43	1	2	3	4	5
46	1	2	3	4	5
59	1	2	3	4	5
62	1	3	2	4	5
83	1	3	2	4	5
86	1	3	2	4	5
88	1	3	2	4	5
89	1	3	2	4	5
90	1	2	3	4	5
91	1	2	3	4	5
94	1	3	2	4	5
95	1	3	2	4	5
96	1	2	3	4	5
99	1	2	3	4	5
103	1	2	3	4	5
106	1	3	2	4	5
109	1	2	3	4	5
115	1	3	2	4	5
116	1	3	2	4	5
127	1	3	2	4	5
129	1	3	2	4	5
135	1	2	3	4	5
136	1	2	3	4	5
140	1	2	3	4	5
142	1	3	2	4	5
147	1	2	3	4	5
148	1	3	2	4	5
152	1	3	2	4	5
159	1	2	3	4	5
181	1	2	3	4	5
184	1	2	3	4	5
187	1	2	3	4	5
188	1	2	3	4	5
205	1	2	3	4	5
214	1	2	3	4	5
215	1	2	3	4	5
219	1	2	3	4	5

Table B-11. BMP ranking at watershed level based on environmental and economic factors.

Subbasin	SC	RM	NG	CT	NT
43	1	2	3	4	5
46	1	2	4	3	5
59	1	2	5	3	4
62	1	2	5	3	4
83	1	2	5	3	4
86	1	2	5	3	4
88	1	2	4	3	5
89	1	2	3	4	5
90	1	2	5	3	4
91	1	2	5	3	4
94	1	2	3	4	5
95	1	2	3	4	5
96	1	2	3	4	5
99	1	2	5	3	4
103	1	2	3	4	5
106	1	2	5	3	4
109	1	2	3	4	5
115	1	2	3	4	5
116	2	1	5	4	3
127	2	1	5	4	3
129	2	1	5	4	3
135	2	1	5	4	3
136	2	1	5	4	3
140	2	1	5	4	3
142	1	3	2	4	5
147	2	1	5	4	3
148	2	1	5	4	3
152	1	2	5	4	3
159	2	1	5	4	3
181	1	2	5	4	3
184	1	2	5	4	3
187	1	2	3	5	4
188	1	2	4	5	3
205	1	2	4	5	3
214	1	2	4	5	3
215	1	2	4	5	3
219	1	2	4	5	3

Table B-12. BMP ranking at subbasin level based on environmental factors.

Subbasin	NG	SC	RM	NT	CT
43	1	2	3	4	5
46	1	2	3	4	5
59	1	2	3	5	4
62	1	2	3	5	4
83	1	2	3	5	4
86	1	2	3	4	5
88	1	2	3	4	5
89	1	2	3	4	5
90	1	2	3	4	5
91	1	2	3	5	4
94	1	2	3	4	5
95	1	2	3	4	5
96	1	2	3	4	5
99	1	2	3	5	4
103	1	2	3	5	4
106	1	2	3	4	5
109	1	2	3	5	4
115	1	2	3	5	4
116	1	2	3	4	5
127	1	2	3	5	4
129	1	2	3	5	4
135	1	2	3	5	4
136	1	2	3	4	5
140	1	2	3	5	4
142	1	2	3	5	4
147	1	2	3	5	4
148	1	2	3	4	5
152	1	2	3	5	4
159	1	2	3	4	5
181	1	2	3	5	4
184	1	2	3	4	5
187	1	2	3	5	4
188	1	2	3	5	4
205	1	2	3	5	4
214	1	2	3	4	5
215	1	2	3	4	5
219	1	2	3	4	5

Table B-13. BMP ranking at watershed level based on environmental factors.

Subbasin	NG	SC	RM	CT	NT
43	1	2	3	4	5
46	2	1	3	4	5
59	3	1	2	4	5
62	5	1	2	3	4
83	5	1	2	3	4
86	2	1	3	5	4
88	2	1	3	4	5
89	2	1	3	4	5
90	5	1	2	3	4
91	5	1	2	3	4
94	2	1	3	4	5
95	2	1	3	4	5
96	2	1	3	4	5
99	5	1	2	3	4
103	2	1	3	4	5
106	4	1	2	3	5
109	2	1	3	4	5
115	2	1	3	4	5
116	3	5	1	4	2
127	4	5	1	3	2
129	4	5	1	3	2
135	4	5	1	3	2
136	4	5	1	3	2
140	3	5	1	4	2
142	1	2	3	4	5
147	3	5	1	4	2
148	3	5	1	4	2
152	3	5	1	4	2
159	4	5	1	3	2
181	3	4	1	5	2
184	5	3	1	4	2
187	1	4	3	5	2
188	1	2	4	5	3
205	2	1	4	5	3
214	2	1	4	5	3
215	3	1	4	5	2
219	2	1	4	5	3

REFERENCES

REFERENCES

Akerblom, S., Meili, M., Bringmark, L., Johansson, K., Kleja, D.B., Bergkvist, B., 2008. Partitioning of Hg between solid and dissolved organic matter in humus layer of boreal forests. Water Air and Soil Pollution 189, 239-252.

Alabaster, J.S., 1972. Suspended solids and fisheries. Proceeding of the Royal Society, London, B 180, 395-406.

Alcamo, J., Vorosmarty, C., Naiman, R. J., Lettenmaier, D., Pahl-Wostl, C., 2008. A grand challenge for freshwater research: understanding the global water system. Environmental Research Letters 3, 1–6.

Agresti, A., 1988. A model for agreement between ratings on an ordinal scale. International Journal of Biometeorology 44, 539-548.

Arabi, M., Frankenberger, J.R., Engel, B.A., Arnold, J.G., 2007. Representation of agricultural conservation practices with SWAT. Hydrologic Processes 22, 3042-3055.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. . Large area hydrologic model development and assessment part 1: Model development. Journal of the American Water Resources Association 34, 73–89.

ASWP, 2012. Pollution assessment and prevention in Alabama. Available at: http://www.aces.edu/waterquality/themes/pollution.htm. Accessed on September 25, 2012.

Auld, H., MacIver, D., Klaassen, J., 2004. Heavy rainfall and waterborne disease outbreaks: The Walkerton example. Journal of Toxicology and Environmental Health Part A 67, 1879–1887.

Babu, V., Unnikrishnan, P., Anu, G., Nair, S. M., 2011. Distribution of Organophosphorus Pesticides in the Bed Sediments of a Backwater System Located in an Agricultural Watershed: Influence of Seasonal Intrusion of Seawater. Archives of Environmental Contamination and Toxicology 60, 597–609.

Balascio, C. C., Palmeri, D. J., Gao, H., 1998. Use of a genetic algorithm and multi-programming for calibration of a hydrologic model. Transaction of the ASAE 41, 615-619.

Benham, B.L., Baffaut, C., Zeckoski, R.W., Mankin, K.R.,Pachepsky, Y.A., Sadeghi, A.M., Brannan, K.M., Soupir, M.L.,Habersack, M.J., 2006. Modeling bacteria fate and transport in watersheds to support TMDLs. Transection of ASABE 49 (4), 987-1002.

Benstead, J.P., Rosemond, A.D., Cross, W.F., Wallace, J.B., Eggert, S.L., Suberkropp, K., Gulis, V., Greenwood, J.L., Tant, C, J., 2009. Nutrient enrichment alters storage and fluxes of detritus in a headwater stream ecosystem. Ecology 90, 2556–2566.

Bhaduri , B., Harbor, J., Bengel, B., Grove, M., 2000. Assessing watershed scale, long term hydrologic impacts of landuse change using a GIS-NPS model. Environmental Management 26, 643-658.

Bhaduri, B., Grove, M., Lowry, C., Harbor, J., 1997. Assessment of long term hydrologic impact from landuse change in the Cuppy-McClure watershed, Indiana. Journal of the American Water Works Association, 89(11), 94-106.

Bicknell, B.R., Imhoff, J.C., Kittle, J.C., Jr, J.L., Donigian, A.S., Johanson, R.C., 1997. Hydrological Simulation Program- Fortran, User's manual for version 11: U.S. Environmental Protection Agency, National Exposure research Laboratory, Athens, G., EPA/600/R-97/080, 755 p. Biogeochemical model pnET_N_DNDC, Journal of Geophysical research 106: 34155-34165.

Bicknell, B.R., Imhoff, J.C., Kittle, J.C., Jobes, T.H., Donigian, A.S., 2000. Hydrological Simulation Program- Fortran, User's manual for release 12. Athens, Ga.: USEPA.

Bilotta, G.S., Brazier, R.E., 2008. Understanding the influence of suspended solids on water quality and aquatic biota. Water Research 42 (12), 2849-2861.

Bilotta, G.S., Burnside, N.G., Cheek, L., Dunbar, M.J., Grove, M.K., Harrison, C., Joyce, C., Peacock, C., Davy-Bowker, J., 2012. Developing environment-specific water quality guidelines for suspended particulate matter. Water Research 46(7), 2324-2332.

Ebionews, 2010. Cause of Dead Zone in Gulf: Tile Drainage Directly Related to Nitrate Loss (2010) Available from: http://www.ebionews.com/news-center/research-frontiers/ag-bio-a-bio-agriculture/26675-cause-of-dead-zone-in-gulf-tile-drainage-directly-related-to-nitrate-loss.html. Accessed on November 25, 2012.

Borah, D.K. 2002. Watershed scale nonpoint source pollution models: Mathematical bases. ASABE Paper No. 022091. ASABE Annual International Meeting / CIGR World Congress. St. Joseph, Mich.: ASABE.

Bosch, D., Theurer, F., Bingner, R., Felton, G., Chaubey, I., 2001. Evaluation of the AnnAGNPS water quality model. Agricultural Non-point Source Water Quality Models: Their use and Application, Southern Cooperative Series Bulletin # 398, 45-62.

Boscha, N.S., Allanb, J.D., Dolanc, D.M., Hand, H., Richardse, R.P., 2011. Application of the Soil and Water Assessment Tool for six watersheds of Lake Erie: Model parameterization and calibration. Journal of Great lakes Research 37,263-271.

Brigham, M.E., Wentz, D.A., Aiken, G.R., Krabbenhoft, D.P., 2009. Mercury cycling in stream ecosystems : water column chemistry and transport. Environmental Science and technology 43, 2720-2725.

Brown, T.C., Froemke, P., 2012. Nationwide assessment of nonpoint source threats to water quality. Bioscience 62(2), 136-146.

Bundy, L.G., Andraski, T.W., powell, J.M., 2001. Management practice effects on phosphorus losses in runoff in corn production systems. Journal of Environmental Quality 30, 1822-1828.

Buyuksonmez, F., Yang, L., Beighley, R.E., 2012. Evaluation of Best Management Practice Products in Preventing Discharge of Metals: A Laboratory Evaluation. Journal of Environmental Quality 41, 800–806.

Calizaya, A., Meixner, O., Bengtsson, L., Berndtsson, R., 2010. Multi-criteria decision analysis for integrated water resources management in the Lake Poopo Basin, Bolivia. Water Resource Management 24, 2267-2289.

Capel, P.D., Larson, S.J., Winterstein, T.A., 2001. The behavior of thirty-nine pesticides in surface waters as a function of scale. Hydrological Process 15, 1251–1269.

Carey, C.M., Lee, H., Trevors, J.T., 2004. Biology, persistence and detection of 432 *Cryptosporidium parvum* and *Cryptosporidium hominis* oocyst. Water Resource 38**,** 818-862.

Carpenter, S.R., 2008. Phosphorus control is critical to mitigating eutrophication. Proceeding of National Academy of Science. USA 105, 11039–11040.

Carpenter, S.R., Caraco, N.E., Correll, D.L., Howarth, W., Sharpley, A.N., Smith, V.H., 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. Ecological Application 8(3), 559-568.

Carter, A.D., 2000. Herbicide movement in soils: principles, pathways and processes. Weed Research 40, 113-122.

CCC. 1998. State of Texas coastal nonpoint source pollution control program. Available at:http://www.glo.texas.gov/what-we-do/caring-for-the-coast/_documents/environmental-protection/anti-pollution/Volume1_1998_TexasCoastalNPSPollutionProgram.pdf. Assesses on July 7, 2011.

Chang, M. 2006. Forest hydrology: An introduction to water and forests. 2nd edition. Boca Raton, Florida. Taylor & Franscis Group.

Chiwa, M., Onikura, N., Ide, J. K, A., 2012. Impact of N-Saturated Upland Forests on Downstream N Pollution in the Tatara River Basin, Japan. Ecosystems 15, 230–241.

Cohen, J., 1960. A coefficient of agreement for nominal scales. Educational and Psychological Measurment 20, 37-46.

Covino, T., McGlynn, B., McNamara, R., 2012. Land use/land cover and scale influences on in-stream nitrogen uptake kinetics. Journal of Geophysical Research 117, doi:10.1029/2011JG001874.

Cunningham, J. H., Benham, B. L., Brannan, K. M., Mostaghimi, S., Dillaha, T. A., Pease,J. W., 2003. An assessment of the quality of the agricultural best management practices implemented in the James River basin of Virginia. Conference paper, page,281-190.

Das, K., Gazi, N. H., 2010. Random excitations in modelling of algal blooms in estuarine systems. Ecological Modelling 222(14), 2495-2501.

Das, S.K., Grewal, A.S., Banerjee, M., 2011. A brief review: Heavy metal and their analysis. Internation Journal of Pharmaceutical Sciences Review and Research 11, 13–18.

Devlin, D.L., McVay, K.A., 2001. Suspended solids: a water quality concern for Kansas. Available at: http://www.ksre.ksu.edu/library/h20ql2/mf2501.pdf. Accessed on September 25, 2012.

Diebel, M.W; Maxted, J.T., Nowak, P.J., Zanden, M.J.V., 2008. Landscape planning for agricultural nonpoint source pollution reduction I: a geographical allocation framework. Environmental Management 42,789-802.

Ding, X. W., Shen, Z. Y., Hong, Q., Yang, Z. F., Wu, X., Liu, R. M., 2010. Development and test of the export coefficient model in the upper reach of the Yangtze River. Journal of Hydrology 383, 233–244.

Dodds, W.K., Bouska, W.W., Eitzmann, J.L., Pilger, T.J., Pitts, K.L., Riley, A.J., Schloesser, J.T., Thornbrugh, D.J., 2009. Eutrophication of U.S. freshwaters: Analysis of potential economic damages. Environmental Science Technology 43(1),12-19.

Driscoll, C.T., Whitall, D., Aber, J., Boyer, E., Castro, M., Cronan, C., Goodale, C.L., Groffman, P., Hopkinson, C., Lambert, K., Lawrence, G., Ollinger, S., 2003. Nitrogen pollution in the northeastern United States: Sources, effects, and management options. BioScience 53, 357–374.

Dubrovsky, N.M., Hamilton, P.A., 2010. The quality of our nation's waters nutrients in the nation's streams and groundwater: National findings and implications. US Geological Survey. Fact sheet 2010-3078.

Dudgeon, D. 2010. Prospects for sustaining freshwater biodiversity in the 21st century: linking ecosystem structure and function. Current Opinion in Environmental Sustainability 2(5-6), 422-430.

Dudgeon, D., Arthington, A. H., Gessner, M. O., Kawabata, Z., Knowler, D., Leveque, C., Naiman, R. J., Prieur-Richard, A-H., Soto, D., Stiassny, M. L. J., Sullivan, C .A., 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biological Review 81, 163-182.

Eatherall, A.,Warwick, M. S.,Tolchard, S., 2000. Identifying sources of dissolved organic carbon on the river Swale, Yorkshire. Science of Total Environment 251-252, 173-190.

Edge, T. A., El-Shaarawi, A., Gannon, V., Jokinen, C., Kent, R., Khan, I. U. H., Koning, W., Lapen, D., Miller, J., Neumann, N., Phillips, R., Robertson, W., Schreier, H., Scott, A., Shtepani, I., Topp, E., Wilkes, G., Van Bochove, E., 2012. Investigation of an *Escherichia coli* Environmental Benchmark for Waterborne Pathogens in Agricultural Watersheds in Canada. Journal of Environmental Quality 41, 21–30.

Fleiss, J.L., Cohen, J., 1973. The equivalence of weighted kappa and the intraclass correlation coefficient as measurements of reliability. Educational and Psychological Measurement 33, 613-619.

Enderlein,U.E., Enderlein, R.E., Williams, W.P., 2012. Water quality requirements. World Health Organization. Available at: http://www.who.int/water_sanitation_health/resourcesquality/wpcchap2.pdf. Accessed on September 25, 2012.

Endreny, T.A., Wood, E.F., 2003. Watershed weighting of export coefficients to map critical phosphorus loading areas. Journal of the American Water Resources Association 36, 1053-1062.

Environment Canada. 2010. Finding a balance between agriculture and the environment. En4-135/2-2010E. National Agri-Environmental Standards Initiative (NAESI).

ERS-USDA. 1996. Production management. Available at: http://www.ers.usda.gov/publications/arei/ah712/AH7124-2.PDF. Assessed on July 8, 2011.

Espejo, L., Kretschmer, N., Oyarzun, J., Meza, F., Nunez, J., Maturana, H., Soto, G., Oyarzo, P., Garrido, M., Suckel, F., Amezaga, J., Oyarzun, R., 2012. Application of water quality indices and analysis of the surface water quality monitoring network in semiarid North-Central Chile.Environmental Monitoring and Assessment 184(9), 5571–5588.

Everard, M., Moggridge, H.L., 2012. Rediscovering the value of urban rivers. Urban Ecosystems 15, 293-314.

Falkenmark, F., Folke, C., 2003.Freshwater and welfare fragility: syndromes, vulnerabilities and challenges—introduction. Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences 358, 1917–1920.

Fayer, R., 2004. Cryptosporidium: a water-borne zoonotic parasite. Veterinary Parasitology 126, 37-56.

Finn, M.P., Scheidt, D. J., Jaromack, G.M., 2002. User's guide for the Agricultural Non-Point Source (AGNPS) pollution model data generator. United States Geological Survey. Report # 03-130.

Fitzhugh, T.W., Richter, B.D., 2004. Quenching urban thirst: growing cities and their impacts on freshwater ecosystems. Bioscience 54, 741–754.

Garfi, M., Ferrer-Marti, L., Bonoli, A., Tondelli, S., 2011. Multi-criteria analysis for improving strategic environmental assessment of water programmes, A case study in semiarid region of Brazil. Journal of Environmental Management 92, 665-675.

Garrido, A., Dinar, A., 2008. Managing water resources in a time of global change. Routledge, Oxon, p. 298.

Gartner, J.D., Renshaw, C.E., Dade, W.B., Magilligan, F.J., 2012. Time and depth scales of fine sediment delivery into gravel stream beds: constraints from fallout radionuclides on fine sediment residence time and delivery. Geomorphology 151-152, 39-49.

Gassman, P.W., Arnold, J.G., Srinivasan, R., Reyes, M., 2010. The worldwide use of the SWAT model: Technological drivers, networking impacts and simulation trends. Watershed Technology: Improving Water Quality and Environment. Universidad Earth, Costa Rica: American Society of Agricultural Engineering.

Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The Soil and Water Assessment Tool: Historical development, applications and future research directions. Transaction of the ASABE 50, 1211–1250.

Ghebremichael, L.T., Veith, T.L., Watzin, M.C., 2010. Determination of critical source areas for phosphorus loss: lake Champlain basin, Vermont. Transaction of ASABE 53, 1595-1604.

Gilliom, R.J., 2007. Pesticides in U.S. streams and ground water. Environmental Science & Technology 41(10), 3407-3413.

Giorgi, F., Bi, X., Pal, J., 2004. Mean, interannual variability and trends in a regional climate change experiment over Europe II: climate change scenarios(2071-2100). Climate Dynamics 23, 839-858.

Giri, S., Mukhtar, S., Wittie, R., 2010. Vegetative covers for sediment control and phosphorus control from dairy waste application fields. Transaction of the ASABE 53(3), 803- 811.

Giri, S., Nejadhashemi, A.P., Woznicki, S.A., 2012a. Evaluation of targeting methods for implementation of best management practices in the Saginaw River Watershed. Journal of Environmental Management 103, 24-40.

Giri, S., Nejadhashemi, A.P., Woznicki, S.A., Zhang, Z., 2012b. Analysis of best management practice effectiveness and spatiotemporal variability based on different targeting strategies. Hydrological Processes, 10. 1002/hyp.9577.

Gitau, M.W., Veith, T.L., Gburek, W.J., 2004. Farm-level optimization of BMP placement for cost-eff ective pollution reduction. Transaction of the ASABE 47, 1923–1931.

Glozier, N.E., Struger, J., Cessna, A.J., Gledhill, M., Rondeau, M., Ernst, W.R., Sekela, M.A., Cagampan, S.J., Sverko, E., Murphy, C., Murray, J.L., Donald, D.B., 2012. Occurrence of glyphosate and acidic herbicides in select urban rivers and streams in Canada, 2007. Environmental Science and Pollution Ressearch19, 821–834.

Gormley, K.L., Teather, K.L., Guignion, D.L., 2005. Changes in salmonid communities associated with pesticides runoff events. Ecotoxicology 14(7), 671-678.

Govers, G., Gimenez, R., Oost, K. V., 2007. Rill erosion: Exploring the relationship between experiments, modeling and field observations. Earth Science Reviews 84, 87-102.

Grynkiewicz, M., Polkowska, Z., Gorecki, T., Namiesnik, J., 2003.Pesticides in precipitation from an urban region in Poland (Gdansk-Sopot-Gdynia Tricity) between 1998 and 2000. Water Air and Soil Pollution 149, 3-16.

Haan, C.T., Barfield, B.J., Hayes, J.C., 1994. Design hydrology and sedimentology for small catchments. 2nd ed. Sandiego, California:Elsevier.

Hangsleben, M., Suh, D., 2006. Sediment Pollution. TSM 424 Semester Project. Available at: http://www3.abe.iastate.edu/tsm424/TSM424TermProj2006/HangslebenSuhFinalPaper.pdf. Accessed on May 15, 2012.

Hanselman, T.A., Graetz, D.A., Wilkie, A.C., 2003. Manure-borne estrogens as potential environmental contaminants: a review. Environmental Science and Technology 37, 5471–5468.

Hansen, N.C., Daniel, T.C., Sharpley, A.N., Lemunyon, J.L., 2002. The fate and transport of phosphorus in agricultural systems. Journal of Soil and Water Conservation 57, 409–416.

Hassan, R., Scholes, R., Ash, N., 2005. Ecosystems and human well-being; current state and trends. 1st edition. Washington, D.C. : Coghill Composition, Inc.

Hathaway, J.M., Hunt, W.F., 2012. Indicator Bacteria Performance of Storm Water Control Measures in Wilmington, North Carolina. Journal of Irrigation and Drainage Engineering 138 (2), 185-17.

Haynes, H., Vignaga, E., Holmes, W.M., 2009. Using magnetic resonance imaging for experimental analysis of fine sediment infiltration into gravel beds. Sedimentology 56, 1961-1975.

Helfrich, L.A., Weigmann, D.L., Hipkins, P., Stinson, E.R., 2009. Pesticides and aquatic animals: a guide to reducing impacts on aquatic systems. Available at: http://pubs.ext.vt.edu/420/420-013/420-013_pdf.pdf. Accessed November 5, 2012.

Hoffman, R.S., Capel, P.D., Larson, S.J., 2000. Comparison of pesticides in eight U.S. urban streams. Environmental Toxicology & Chemistry 19, 2249–2258.

Hogan, J. N., Daniels, M. E., Watson, F. G., Conrad, P. A., Oates, S. C., Miller, M. A., Hardin, D., Byrne, B. A., Dominik, C., Melli, A., Jessup, D. A., Miller, W. A., 2012. Longitudinal poisson regression to evaluate the epidemiology of cryptosporidium, giardia, and fecal indicator bacteria in coastal California wetlands. Application of Environmental Microbiology 78 (10), 3606.

Hutchison, M.L., Walters, L.D., Avery, S.M., Synge, B.A., Moore, A., 2004.Levels of zoonotic agents in British livestock manures. Letters in Applied Microbiology 39,207–214.

Ibekwe, A.M., Murinda, S.E., Graves, A.K., 2011. Microbiological evaluation of water quality from urban watersheds for domestic water supply improvement. International Journal of Environmental Research and Public Health 8, 4460-4476.

Ice, G., 2004. History of innovative best management practice development and its role. Addressing of Environmental Engineering 130, 684-689.

IWR, 2012. High Impact Targeting, A tool for optimizing sedimentation reduction efforts in the Great Lakes Basins. Available at: http://www.iwr.msu.edu/hit2/. Accessed on November 14, 2012.

Jeffrey, J.S., Kirk, J.H., Atwill, E.R., Cullor, J.S., 1998. Prevalence of selected microbial pathogens in processed poultry waste used as dairy cattle feed. Poultry Science 77, 808–819.

Jenkins, M.B., Endale, D.M., Schomberg, H. H., Sharpe, R.R., 2006. Fecal bacteria and sex hormones in soil and runoff from cropped watersheds amended with poultry litter. Science of the Total Environment 358, 164– 177.

Jenkins,, M. B., Endale, D.M., Schomberg, H. H., Hartel, P. G., Cabrera, M. L., 2009. 17b-Estradiol and testosterone in drainage and runoff from poultry litter applications to tilled and no-till crop land under irrigation. Journal of Environmental Management 90, 2659–2664.

Jenks, G. F., 1967. The Data Model Concept in Statistical Mapping, International Yearbook of Cartography 7: 186–190.

Jha, M.K., Schilling, K.E., Gassman, P.W.,Wolter, C.F., 2010. Targeting land use change for nitrate nitrogen load reductions in an agricultural watershed. Journal of Soil Water Conservation 65, 342-352.

Johnson, A.C., Williams, R.J., Matthiessen, P., 2006. The potential steroid hormone contribution of farm animals to freshwaters, the United Kingdom as a case study. Science of Total Environment 362,166–78.

Johri, N., Jacquillet, G., Unwin, R., 2010. Heavy metal poisoning: The effects of cadmium on the kidney. BioMetals 23,783–792.

Jokinen, C. C., Edge, T. A., Koning, W., Laing, C. R., Lapen, D. R., Miller, J., Mutschall, S., Scott, A., Taboada, E. N., Thomas, J. E., Topp, E., Wilkes, G., Gannon, V. P. J., 2012. Spatial and Temporal Drivers of Zoonotic Pathogen Contamination of an Agricultural Watershed. Journal of Environmental Quality 41,242–252.

Jones, K.B., Neale, A.C., Nash, M.S., van Remortel, R.D., Wickham, J.D., Riitters, K.H., O'Neill, R.V., 2001. Predicting nutrient and sediment loadings to streams from landscape metrics: A multiple watershed study from the United States Mid-Atlantic region. Landscape Ecology 16, 301–312.

Jordan, P., Haygarth, P.M., Shortle, G., Harris, R.C., 2012. Catchment science and policy for agriculture and water quality. Environmental Science &Policy 24, 1-3.

Juniori R.S., Silva, J.D., 2011. Sensibility analysis of the pearl model for pesticide leaching in the state of Mato Grosso Do Sul, Brazil. Engineering Agricultural Jaboticabal 31(5), 965-973.

Kaplowitza, M. D., Lupi, F., 2012. Stakeholder preferences for best management practices for non-point source pollution and stormwater control. Landscape and Urban Planning 104, 364– 372.

Katrijn, M.A., Seuntjens, P., Vanrolleghema, P.A., 2007. Monitoring and modeling pesticide fate in surface waters at the catchment scale. Ecological Modeling 2 0 9, 53–64.

Kazi, T.G., Arain, M.B., Jamali, M.K., Jalbani, N., Afridi, H.I., Sarfraz, R.A., Baig, J.A., Shah, A.Q., 2009. Assessment of water quality of polluted lake using multivariate statistical techniques: A case study. Ecotoxicology and Environmental Safety 72(2), 301-309.

Kellog, R.L., Lander, C.H., Moffitt, D.C., Gollhon, N., 2000. Manure nutrients relative to the capacity of cropland and pastureland to assimilate nutrients: spatial and temporal trends for the United States. USDA Natural Resources Conservation Service, Editor, Fort Worth, TX. Available at: http://www.ncrcs.usda.gov/technical/nri/pubs/manntr.pdf. Accessed on November 5, 2012.

Kjaer, J., Olsen, P., Bach, K., Barlebo, H.C., Ingerslev, F., Hansen, M., 2007. Leaching of estrogenic hormones from manure-treated structured soils. Environmental Science and Technology 41, 3911–3927.

Kolodziej, E.P., Sedlak, D.L., 2007. Rangeland grazing as a source of steroid hormones to surface waters. Environmental Science & Technology 41, 3514–20.

Kolpin, D.W., Thurman, E.M., Lee, E.A., Meyer, M.T., Furlong, E.T., Glassmeyer, S.T., 2006. Urban contributions of glyphosate and its degradate AMPA to streams in the United States. Science of Total Environment 354, 191–197.

Kotti, M.E., Vlessidis, A.G., Thanasoulias, N.C., Evmiridis, N.P., 2005.Assessment of river water quality in Northwestern Greece. Water Resources Management 19, 77–94.

Kovacsa, A., Hontib, M., Zessnera, M., Ederc, A., Clementd, A., Bloschl, G., 2012. Identification of phosphorus emission hotspots in agricultural catchments. Science of The Total Environment 433, 74-88.

Krause, P., Boyle, D. P., Base, F., 2005. Comparison of different efficiency criteria for hydrological model assessment. Advances in Geoscience 5, 89–97.

Kreuger, J., 1996.Pesticides in stream water within an agricultural catchment in southern Sweden, 1990. The Science of the Total Environment 216, 227-251.

Kreuger, J., Brink, N., 1998. Losses of pesticides from agriculture. In: Pesticides: Food and Environmental Implications. International Atomic Energy Agency, Vienna, pp. 101–112.

Laia, Y.C., Yangb, C.P., Hsiehc, C.Y., Wua, C.Y., Kao, C.M., 2011. Evaluation of non-point source pollution and river water quality using a multimedia two-model system. Journal of Hydrology 409(3-4), 583-595.

Lebo, M.E., Paerl, H. W., Peierls, B., 2012. Evaluation of Progress in Achieving TMDL Mandated Nitrogen Reductions in the Neuse River Basin, North Carolina. Environmental Management 49, 253–266.

Lee, J.G., Selvakumar, A., Alvi, K., Riverson, J., Zhen, J.X., Shoemaker, L., Lai, F., 2012. A watershed-scale design optimization model for stormwater best management practices. . Environmental Modelling & Software 37, 6-18.

Lee, M.D., Newell, D.G., 2006. *Campylobacter* in poultry: Filling an ecological niche. Avian Diseases 50,1–9.

Lerch, R.N., Sadler, E.J., Sudduth, K.A., Baffaut, C., Kitchen, N.R., 2011. Herbicide transport in Goodwater Creek experimental watershed: I. longterm research on atrazine. Journal of the American Water Resources Association 47(2), 209-223.

Leung, A.O.W., Duzgoren-Aydin, N.S., Cheung, K.C., Wong, M.H., 2008. Heavy metals concentrations of surface dust from e-waste recycling and its human health implications in Southeast China. Environmental Science and Technology 42, 2674–2680.

Linkov, I., Steevens, J., 2013. A detailed analysis of the theoretical foundation of different MCDA. Chapter 35 Appendix A Multi-criteria decision analysis. Available at: http://www.epa.gov/cyano_habs_symposium/monograph/Ch35_AppA.pdf. Accessed on May 1, 2013.

Lintelmann, J., Katayama, A., Kurihara, N., Shore, L., Wenzel, A., 2003. Endocrine disruptors in the environment. Pure and Applied Chemistry 75, 631–681.

Lorenz, E., 2009. Potential health effects of pesticides. Agricultural Communication and Marketing 18,1-8.

Love, B. J., Einheuser, M.D., Nejadhashemi, A. P., 2011. Effects on aquatic and human health due to large scale bioenergy crop expansion, Science of The Total Environment, 409(17), 3215-3229.

LRRB, 2010. Improved automatic sampling for suspended solids. Available at: http://www.dot.state.mn.us/research/TS/2010/201038TS.pdf. Accessed on September 25, 2012.

Maas, R. P., Smolen, M. D., Dressing, S. A., 1985. Selecting critical areasfor nonpoint source pollution control. Journal of Soil and Water Conservation 40(1), 68–71.

Maciej, D., 2000. Activities in nonpoint pollution control in rural areas of Poland. Ecological Engineering 14, 429–434.

Malcolm, R. L., 1985, Geochemistry of stream fulvic and humic substances, in Aiken, G. R., McKnight, D. M., Wershaw, R. L., MacCarthy, P., Humic Substances in Soil, Sediment andWater,Geochemistry, Isolation, and Characterization, Wiley-Interscience, New York, USA, pp. 181–209.

Mallin, M.A., 2000. Impacts of industrial animal production on rivers and estuaries. American Scientist 88, 26–37.

Mallin, M.A., Cahoon, L.B., 2003. Industrialized animal production — a major source of nutrient and microbial pollution to aquatic ecosystems. Population and Environment 24, 369–379.

Malone, S.J., 2009. Agricultural Nonpoint Source Pollution Management: Water Quality Impacts of Balm Road Treatment Marsh, Hillsborough County, Florida. Master of Science Thesis. University of South Florida, Tampa, Florida.

MARC, 2012. Mid-America Regional Council. What is sediment pollution. Available at : http://cfpub.epa.gov/npstbx/files/KSMO_Sediment.pdf. Accessed on May 23, 2012.

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

Marinoni, O., 2009. Macro ext_ahp.dll: Available at: http://arcscripts.esri.com/details.aspdbid=13764. Acessed on January 15, 2013.

Matthiessen, P., Arnold, D., Johnson, A.C., Pepper, T.J., Pottinger, T.G., Pulman, K.G.T., 2006. Contamination of headwater streams in the United Kingdom by oestrogenic hormones from livestock farms. Science of the Total Environment 367, 616–630.

Meybeck, M., 2004. The global change of continental aquatic systems: dominant impacts of human activities. Water Science and Technology 49, 73-83.

Michel, P., Wilson, J.B., Martin, S.W., Clarke, R.C., McEwen, S.A., Gyles C.L., 1999. Temporal and geographical distributions of reported cases of *Escherichia coli* O157:H7 infection in Ontario. Epidemiology & Infection 122,193–200.

Millennium Assessment. 2005. Ecosystems and Human Well- Being: Synthesis. Island Press: Washington, DC.

Milner, M.J., Kochian, L.V., 2008. Investigating heavy-metal hyperaccumulation using Th laspi caerulescens as a model system. Annals of Botany102, 3–13.

Moore, P.A., Daniel, T.C., Sharpley, A.N., Wood, C.W.,1995. Poultry manure management: environmentally sound options. Journal of Soil Water Conservation 50, 321–337.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Binger, R. L., Harmel, R. D., Veith, T. L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transaction of the ASABE 50, 885-900.

Morrison, J., Gleick, P., 2004. Fresh water resources: Managing the risks facing the private sector. Pacific Institute, Okland, California.

Mulholland, P. J., Webster, J. R., 2010. Nutrient dynamics in streams and the role of J-NABS, Journal of the North American Benthological Society 29(1), 100-117.

Muthukrishnan, S., 2002. Development and testing of an integrated water pollution assessment tool for analyzing impacts of urban sprawl. Ph.D. Purdue University.

Muttiah, R. S., Wurbs, R. A., 2002. Scale-dependent soil and climate variability effects on watershed water balance of the SWAT model. Journal of Hydrology 256, 264-285.

Napier-Munn, T.J., Meyer, D.H., 1999. A modified paired t-test for the analysis of plant trials with data auto-correlated in time. Minerals Engineering 12, 1093-1100.

Nash, J. E., Sutcliffe, J. V., 1970. River flow forecasting through conceptual models: Part 1. A discussion of principles. Journal of Hydrology 10, 282-290.

Neitsch, S. L., Arnold, J. G., J. R. Kiniry., Williams, J. R., 2005. Soil and Water Assessment Tool : Theoretical documentation. Temple, Tex.: USDA-ARS Grassland, Soil and Water Research Laboratory.

Nejadhashemi, A. P., Mankin, K. R., 2007. Recommended practices for modeling BMPs using SWAT model. Topeka, Kans.: Kansas Water Office.

Nejadhashemi, A.P., Woznicki, S.A., Mankin, K.R., 2011. Comparision of four models(STEPL, PLOAD, L-LHIA, ans SWAT) in simulating sediment, nitrogen, and phosphorus loads and pollutant source areas. Transections of the ASABE 54, 875-890.

Newcombe, C.P., MacDonald, D.D., 1991. Effects of suspended sediments on aquatic ecosystems. North American Journal of Fisheries Management 11, 72-82.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., Williams, J. R., 2005. Soil and Water Assessment Tool: Theoretical documentation. Temple, Tex.: USDA-ARS Grassland, Soil and Water Research Laboratory.

Nouri, J; Karbassi, A.R., Mirkia, S., 2008. Environmental management of coastal regions in the Caspian sea. International Journal of Environmental Science and Technology 5, 43-52.

NRCS, 2008. Conservation practice standard, stripcropping. Available at: ftp://ftp-fc.sc.egov.usda.gov/NHQ/practice-standards/standards/585.pdf. Assessed on May 20, 2013.

NRCS, 2011. Field office technical guide, Statewide conservation practice typical installation cost information.

NWP 2011. Nutrient and pesticide management extension outreach for producers. Available at: http://www.usawaterquality.org/themes/npm/extension/producers.html. Assessed on July 7, 2011.

NSW-DPI, 2012. Department of Primary Industries, New South Wales, Australia. Soil erosion solutions. Available at: http://www.dpi.nsw.gov.au/__data/assets/pdf_file/0003/255153/fact-sheet-1-types-of-erosion.pdf. Accessed on May 25, 2012.

Olson, M.E., Thorlakson, C.L., Deselliers, L., Morck, D.W., McAllister.T.A.,1997. *Giardia* and *Cryptosporidium* in Canadian farm animals. Veterinary Parasitology 68,375–381.

Ondrusek, M., E. Stengel, C. S. kinkade, R. L. Vogel, P. Keegstra, C. Hunter, C. Kim. 2012. The development of a new optical total suspended matter algorithm for the Chesapeake Bay. Remote Sensing of Environment 119, 243-254.

Opporto, B., Estaban, J.I., Aduriz, G., Juste, R.A., Hurtado, A., 2007. Prevalence and strain diversity of thermophilic campylobacters in cattle, sheep and swine farms. Journal of Applied Microbiology 99,1–8.

Osmond, D., Meals, D., Hoag, D., Arabi, M., Luloff, A., Jennings, G., McFarland, M., Spooner, J., Sharpley, A., Line, D., 2012. Improving conservation practices programming to protect water quality in agricultural watersheds: lessons learned from the national institute of food and agriculture –conservation effects assessment project. Journal of Soil and Water Conservation 67 (5), 122-127.

Ou, Y., Wang, X.Y., 2008. Identification of critical source areas for nonpoint source pollution in Miyun reservoir watershed near Beijing China. Water Science and Technology 58, 2235–2241.

Ouyang, W., Wang, X., Hao, F., Srinivasan, R., 2009. Temporal-spatial dynamics of vegetation variation on non-point source nutrient pollution. Ecological Modeling 220, 2702–2713.

Palmer, M.A., Bernhardt, E.S., Chornesky, E.A., Collins, S.L., Dobson, A.P., Duke, C.S., Gold, B.D., Jackson, R.B., Kingsland, S.E., Kranz, R.H., Mappin, M.J., Martinez, M.L., Micheli, F., Morse, J.L., Pace, M.L., Pascual, M., Palumbi, S.S., Reichman, O.J., Townsend, A.R., Turner, M.G., 2005. Ecological science and sustainability for the 21st century. Frontiers in Ecology and the Environment 3, 4–11.

Panagopoulos, Y., Makropoulos, C., Mimikou, M., 2011. Reducing surface water pollution through the assessment of the cost effectiveness of BMPs at different spatial scales. Journal of Environmental Management 92, 2823-2835.

Parajuli, P.B; Mankin, K.R., Barnes, P.L., 2008. Applicability of targeting vegetative filter strips to abate fecal bacteria and sediment yield using SWAT. Agricultural Water Management 95, 1189-1200.

Parajuli, P.B., Nelson, N.O., Frees, L.D., Mankin, K.R., 2009. Comparison of AnnAGNPS and SWAT model simulation results in USDA-CEAP agricultural watersheds in south-central Kansas. Hydrological Processes 23, 748-763.

Paul, S., 2003. Bacteria total maximum daily load(TMDL): development and evaluation of a new classification scheme for impaired waterbodies of Texas. Doctoral dissertation. Texas A & M University, College Station, Texas.

Paukert, C. P., Pitts, K.L., Whittier, J.B., Olden, J. D., 2010. Development and assessment of a landscape-scale ecological threat index for the Lower Colorado River Basin. Ecological Indicators, 11(2), 304-310.

Pejman, A.H; Nabi Bidhendi, G.R., Karbassi, A.R., Mehrdadi, N., Esmaeili Bidhendi, M.,2009. Evaluation of spatial and seasonal variations in surface water quality using multivariate statistical techniques. International Journal of Environmental Science and Technology 6(3), 467-476.

Persyn, R. A., Glanville, T. D., Richard, T. L., Laflen, J. M., Dixon, P. M., 2005. Environmental effects of applying composted organics to new highway embankments: Part III. Transection of the ASABE 48(5), 1765-1772.

Pimentel, D., Houser, J., Preiss, E., White, O., Fang, H., Mesnick, L., Barsky, T., Tariche, S., Schreck, J., Alpert, S., 1997. Water resources: agriculture, the environment, and society. American Institute of Biological Sciences 47, 97-106.

Polyakov, V., Fares, A., Kubo, D., Jacobi, J., Smith, C., 2007. Evaluation of a non-point source pollution model, AnnAGNPS, in a tropical watershed. Environmental Modeling and Software 22, 1617-1627.

Postel, S., 2000. Entering an era of water scarcity: The challenges ahead. Ecological Applications 10(4), 941-948.

Postel, S., Richter, B., 2003. Rivers for Life : Managing Water for People and Nature. Island Press, Washington D.C., U.S.A.

Qiu, Z., 2009. Assessing critical source areas in watersheds for conservation buffer planning and riparian restoration. Environmental Management 44, 968-980.

Rabalais, N. N., Diaz, R. J., Levin, L. A., Turner, R. E., Gilbert, D., Zhang, J., 2010. Dynamics and distribution of natural and human-caused hypoxia. Biogeosciences 7(2), 585–619.

Raisanen, J., Hansson, U., Ullerstig, A., Doscher, R., Graham, L.P., Jones, C., Meier, H.E.M., Samuelsson, P., Willen, U., 2004. European climate in the late twenty-first century: regional simulations with two driving global models and two forcing. Climate Dynamics 22 (1), 13-31.

RAMP. 1996. Water quality parameters. River Assessment Monitoring Project, Kentucky Water Watch. Available at: http://www.state.ky.us/nrepc/water/ramp/rmtss.htm. Accessed on June 6, 2012.

Rao, N.S., Easton, Z.M., Schneiderman, E.M., Zion, M.S., Lee, D.R., 2009. Modeling watershed-scale effectiveness of agricultural best management practices to reduce phosphorus loading. Journal of Environmental Engineering 90, 1385-1395.

Rasmussena, J.J., Baattrup-Pedersena,A., Wiberg-Larsena, P., McKnightb, U.S., Kronvanga B., 2011. Buffer strip width and agricultural pesticide contamination in Danish lowland streams: Implications for stream and riparian management. Ecological Engineering 37(12), 1990–1997.

Revenga, C., Campbell, I., Abell, R., Devilliers, P., Bryer, M., 2005. Prospects for monitoring freshwater ecosystems towards the 2010 targets. Philosophical Transactions of the Royal Society B 360, 397–413.

Riebschleager, K.J., 2008. Development and application of the spatially explicit load enrichment calculation tool (SELECT) to determine potential E. Coli loads in watersheds. Master Thesis. Texas A & M University, College Station, Texas.

Ritter, W.F., Shirmohammadi, Adel., 2001. Agricultural nonpoint source pollution: Watershed management and hydrology. Boca Raton, Florida: CRC Press.

Rouse, J.D., Bishop, C.A., Struger, J., 1999. Nitrogen pollution: an assessment of its threat to amphibian survival. Environmental Health Perspectives 107 (10), 799–803.

Saaty, T.L., 1980. The analytic hierarchy process, Mcgraw-Hill, New York.

Sala, O.E., Chapin, F.S., Armesto, J. J., Berlow, R., Bloomfield, J., Dirzo, J., Huber-Sanwald, R., Huenneke, E., Jackson, L.F., Kinzig, R.B., Leemans, A., Lodge, R., Mooney, D., Oesterheld, H.A., Poff, M., Sykes, N.L., Walker, M.T., Walker, B.H., M& Wall, D.H., 2000. Global biodiversity scenarios for the year 2100. Science 287, 1770–1774.

Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan,R., Hauck, L.M., 2001b. Validation of the SWAT Model on a Large River Basin With Point and Nonpoint Sources. Journal of the American Water Resources Association 37, 1169-1187.

Santhi, C., Srinivasan, R., Arnold, J.G., Williams, J.R., 2006. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. Environmental Modelling & Software 21, 1141-1157.

Scalley, H., Scatena, F. N., Moya, S., Lugo, A. E., 2012. Long-term dynamics of organic matter and elements exported as coarse particulates from two Caribbean montane watersheds. Journal of Tropical Ecology 28, 127-139.

Schilling, K.E., Wolter, C.F., 2009. Modeling nitrate-nitrogen load reduction strategies for the Des Moines river, Iowa using SWAT. Environmental Management 44, 671-682.

Sharpley, A.N., Daniel, T.C., Edwards, D.R., 1993. Phosphorus movement in the landscape. Journal of Production Agriculture 6, 492–500.

Sharpley, A.N., Daniel, T., Sim, T., Lemunyon, J., Stevens, R., Parry, R., 2003.Agricultural phosphorus and eutrophication , second edition. USDA-ARS. Publication no. ARS 149.

Shen, J., Cui, Z., Miao, Y., Mi, G., Zhang, H., Fan, M., Zhang, C., Jian, R., Zhang, W., Li, H., Chen, X., Li, X., Zhang, F., 2013. Transforming agriculture in China:From solely high yield to both high yield and high resource use efficiency. Global Food Security 2, 1-8.

Shi, Q., Deng, X., Wu, F., Zhan, J., Xu, L., 2012. Best management practices for agricultural non-point source pollution control using PLOAD in Wuliangsuhai watershed. Journal of Food, Agriculture & Environment 10 (2), 1 3 8 9 - 1393.

Shore, L.S., Correll, D.L., Chakraborty, P.K., 1995. Fertilization of fields with chicken manure as a source of estrogens in small streams. In: Steele K, editor. Animal Waste and the Land-Water Interface. Boca Raton, FL: Lewis Publishers. p. 155–62.

Shortle, J. S., Horan, R. D., Blandford, D., 2012. Reforming Agricultural Nonpoint Pollution Policy in an Increasingly Budget-Constrained Environment. Environmental Science and Technology 46, 1316-1325.

Sin, S.N., Chua, H., Lo,W., Ng, L.M., 2001. Assessment of heavy metal cations in sediments of Shing Mun River , HongKong. Environment International 26, 297-301.

Sommerlot, A.R., 2012. Developing new modeling techniques to evaluate the environmental and economic impacts of individual management practices at the field and watershed scale. Master Thesis. Michigan State University, East Lansing, Michigan.

Soupir, M. L., Mostaghimi, S., Yagow, E. R., 2006. Nutrient Transport from Livestock Manure Applied to Pastureland Using Phosphorus-Based Management Strategies. Journal of Environmental Quality 35, 1269–1278.

Srebotnjak, T., Carr, G., Sherbinin, A.d., Rickwood, C., 2012. A global water quality index and hot deck imputation of missing data. Ecological Indicators 17, 108-119.

Srinivasan, M.S., Gerard-Marchant, P., Veith, T.L., Gburek, W.J., Steenhuis, T.S., 2005. Watershed scale modeling of critical source areas of runoff generation and phosphorus transport. Journal of the American Water Resources Association 41, 361–377.

Staddon, C., 2010. Managing Europe's Water Resources: Twentyfirst Century Challenges. Ashgate Publishing Ltd, Farnham, p. 290.

Teixeiraa, M.R., Nunesb, L.M., 2011. The impact of natural organic matter seasonal variations in drinking water Quality. Desalination and Water Treatment 36,344–353.

Tetra Tech, 2006. Spreadsheet Tools for the Estimation of Pollutant Load (STEPL), User's guide, Version 4.0. Available on line at: http://it.tetratech-ffx.com/stepl/STEPLmain_files/STEPLGuide400.pdf. Accessed on November 14, 2012.

Thomas, K.M., Charron, D.F., Waltner-Toews, D., Schuster, C., Maarouf, A.R., Holt, J.D., 2006. A role of high impact weather events in waterborne disease outbreaks in Canada. 1975–2001. International Journal of Environmental Health Research 16,167–180.

TNRCC. 1999. Texas nonpoint-source pollution assessment report and management program. Publ. No. SFR-68/99. Austin, Tex.: Texas Natural Resource Conservation Commission.

Trenberth, K.E., Dai, A., Rasmussen, R.M., Parsons, D.B., 2003. The changing character of precipitation. Bulletin of the American Meteorological Society 84, 1205-1217.

Tripathi, M.P., R.K.Panda., N.S. Raghuwanshi. 2003. Identification and prioritisation of critical subwatersheds for soil conservation management using the SWAT model.Biosystems Engineering 85(3), 365-379.

Tsakovski, S., Kudlak, B., Simeonov, V., Wolska, L., Gracia, G., Namiesnik, J., 2012. Relationship between heavy metal distribution in sediment samples and their ecotoxicity by the use of the Hasse diagram technique. Analytica Chemica Acta 719, 16-23.

Tuppad, P., Srinivasan, R., 2008. Bosque River environmental infrastructure improvement plan: Phase II BMP modeling report. Publ. No. TR-313. College Station, Tex.: Texas A&M Univ., Texas AgriLife Research.

Tuppad, P., Mankin, K.R., Mcvay, K.A., 2010. Strategic targeting of cropland management using watershed modeling. Agricultural Engineering International: CIGR Journal 12, 3-4.

Tuppad, P., N. Kannan., R. Srinivasan., C.G. Rossi., J.G. Arnold. 2010. Simulation of agricultural management alternatives for watershed protection. Water Resource Management 24, 3115-3144.

Ullrich, A., M. Volk., 2009. Application of the Soil and Water Assessment Tool (SWAT) to predict the impact of alternative management practices on water quality and quantity. Agricultural Water Management 96, 1207-1217.

UNEP, 2005. Water: facts and trends. Available at: http://www.unwater.org/downloads/Water_facts_and_trends.pdf. Accessed on November 25, 2012.

UNEP,2005. Challenges of water scarcity.http://www.siwi.org/documents/Resources/Reports/Challenges_water_scarcity_business_case_study_2005.pdf.

UNEP GEM Water, 2006. Water quality for ecosystem and human health. Available at: http://www.unep.org/gemswater/Portals/24154/publications/pdfs/water_quality_human_health.pdf. Accessed on September, 2012.

UNEP GEM Water, 2008. Water quality for ecosystem and human health. Available at: http://www.unep.org/gemswater/Portals/24154/publications/pdfs/water_quality_human_health.pdf. Accessed on September, 2012.

UNEP, 1998. Best management practices for agricultural nonpoint sources of pollution. CEP technical report no. 41. Available at: http://www.cep.unep.org/publications-and-resources/technical-reports/tr41en.pdf. Accessed September 25, 2012.

UN-Water, 2013. Water use statistics. Available at: http://www.unwater.org/statistics_use.html. Accessed on August 8, 2013.

USDA, 2012. Agricultural resources and environmental indicators. Available at: http://www.ers.usda.gov/media/873632/waterquality.pdf. Assessed on October 15, 2012.

USDA- NRCS, 2010. Conservation practice. Available at: http://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/?ss=16&navtype=SUBNAVIGATION&cid=nrcs143_026849&navid=120160340000000&pnavid=120160000000000&position=Not%20Yet%20Determined.Html&ttype=detailfull&pname=Conservation%20Practices%20|%20NRCS. Accessed on October 15, 2012.

USDA, 1992. Agricultural Waste Management Handbook. Chapter 3: Agricultural wastes and water, air, and animal resources. USDA Natural Resources Conservation Service.

USDA, 1992. Chapter 3: Agricultural wastes and water, air, and animal resources. USDA Natural Resources Conservation Service, editor. Agricultural Waste Management Handbook.

USDA, 1997. Water quality and agriculture: Status, conditions, and trends. Working Paper #16. United States Department of Agriculture, Natural Resources Conservation Service.

USDA, 2012. Water quality impacts of agriculture. Available at: http://www.ers.usda.gov/media/873632/waterquality.pdf. Accessed on September 25, 2012.

USDA,2005. About Rangeland. Avaialble at: http://www. fs.fed.us/rangelands/whoweare/index.shtml. Accessed on September 25, 2012.

USDA-ERS, 1997. Agricultural Resources and Environmental Indicators, Agricultural Handbook No. 712.

USDA 2010. No-till farming is a growing practice . Economic Information Bulletin No. 70. Available at: http://www.ers.usda.gov/Publications/EIB70/EIB70.pdf. Assessed on July 8, 2011.

USDA-NRCS, 2005. National conservation practice standards -NHCP. Washington, D.C. Available at: www.nrcs.usda.gov/Technical/Standards/nhcp.html . Accessed 25 July 2011.

USDA-NRCS, 2011. Strip Cropping. Available at: http://www.sera17.ext.vt.edu/Documents/BMP_strip_cropping.pdf. Accessed 25 July 2011.

USDA 1996. AREI/ Production management. Avaiable at: http://www.ers.usda.gov/publications/arei/ah712/AH7124-2.PDF. Assessed on July 9, 2011.

USDA-NRCS. 2005. National conservation practice standards -NHCP. Washington, D.C.:USDA National Resources Conservation Service. Available at: www.nrcs.usda.gov/Technical/Standards/nhcp.html.

USDA-NRCS, 2011. Phosphorus best management practices : protecting water quality.Little Rock, Arkansas. Available at: http://www.sera17.ext.vt.edu/Documents/BMP_strip_cropping.pdf. Assessed on July 8, 2011.

USEPA .2005. Non point source pollution: The nation's largest water quality problem. Publication no. EPA841-F-96-004A. Available at: http://water.epa.gov/polwaste/nps/outreach/point1.cfm. Accessed on September 25, 2012.

USEPA 2003. National management measures for the control of non-point pollution from agriculture. EPA-841-B-03–004. Washington, DC: US Environmental Protection Agency, Office of Water; p. 2–8.

USEPA, 2003. Agricultural nonpoint source pollution. Available at: http://water.epa.gov/polwaste/nps/agriculture/agmm_index.cfm. Accessed on September, 25, 2012.

USEPA, 2005. Non point source pollution: The nation's largest water quality problem. Publication no. EPA841-F-96-004A. Available at: http://water.epa.gov/polwaste/nps/outreach/point1.cfm. Accessed on September 25, 2012.

USEPA, 2009. Saginaw River and Bay. Available at: http://www.epa.gov/glnpo/aoc/saginaw-river/index.html. Accessed on September 25, 2012.

USEPA, 2005. Total maximum daily loads: national section 303(d) List Fact Sheet: top 100 impairments. USEPA office of water, Washington, DC.

USEPA, 1992. The quality of our nation's water. Available at: http://www.epa.gov/owow/305b/water.pdf. Accessed on September 25, 2012.

USEPA, 2002. National Water Quality Inventory - 2000 Report to Congress. EPA 841-F-02-003. Office of Water (4503-T). U.S. Environmental Protection Agency, Washington, D.C.

USEPA, 2002. The Twenty Needs Report: How research can improve the TMDL program. EPA 841-B-02-002. USEPA Office of Water, Washington, DC.

USEPA, 2003. Agricultural nonpoint source pollution. Available at: http://water.epa.gov/polwaste/nps/agriculture/agmm_index.cfm. Accessed on September, 25, 2012.

USEPA, 2007. Total maximum daily loads with storm water sources: a summary of 17 TNDLs. EPA 841-R-07-002. Available at: http://water.epa.gov/lawsregs/lawsguidance/cwa/tmdl/upload/17_TMDLs_Stormwater_Sources.pdf. Accessed on September 25, 2012.

USEPA, 2008. Total Maximum Daily Loads: National Section 303(d) List Fact Sheet:Top 100 Impairments. U.S. Environmental Protection Agency: Washington, D.C.

USEPA, 2012. National management measures for the control of nonpoint pollution from agriculture. EPA-841-B-03-004. Washington , DC.

USEPA, 2012. National Management Measures to Control Nonpoint Pollution from Agriculture. Available at: http://water.epa.gov/polwaste/nps/agriculture/upload/2003_09_24_NPS_agmm_chap1.pdf. Accessed on September 25, 2012.

USEPA,1993. Guidance Specifying Management Measures for Sources of Nonpoint Pollution in Coastal Waters. EPA-840-B-92-002. U.S.Environmental Protection Agency, Washington, DC.

USEPA. 1999. Protocol for developing nutrient TMDLs. EPA-841-B-99-007. Washington DC: United States Environmental Protection Agency, Office of Water.

USEPA. 2001c. Protocol for developing pathogen TMDLs (First Edition). EPA/841/R-00/002. Washington D.C.: Office of Water, US Environmental Protection Agency.

USEPA. 2009. National water quality inventory: Report to congress, 2004 reporting cycle. USEPA Doc. 841-R-08-001. U.S. EPA, Washington, DC.

USEPA, 2001. PLOAD version 3.0. An arcview GIS tool to calculate nonpoint source of pollution in watershed and stormwater projects. User's manual. Available on line at:

http://water.epa.gov/scitech/datait/models/basins/upload/2002_05_10_BASINS_b3docs_PLOAD_v3.pdf. Accessed on November 14, 2012.

USEPA, 2012. Point source pollution. Available at: http://www.riverproject.org/point-source-pollution.html. Accessed on September 25, 2012.

USEPA, 2012. What is nonpoint source pollution? Available at: http://www.epa.gov/owow/NPS/forestrymgmt/pdf/ch1.pdf. Accessed on September 25, 2012.

USEPA , 2009. National water quality inventory: Report to congress, 2004 reporting cycle. USEPA Doc. 841-R-08-001. U.S. EPA, Washington, DC. Available at: http://www.epa.gov/owow/305b/2004report/2004_305Breport.pdf. Accessed 20 July 2011.

USGS, 2006. Nutrients in streams and rivers across the nation, 1992–2001. Available at: http://pubs.usgs.gov/sir/2006/5107/pdf/SIR06-5107_508.pdf. Accessed on September 25, 2012.

USGS, 2012. Where is earth's water located. Available at: http://ga.water.usgs.gov/edu/earthwherewater.html. Accessed on May15, 2012.

USGS, 2012. Nitrogen and water. Problems with excess levels of nitrogen in the environment. Available at: http://ga.water.usgs.gov/edu/nitrogen.html. Accessed on August 8, 2013.

Van Griensven, A., Meixner, T., Grunwald, S., Bishop,T., Diluzio, M., Srinivasan,R., 2006. A global sensitivity analysis tool for the parameters of multi-variable catchment models. Journal of Hydrology 324, 10-23.

Valcour, J.E., Michel, P., McEwen, S.A., Wilson, J.B., 2002. Associations between indicators of livestock farming intensity and incidence of human Shiga toxin-producing *Escherichia coli* infection. Emerging Infectious Diseases 8, 252–257.

Varol, M., Sen, B., 2012. Assessment of nutrient and heavy metal contamination in surface water and sediments of the upper Tigris River, Turkey. CATENA 92, 1-10.

Verma, S., Markus, M., Cooke, R.A., 2012. Development of error correction techniques for nitrate-N load estimation methods. Journal of Hydrology 433, 12-25.

Vitousek, P. M., Naylor, R., Crews, T., David, M. B., Drinkwater, L. E., Holland, E., Johnes, P. J., Katzenberger, J., Martinelli, L. A., Matson, P. A., Nziguheba, G., Ojima, D., Palm, C. A., Robertson, G. P., Sanchez, P. A., Townsend, A. R., Zhang,F. S., 2009. Nutrient imbalance in agricultural development. Science 324, 23-33.

Wali, U.G., Nhapi, I., Ngombwa, A., Banadda, N., Nsengimana, H., Kimwaga, R. J., Nansubuga, I., 2011. Modelling of nonpoint source pollution in Akagera Transboundary River in Rwanda. The Open Environmental Engineering Journal 4, 124-132.

Wang, L; Robertson, D.M., Garrison,P.J., 2007. Linkages between nutrients and assembles of macroinvertebrates and fish in wadeable streams: Implication to nutrient criteria development 39, 194-212.

Wanga, X., Wanga, Q., Wua, C., Liang, T., Zhengc, D., Weid, X., 2012. A method coupled with remote sensing data to evaluate non-point source pollution in the Xin'anjiang catchment of China. Science of the Total Environment 430, 132-143.

Weston, D.P., Holmes, R.W., Lydy, M.J., 2009. Residential runoff as a source of pyrethroid pesticides to urban creeks. Environmental Pollution 157, 287–294.

White, E.M., Kieber, D.J., Sherrard, J., 2010. Carbon dioxide and carbon monoxide photoproduction quantum yields in the Delaware Estuary. Marine Chemistry 118, 11–21.

White, M.J., Storm, D.E., Busteed, P.R., Stoodley, S.H., Phillips, S.J., 2009. Evaluating nonpoint source critical source area contributions at the watershed scale. Journal of Environmental Quality 38, 1654-1663.

Wilkes, G., Edge, T.A., Gannon, V.P.J., Jokinen, C., Lyautey, E., Neumann, N.F., Ruecker, N., Scott, A., Sunohara, M., Topp, E., Lapen, D.R.,2011. Associations among pathogenic bacteria, parasites, and environmental and land use factors in multiple mixed-use watersheds. Water Research 45(18), 5807-5825.

Wilkes, G., Edge, T., Gannon, V., Jokinen, C., Lyautey, E., Medeiros, D., Neumann,N., Ruecker, N., Topp, E., Lapen, D.R., 2009. Seasonal relationships among indicator bacteria, pathogenic bacteria, *Cryptosporidium* oocysts, *Giardia* cysts, and hydrological indices for surface waters within an agricultural landscape. Water Resource 43,2209–2223.

Williams, J.R., Izaurralde, R.C., 2005. The APEX model. In: Joint global change research institute, B.A., suite 201, College park, MD 20740-2496. 720 East Blackland Rd., temple, TX 76502-9622: Texas agricultural experimentation station.

Williams, J.W., Izaurralde, R.C., Steglich, E.M., 2008. Agricultural Policy/Environmental Extender Model, Theoretical documentation. BREC report # 2008-17.

Winchell, M., Srinivasan, R., Di Luzio, M., Arnold, J. G., 2007. ArcSWAT interface for SWAT 2005: User’s guide. Grassland Soil and Water Research Lab, available at: http://www.geology.wmich.edu/sultan/5350/Labs/ArcSWAT Documentation.pdf.

Woznicki, S.A; Nejadhashemi, A.P., Smith, C.M., 2011. Assessing best management practice implementation strategies under climate change scenarios. Transaction of the ASABE 54, 171-190.

Wu, L., Long, T., Liu, X., Mmereki, D., 2012. Simulation of soil loss processes based on rainfall runoff and the time factor of governance in the Jialing River Watershed, China. Environmental Monitoring and Assessement 184, 3731-3748.

Yang, W; Sheng, C., Voroney, P., 2005. Spatial targeting of conservation tillage to improve water quality and carbon retention benefits. Canadian Journal of Agricultural Economics 53, 477-500.

Yang, L., Ma, K., Guo, Q., Zhao, J., Luo, Y., 2006. Zoning planning in non-point source pollution control in in Hanyangdistrict. Huan Jing ke Xue 27(1), 31-6.

Yatsalo, B.I., Kiker, G.A., Kim, J., Bridges, T.S., Seager, T.P., Gardner, K., Satterstrom, F.K., Linkov, I., 2007. Application of multi-criteria decision analysis tool to two contaminated sediment case studies. Intergrated Environmental Assessment and Management 3(2), 223-233.

Yonkos, L.T., Fisher, D.J., Van-veld, P.A., Kane, A.S., McGee, B.L., Staver, K.W., 2010. Poultry-litter induced endocrine disruption in fathead minnow, sheepshead minnow, and mummichog laboratory exposures. Environmental Toxicology and Chemistry 29, 2328–2340.

Young, K. D., Thackston, E. L., 1999. Housing density and bacterial loading in urban streams. Journal of Environmental Engineering 1177-1180.

Young, W.F., Whitehouse, P., Johnson, I., Sorokin, N., 2004. Proposed predicted-no-effect concentrations (PNECs) for natural and synthetic steroid estrogens in surface waters. Technical Report, P2-T04/1.

Young, K.D., Kibler, D.F., Benham, B.L., Loganathan, G.V., 2009. Application of the analytical hierarchial process for improved selection of stormwater BMPs. Journal of Water Resources Planning and Management 135(4), 264-275.

Yousefpour, R., 2013. Bioenergy production and soil conservation from Norway spruce (Picea abies L. Karst) plantation in Denmark. Agroforest Systems 87, 287-294.

Zanardo, S., Basu, N. B., Botter, G., Rinaldo, A., Rao, P. S. C., 2012. Dominant controls on pesticide transport from tile to catchment scale: Lessons from a minimalist model. Water Resources Research 48, W04525.

Zhang, X., Srinivasan, R., Arnold, J., Izaurralde, R.C., Boasch, D., 2011. Simultaneous calibration of surface flow and baseflow simulations: a revisit of the SWAT model calibration framework. Hydrological Processes 25, 2313-2320.

Zhoua, T., Wub, J., Penga, S., 2012. Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China. Ecological Indiactors 23, 166-175.

Zhu, Q., Schmidt, J.P., Bryant, R.B., 2012. Hot moments and hot spots of nutrient losses from a mixed land use watershed. Journal of Hydrology 415, 393-404.
T