Optimization of Best Management Practices to Reduce Phosphorus Runoff in the Grand River Watershed Using a Multi-Objective Optimization Algorithm

by

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Authors Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including a required final revision, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

As water quality issues become an increasingly global concern, public administrators are looking for new ways to reduce water pollution from different sources, including agricultural runoff. Best management practices are agri-environmental activities, which aim to decrease the impact of agricultural activities on the environment as compared to conventional management practices. However, the selection of best management practices distribution is not without challenges and therefore an optimization model is introduced here to support policy and decision-making and minimize nutrients load with the limited available resources. Therefore, this research sets out a multi-objective optimization model to optimize phosphorus reductions in the Grand River watershed and conduct an economic analysis of best management practices and assess their cost-effectiveness. A set of optimal solutions is generated from the Pareto-optimal front within the constraints of two objective functions designed to achieve a reduction in total phosphorus load at minimal costs to support decision making and watershed management. With maximum retention of total phosphorus, the optimization results show that nutrient management plan is the most cost-effective best management practice, while manure storage is the least cost-effective best management practice. Regarding the minimization of total phosphorus load, none of the single best management practices for cover crops, nutrient management plan, and buffer strips could achieve a total phosphorus reduction of greater than 20%. According to the optimization of best management practices combinations, up to 32% of the total phosphorus load can be reduced at a minimum unit cost of $1,328 per hectare per year. The combination of cover crops and nutrient management plan is the most recommended best management practices for the entire Grand River watershed. In order to improve water quality based on existing best management practices, implementing a combination of best management practices is a good option for the Grand River Conservation Authority.

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1 Introduction

1.1 Background

Water is the source of life, and water quality is closely interlinked with people's daily lives. However, with the increase of industrial plants and population, increasing impurities and waste materials are being created, and these have polluted surface waters and groundwater aquifers, attracting considerable attention. Water quality is the reflection and reaction of water composition to all inputs and processes (Krenkel, 2012). If the waters are changed in condition or composition directly or indirectly and become unsuitable, or less suitable for the functions or purpose in their natural state due to human activity, the World Health Organization (WHO) may evaluate them as polluted (WHO, 2004). Human-caused water problems, such as eutrophication, aquatic toxicity, and drinking water contamination are occurring around the world. Nutrients, particularly nitrogen and phosphorus, have been considered to be significant threats to coastal waters health (Andersen et al., 2004). Due to increased human activities, mainly from domestic sewage discharges, agriculture and urban development, the nutrient level of many different water bodies has been accelerated in the last few decades (Mainstone & Parr, 2002).

Increasing levels of nitrogen and phosphorus degrade aquatic ecosystems and change the ecological structure of water bodies (Watson et al., 2016). In addition, water quality problems also cause various economic burdens on society such as the increasing costs of water treatment and the reduced utility of water to humans. Massive cyanobacteria (blue green algae) blooms, which can produce cyanotoxin, could threaten human health and cause high economic costs for water treatment facilities (Wolf & Klaiber, 2017a). In addition to public health risks, toxin residuals in aquaculture can affect the quality of aquatic food, also resulting in regional economic losses (Chislock et al., 2013). Other common economic losses associated with eutrophication are losses in waterfront properties, commercial fisheries and tourism (Withers et al., 2014). Recreational benefits, especially swimming, boating and fishing, are reduced due to water quality degradation (Wolf & Klaiber, 2017b).

Currently, agriculture is considered as a leading driver of water contamination in many areas around the world (Krug, 1993; Agrawal, 1999; Daniel et al., 1998;

Arheimer et al., 2004; Moss, 2008; Withers et al., 2014). Compared with industrial pollution, agricultural water pollution does not have a single point source where individual behaviors can be easily measured and monitored. The nutrients such as nitrogen and phosphorus are washed out by precipitation from the topsoil and get diffused into various water channels and fields. To locate the origin of these nutrients is difficult and costly, and this is called a non-point source (NPS) emission problem. Intensive agricultural practices, such as tillage, grazing, and extensive usage of pesticides and fertilizers, are significant contributors to NPS pollution. Farmers apply high nutrients in the form of sludge, chemical fertilizers, and manure through farming activities. These nutrients can be washed into aquatic ecosystems, resulting in water eutrophication.

As water quality issues become an increasingly global concern, public administrators are looking for new ways to reduce water pollution from different sources, including agricultural runoff. Located at the border of the United States and Canada, the Great Lakes contain 20% of the world's fresh water and are an invaluable resource for the economic and cultural development of their surrounding regions. However, eutrophication in the Great Lakes harms local water supplies, limits recreational opportunities, and poses a threat to public health (Bejankiwar et al., 2013). Since NPS—mainly from agriculture activities—are typically the major sources of nutrient pollution reaching water, the International Joint Commission (IJC) identified the need to carry out agricultural best management practices (BMPs) to meet reduction targets and sustain the Great Lakes ecosystem (IJC, 2014; Scavia et al., 2017). BMPs are agri-environmental practices designed to decrease the impact of agricultural activities on the environment as compared to conventional management practices. The US Environmental Protection Agency (USEPA) defined BMPs as alternative management practices to reduce environmental impacts, and a schedule of activities to enhance conservation procedures (USEPA, 1998). Agriculture and Agri-Food Canada (2018) have also defined BMPs as farming practices designed to minimize their negative impacts on the environment. Although BMPs have been implemented around the Great Lakes to protect water quality, the effectiveness of BMPs is affected by different factors, such as climates change and farmers' behaviour (Wilson et al., 2018; Bosch et al., 2014). To better improve water quality and achieve nutrient reduction targets, it is critical to apply optimization models to evaluate the cost-effectiveness of

BMPs implementation to support policy implementation and decision-making in the Great Lakes.

1.2 Objectives

One of the important goals of applying BMPs is to reduce agriculture-caused environmental impacts on both ground and surface water quality. On the Canadian side, the Grand River is the largest watershed draining into Lake Erie, the most polluted Great Lake, accounts for the majority of the total phosphorus loading into the eastern basin of Lake Erie (Loomer & Cooke, 2011). The Grand River Conservation Authority (GRCA), a water and natural resource management organization that works with provincial and federal government, municipalities, and landowners to implement programs that improve water quality, maintain water supply, and protect aquatic ecosystems, has implemented a variety of BMPs to improve and protect water quality in the agricultural landscape of the Grand River watershed (Liu et al., 2015; GRWMP, 2014). According to the primary agricultural practices, local climate conditions, and pollution characteristics, different BMPs suites have been adopted in different agricultural areas (Macrae et al., 2021). Examples of BMPs that have been developed for Canadian agriculture include, nutrient or fertilizer management, cover crops, buffer strips, manure storage, cropland retirement, erosion control structures, no-tillage, and livestock restriction (AAFC, 2019). The benefit of focusing on BMPs is that their adoption can be easily monitored.

Although it is easy to monitor the effectiveness of BMPs, the costs are not as easily understood. In the Grand River watershed, past research has been done assessing BMPs' effectiveness; however, to my knowledge, no one has measured the economic costs of BMPs in this area. In addition to assessing the effectiveness of BMPs, limited knowledge on identifying cost-effective solutions for reducing NPS pollution in the Grand River watershed is deemed worthy of research. Therefore, this research sets out a multi-objective optimization model to optimize phosphorus reductions in the Grand River watershed and conduct an economic analysis of BMPs and assess their cost-effectiveness. The overall objective of this study is to investigate the cost-effectiveness of BMPs implementation in the Grand River watershed, as well as to support effective decision-making in this area. Additionally, this study aims to answer the following questions:

i. How cost-effective are BMPs implemented in the Grand River watershed?

ii. How to make existing BMPs more cost-effective to achieve the nutrient reduction target in the Grand River watershed?

1.3 Thesis Structure

This thesis first introduces the background and research objectives in Chapter 1. Then, Chapter 2 summarizes the literature of past studies on cost-effectiveness analysis (CEA) of BMPs and reviews existing studies of BMPs optimization. Chapter 3 describes the study area, data preparation, and proposed optimization model. The optimization results are concluded in the Chapter 4, and conclusions are presented in the last chapter.

2 Literature Review

2.1 Description of Best Management Practices

BMPs are agricultural pollution prevention measures designed to minimize the impact of agricultural activities on water bodies without sacrificing economic productivity. Numerous BMPs have been implemented across North America. As awareness of NPS contamination has grown since the 1960s, the Farm Safety Act of 1985 mandated BMPs specifically for the treatment of agricultural water contaminants in the US (Logan, 1993). Initially, voluntary adoption and nonfunded BMPs—such as conservation tillage and livestock waste management—were implemented at the state and national level in US but with little effect (Herdendorf, 1983). In 1987, a national program was established in Section 319 of the Clean Water Act to fund the implementation of BMPs to control NPS pollution (Copeland, 2016). In order to protect water quality and soil health, the Government of Canada provides farmers with funds to encourage implementing BMPs under the Farm Stewardship Program (Agriculture and Agri-Food Canada, 2018). Structural and non-structural BMPs are two types of common BMPs (Prokopy et al., 2008). Structural BMPs are permanent and stationary BMPs implemented to reduce pollutants discharged into water, such as buffer strips, manure storage, and retention pound (USEPA, 2013). Non-structural BMPs incorporate existing agricultural landscapes into the practice in order to manage pollutants at the source, such as cover crops, nutrient management plan (NMP), and conservation tillage (USEPA, 2013).

In an effort to improve surface and groundwater quality, the GRCA delivered the Rural Water Quality Program (RWQP) in 1988 to protect water quality in the Grand River watershed. (Liu et al., 2015; GRWMP, 2014). Various BMPs have been introduced to minimize the transfer of nutrient in this program, and the government has provided financial incentives for BMPs implementation, including an annual incentive for individual BMP projects or a grant to cost share a project implementation. The benefits of BMPs implementation involve economic expansion, development of sustainable agriculture, improved recreational opportunities, and a healthy aquatic ecosystem (Sharpley et al., 2006). This research focuses on six types of BMPs: cover crops, NMP, buffer strips, manure storage, milkhouse waste management, and livestock access restriction. Cover crops aim to reduce watercourse erosion, retain nutrients, and protect soil health, rather than realizing personal cash value by growing crops. Under RWQP (2014), farmers who implement cover crop projects can receive a performance incentive per acre, up to a maximum of 30 acres per applicant. NMP is a written plan to manage nutrients and prevent water contamination from manure and nutrient application by addressing nutrient sources and all manure produced on the farm through nutrient management software. Up to 50% of the cost-share is available for each project. Buffer strips protect water quality by creating permanent vegetative buffers along the watercourses to intercept runoff, and applicants receive a 75% cost-share and annual performance incentives per acre for up to three years. Manure storage and milkhouse waste management are similar BMPs that collect livestock manure and milkhouse waste in storage tanks to eliminate the contamination in the water, each project could receive a 50% cost-share of implementation. The detailed calculation of each BMP cost is described in Chapter 3.

2.2 Cost-Effectiveness Analysis

Past research has been done evaluating the effectiveness of BMPs in Canada (e.g., Rousseau et al., 2013; Stang et al., 2016; Crossman et al., 2016; Hanief & Laursen, 2019); nevertheless, limited research has measured the economic costs of BMPs (Yang et al., 2013). CEA, as an economic analysis tool, aims to identify the lowest-cost measure taken in a water eutrophication region to achieve a specific outcome, typically a policy objective. Over the past few decades, various methodologies that integrate hydrologic and economic models have been developed to evaluate the cost-effectiveness of BMPs. A range of methods—such as optimization models (Cools et al., 2011), regression models (Ripa et al., 2006), linear programming (Fröschl et al., 2008), and bio-economic modeling (Semaan et al., 2007)—are applied to assess the costs and effects of nutrient abatement policies in cost-effectiveness studies (Balana et al., 2011).

Different purposes and study areas explain and are responsible for the differences and complexity levels of the models employed to evaluate the cost-effectiveness of nutrient reduction measures. With regard to optimization models, in most cases, linear optimization models are employed. For example, in the Grote Nete River basin in Belgium, Cools et al. (2011) applied a simple optimization model to rank nitrogen abatement measures. Fröschl et al. (2008) used a linear optimization model to analyze the cost-effectiveness of nutrient reduction measures to minimize the nutrient load of water entering the Black Sea. Although linear optimization models are popular in many studies because of their ease of use, their inability to incorporate uncertainty and nonlinearity is a key drawback. (Balana et al., 2011). Similarly, due to the nonlinear nature of costs and effectiveness, nonlinear optimization programming has been widely practiced in CEA through integrating economic and simulation models in recent years. To better improve nonlinear optimization algorithms in BMPs placement and selection, Sebti & Bennis (2016) used simulated annealing (SA), linear programming, and a nonlinear genetic algorithm (GA) on a combined sewer. After modification, BMPs placement solutions of GA and SA are much cheaper than solutions obtained from linear programming. Liu et al. (2016b) applied a nonlinear optimization algorithm (AMALGAM) to help decision maker optimally select and implement BMPs in central Indiana, USA. The nondominated sorting genetic algorithm (NSGA-II), a widely used nonlinear optimization model, combined with a hydrological model, has been applied in different countries to evaluate the cost-effectiveness of BMPs. For example, Maringanti et al. (2011) used a BMP tool and NSGA-II to evaluate the right combination of BMPs to achieve the maximum pollutant reduction at the lowest cost in the Wildcat Watershed in north-central Indiana, USA. Zare et al. (2012) applied the stormwater management model and NSGA-II to derive a Pareto-optimal front, which includes the tradeoff between the minimization of BMPs total costs, runoff quantity minimization, and runoff quality maximization in Tehran, Iran. Noor et al. (2017) used the SWAT coupled with NSGA-II to analyze cost-effectiveness of BMPs in sediment yield reduction in the Mehran watershed, Iran. Geng et al. (2019) combined NSGA-II and SWAT to derive the optimal combination of BMPs under the conditions of achieving the maximum pollutant reduction and minimum total costs input in Miyun Reservior, China.

In addition to optimization models, other methods have also been used to evaluate the BMPs' cost-effectiveness. To evaluate the impacts of different policies on nitrate leaching reduction, Semaan et al. (2007) applied bioeconomic modeling approaches, including multi-objective programming models and agronomic simulation models, to assess the costs of these measures in southern Italy. Fezzi et al. (2010) examined regression models to assess the costs of agricultural practices in water framework directive to predict such costs for any known land use pattern area. Ripa et al. (2006) combined a field simulation model with a regression model to evaluate phosphorus reduction in different areas with and without BMPs implementation in Italy. To explore the conditions for cost minimization, Iho (2004) developed a numerical model to provide a cost-effective solution for NPS pollution in southwestern Finland. In Denmark, Schou et al. (2000) integrated the agriculture sector by applying geographic information system (GIS)-based spatial disaggregation, a partial equilibrium model, farm account statistics, and a nitrate loading model and then analyzed nitrogen policies according to their effects on nitrate leaching and farmers' revenue. Dai et al. (2018) established a Soil and Water Assessment Tool (SWAT)-based fuzzy credibility chance-constrained programming model to simulate NPS pollution and optimize BMPs in China. Although each of these different methods can analyze the cost-effectiveness of abatement policies, a comparison of the different methods used in these studies also reveals the methodological limitations of CEA. For example, Balana et al. (2011) indicated that most studies only focused on the most cost-effectiveness measures, which ignored the co-benefits of the joint measures. Therefore, in real-world research, appropriate methodologies and BMPs selection should be improved.

In Canada, one of the important goals of applying BMPs is to reduce the agriculture-caused environmental impacts on both ground and surface water quality; therefore, a cost-effectiveness analysis is necessary to evaluate BMPs performance. In Southern Manitoba, a multi-objective genetic algorithm (MOGA) was introduced to achieve cost-effective BMPs placement (Wu et al., 2018). The findings stated that the spatial optimization method of BMPs can achieve a greater reduction result of surface water compared with conventional methods, and similar studies can get valuable references from the current results. Sebti et al. (2016) used linear optimization programming to minimize the total costs of BMPs placement in the Greater Montreal region, and the results indicated the feasibility of implementing BMPs at minimal costs to achieve the goal of ground water quality control. Shao et al. (2017) created a decision support system that integrates a SWAT model, an optimization model, and a farm economic model to evaluate the BMPs' cost-effectiveness in Gully Creek watershed in southern Ontario, Canada. In addition to assessing the cost-effectiveness of BMPs, GIS-based optimization algorithms can also examine the types and distribution of BMPs under the corresponding budget constraints and environmental reduction targets. Pyo et al. (2017) used a multi-objective NSGA combined with SWAT to minimize total phosphorus in Lake Erie; the optimization results showed a preference selection for single or a maximum of two BMPs in the given subwatersheds because of the high acceptance of these BMPs by stakeholders. To restore lake's ecological health and model phosphorus reduction targets, Weiss et al. (2018) used a GA to optimize the application of BMPs in Lake Simcoe, Ontario. Since the optimization model is constrained to be the least costly and most beneficial to phosphorus reduction, an optimized spatial BMPs distribution can help conservation authorities select optimal BMPs within the watershed. Overall, the application of optimization models to assess the cost-effectiveness of BMPs in Canadian watersheds shows good performance and provides references to future studies.

In the Grand River watershed, watershed-scale water quality models are widely applied to evaluate the effectiveness of BMPs. Liu et al. (2016) applied a SWAT model to assess the potential effects of BMPs in the Grand River watershed and indicated that NMP and wetland restoration are more effective in reducing nutrients levels. Based on the application of SWAT model, Hanief and Laursen (2019) noted that bank stabilization is the most effective BMP to reduce sediments and phosphorus. Aside from the SWAT model, Das et al. (2008) used AnnAGNPS to simulate the sediment yield and hydrology from NPS pollution in the upper Grand River watershed. Singh et al. (2012) applied the CANWET model for hydrologic simulation in the Grand River watershed. However, compared with effectiveness analysis, research on cost analysis of Grand River basin is limited. Yang et al. (2011) evaluated three BMPs in Fairchild Creek, located in the lower Grand River watershed, and concluded that buffer strips are the most cost-effective measure. Liu et al. (2013) conducted a multi-objective optimization model together with a SWAT model to evaluate buffer strips, conservation tillage, and fertilizer reduction in the Fairchild Creek, and the results showed that buffer strips constitute the most cost-effective BMP for reducing total phosphorus. However, there is no research on the BMPs' cost-effectiveness in the entire Grand River watershed. Accordingly, my research will integrate hydrologic model with economic analysis, including a nonlinear optimization model, to evaluate BMPs for future decision support.

2.3 Multi-Objective Optimization Model

The selection and placement of BMPs are restricted by different factors, including cost, climate, land use. (Maringanti et al., 2011). Generally, owing to limited budgets, BMP implementation plans need to take maximum pollution reduction and minimal financial costs into account. Three optimization techniques can help to attain this goal.

The first approach assesses the relative pollutant index and costs individually by setting a fixed number of scenarios, such as particular land use type (Guo et al., 2008; Hundecha & Bardossy, 2004). The comparison between the results of different BMP scenarios in a limited number can lead to the final solution. However, since this approach is dependent on the managers' experience, the results are not sufficiently accurate, although the approach is straightforward to practice (Qi et al., 2020). Therefore, this type of solution may not be cost-effective enough to achieve the reduction target in the watershed (Deb et al., 1999). The second technique integrates economic factors and environmental goals into one objective function, such as GA (Kaini et al., 2012; Qi et al., 2008). GA is an evolutionary-biology-mimicking technique to solve nonlinear or non-differentiable optimization problems. A single optimal solution can be attained through the combination of the watershed model and optimization algorithm. This technique tends to be more objective than the previous one while requiring more time, as each simulation requires the necessary model runtime for each population (Qi et al., 2020). The last technique conducts a selection across a set of solutions by combining a distributed watershed model with a multi-objective optimization algorithm, such as MOGA. This method shares similarities with the second one, but it operates between conflicting objective functions and provides a series of distinct tradeoff between BMPs (Qi et al., 2020).

The objective of this study is to optimize phosphorus reduction at minimal costs; therefore, a MOGA is required to visualize the tradeoff between the two objective functions during the optimization process. The nondominated sorting genetic algorithm (NSGA-II), as a widely accepted multi-objective optimization model, is well-suited in this research to optimize economic costs and hydrologic benefits in BMPs selection and placement (Konak et al., 2006; Maringanti et al., 2011). According to Deb et al. (2002), NSGA-II is an improvement of the conventional GA that can search a large space of objective functions and variables and save more time in model operation. Except for the traditional GA procedure of selection, crossover, and mutation, nondominated sorting and the elitist principle are two essential features adopted by NSGA-II. Since each generation (simulation) has a group of optimal solutions that can be compared with the population size, which can enter to the next generation (Maringanti et al., 2009), this non-dominant solution is called the elite set. A population of elites has the opportunity to be taken to the next generation with and after each generation, a small part of the generation will be replaced by individuals from the elite group. Moreover, NSGA-II is one of the most well-accepted optimization techniques that provides an optimal tradeoff curve between economic and multiple environmental objectives in watershed analysis. Normally, NSGA-II generates the Pareto-optimal front that is convex to the origin under the minimization condition. The better the solution generated, the closer the front gets toward the origin. In NSGA-II, elitist principles help to realize greater convergence (Deb et al., 2002). Although, multi-objective optimization models coupled with hydrological models are popular in CEA of BMPs, to my knowledge, limited research (Liu et al., 2013) has applied this methodology in the Grand River watershed. The optimization results will provide decision-makers with a more intuitive analysis to facilitate better decision making. A detailed description of the procedure of NSGA-II can be found in Chapter 3.

3 Materials and Methodologies

3.1 Case Study Area

The Grand River watershed is the largest watershed in south-central Ontario, with a drainage area of 6,800 square kilometers (Figure 3-1). As the largest tributary of Lake Erie, the Grand River runs 310 kilometers from the Dufferin Highlands to Lake Erie at Port Maitland, with an elevation difference of 351 meters (GRWMP, 2013). Because the Grand River Basin is located in a landscape formed during the last glacial period, it has a high degree of variability in its soils and topography. The watershed includes two First Nations territories and 39 municipalities, as well as four major tributaries, including the Eramosa River, the Speed River, the Nith River, and the Conestogo River Although 90% of the watershed is considered rural, the central portion of the watershed is highly urbanized and contains the fastest-growing areas, including the cities of Cambridge, Guelph, Kitchener, Waterloo, and Brantford (Loomer & Cooke, 2011). According to Irvine (2018), approximately 994,000 people receive drinking water from municipal water systems, which is projected to reach 1.44 million by 2024, and there are 30 municipal wastewater treatment plants (WWTPs) in the watershed that discharge treated effluent into the river.

With the rapid growth of population and urbanization, the Grand River watershed is facing a pressure on the existing water supply and a greater risk of water contamination. The growing population requires a reliable quantity and quality water supply to support communities and efficient wastewater services to treat wastewater discharged into the river without harming the natural environment. It is therefore imperative to upgrade municipal wastewater treatment systems and call on people to conserve water. In addition, intensive agricultural production and climate change are two other major pressures affecting water resources in the watershed (SOWR, 2020). Water supply for crop irrigation and livestock production is necessary; however, the runoff from the agricultural landscape can cause water quality contamination. Meanwhile, climate change affects the amount and timing of precipitation, which in turn lead to changes in flow condition. Therefore, it is necessary and urgent to identify treatment practices to combat water pollution based on topography, climate, and different types of agricultural activities.

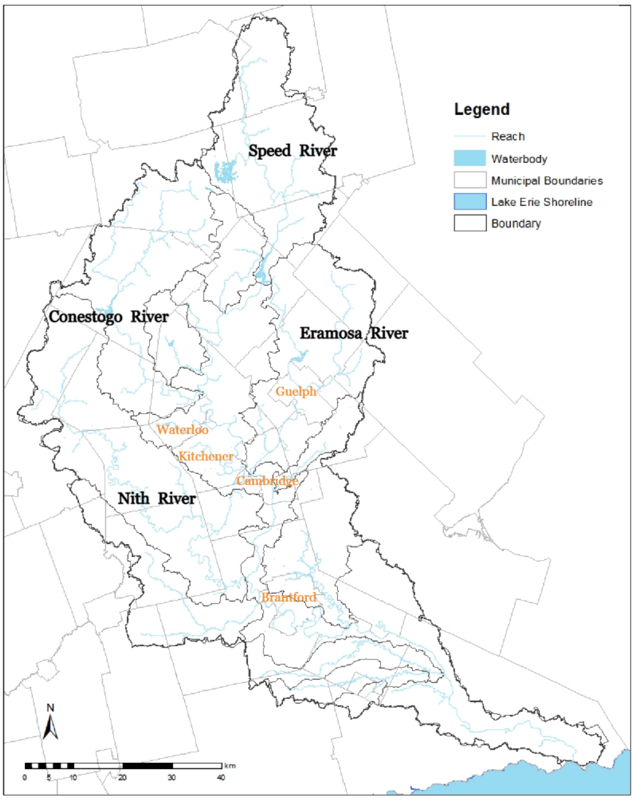

Figure 3-1 Map of major tributaries in the Grand River watershed. Data Source: GRCA, 2012.

The Grand River watershed is divided into three distinct areas by geomorphological description: the upper till plain, the central gravel moraine, and the lower clay plain. The upper till plain is located in the northwestern part of the Grand River watershed, with varying terrain and low permeability (LESPRT, 2008). Due to the soil type, which is rich in salt and clay, the upper region is poorly drained; as a result, artificial drainage is adopted in this area, which makes this area a highly productive agricultural area (GRWMP, 2014). The central gravel moraine is located in the southwestern part of the watershed and is highly varying in elevation, consisting of a series of gravels and moraines (LESPRT, 2008). The soils of some hilly areas are well drained and rich and are intensively used for agricultural production (GRWMP, 2013). According to the distribution of livestock density and fertilizer use, the upper and central regions are the most intensive agricultural production areas, which results in a significant portion of the phosphorus load in water bodies (GRWMP, 2013). In addition, the central region covers major urbanized areas and WWTPs, which exacerbates water degradation in this area (Loomer & Cooke, 2011). For example, wastewater discharges from large Kitchener-Waterloo WWTPs account for 70% of the total phosphorus in the upper-central region during the summer low flows (GRWMP, 2013). The lower clay plain is located in the southeastern part of the watershed and is characterized by heavy clay soils (LESPRT, 2008). Phosphorus transport in the Grand River watershed is primarily in the dissolved form from NPS via overland runoff (GRWMP, 2014). Due to poor drainage capacity, high levels of runoff from the lower region carry phosphorus-laden particles from upstream and discharge into Lake Erie. Land use in this region is predominately for soybean and corn production and livestock pasture (GRWMP, 2013). During high spring flows, agricultural NPS pollution accounts for 90% of the total phosphorus load in the entire watershed as a result of snowmelt and heavy rains (GRWMP, 2013). According to the Grand River Watershed Management Plan (2019), total phosphorus concentration levels are five times higher in the spring than in the summer, indicating that agricultural NPS pollution is crucial in the degradation of water bodies in the Grand River watershed.

The Grand River watershed is one of the most productive agricultural zones in Canada (GRWMP, 2014). The Grand River is also the largest tributary of Lake Erie, and it accounts for 54% of the total phosphorus load in the eastern basin of Lake Erie (ECCC & USEPA, 2018). Under the Canada-Ontario Lake Erie Action Plan, a target of a further 40% reduction in phosphorus levels (from 2008 levels) target was adopted for the central and western basin of Lake Erie (ECCC, 2018). However, with the lack of scientific certainty, there are no specific phosphorus load reduction objectives for the eastern basin of the Lake Erie and Grand River watershed (SOWR, 2020; ECCC 2018). A preventative approach will be taken by the government of Ontario to addressing phosphorus loading to the eastern basin of Lake Erie until a target with sufficient scientific evidence is established (ECCC, 2018). Eutrophication in the Grand River watershed is primarily caused by the growth of aquatic primary producers (e.g., algae and plants). Urbanization, point source discharges, and agricultural land use, are the three main factors affecting water pollution in the watershed. Agricultural activities are the largest contributor to water contamination, as 61% of the land in the watershed is used for agricultural production (SOWR, 2020). Agricultural production in the watershed can be roughly divided into crop production and livestock production (GRWMP, 2014). Farmers apply large amounts of nutrients to the land during their farming activities, and these nutrients can be washed into aquatic ecosystems, resulting in water eutrophication. Nutrients are necessary for the growth of plants and animals, but excessive amounts of nutrients that enter water bodies can damage aquatic ecosystems and change the ecological structure of water bodies (Watson et al., 2016). For this reason, agricultural BMPs are the most effective measures to control nutrients emissions from the NPS. GRCA continues to promote nutrient management through RWQP, and over 6,000 projects have been implemented in the agricultural landscape since 1999 (GRWMP, 2019).

3.2 Data Description

Data used in this research can be divided into three types: costs of BMPs, kilograms of total phosphorus retained on the land, and kilograms of total phosphorus load in the watershed. The first two types of data are provided by GRCA, and the last type of data is simulated by the SWAT model, which was calibrated and validated over a 30-year period by Dr. Rute Pinto of the Ecohydrology Group in the Department of Earth and Environmental Sciences at the University of Waterloo. Since precipitation and temperature changes over the past 30 years were included in the calibration of SWAT, the results of the study also partially capture the effects of climate change on hydrologic flow and nutrient runoff in SWAT. Both costs and total phosphorus data of BMPs are obtained from RWQP, with data covering 4,234 projects from Aug 1998 to Jun 2017, including eight different types of BMPs. The RWQP is funded by municipal governments, including Waterloo Region, Guelph, Brantford, Brant County, Oxford County, and Wellington County, and is intended to promote BMPs implementation and provide financial assistance to farmers for adopting BMPs to improve water quality (GRWMP, 2014). This research addresses six types of BMPs in RWQP: cover crops, NMP, buffer strips, manure storage, milkhouse waste management, and livestock access restriction. Due to the missing information of location and phosphorus retention data of BMPs, only data of 1,685 projects are used in this research; the percentage of each type of BMP is represented in Figure 3-2. Manure storage, buffer strips, and NMP accounts for a similar share, a total of 65%, followed closely by livestock access restriction and cover crops. Milkhouse waste management accounts for the smallest share, less that 10%.

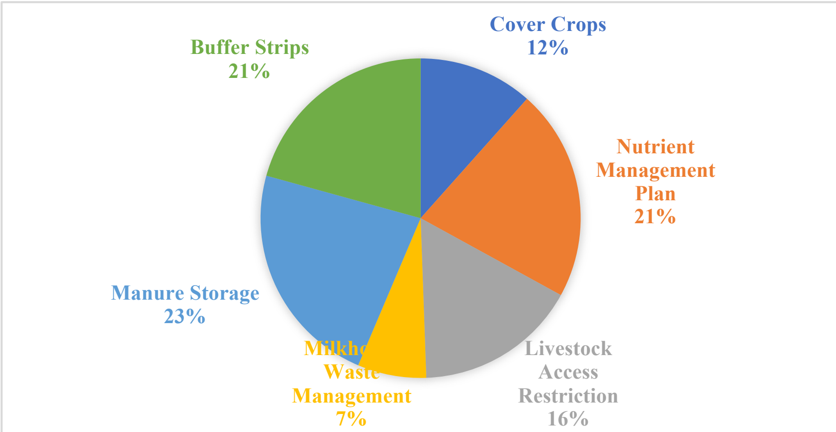

Figure 3-2 Percentage of each type of BMP

In RWQP, the costs of BMPs include the actual costs of projects and the grant paid to farmers for specific projects. Grant payments include cost-sharing, which is a partial reimbursement for the costs of BMPs implementation, and annual incentive payments, which are compensation payments for the annual loss of income due to BMPs implementation. The amount of annual phosphorus kept on the land for each BMP is calculated by the GRCA, and this amount is also related to the scale of the project implementation. Since there is no specific project size for manure storage, milkhouse waste management, and livestock access restriction, we assume the same size for each type of BMP. For example, we assume that manure and milkhouse waste each comprise half of the storage tank; therefore, the size of the project is equivalent to half of the storage area, which is 39.05 hectares. For livestock access restriction, the size of each project equals the total fence length within the entire watershed (152,000 m) divided by the total number of projects (265), multiplied by the minimum distance from the bank (3 m) yielding an average size of 0.172 ha per project. The kilograms of total phosphorus load in the watershed are simulated by the SWAT model. Due to the data limitations, three BMPs scenarios (cover crops, buffer strips, NMP) are selected in the SWAT to assess environmental effectiveness. SWAT output includes baseline for total phosphorus loading, total phosphorus loading for three single BMPs, and total phosphorus loading for four combinations of BMPs.

3.3 Methodologies

3.3.1 Cost-Effectiveness Analysis

According to the Treasury Board of Canada Secretariat (2007), economic analysis tools provide guidance and direction to the government in selecting policy instruments. CEA aims to identify the lowest-cost measure taken in the Grand River watershed to achieve a phosphorus reduction target. It seeks to measure the utilization (cost) and outcomes (effectiveness) of two more alternatives to compare the efficiency of resource utilization and help determine which BMP is the most appropriate based on the value of its effectiveness (Berbel et al., 2011; Bambha & Kim, 2004). Once the costs and effectiveness of BMPs have been assessed, important questions for evaluating BMPs, such as how to achieve the stated goals with the available funds or whether the goals can be achieved at a lower cost, can be answered by CEA (Lescot et al., 2013). This paper sets out a multi-objective optimization model to optimize nutrient reductions in the Grand River watershed and conduct an economic analysis of BMPs and assess their cost-effectiveness.

3.3.2 NSGA-II Optimization Process

NSGA-II is selected as a multi-objective optimization model to evaluate cost-effectiveness of BMPs. The optimization process of NSGA-II (Figure 3-3) is summarized below:

1. Population initialization
2. Obtain data for two objective functions
3. Population undergoes a series of procedures, including nondominated sorting, crowding distance comparison, and GA process (selection, crossover, and mutation).
4. NSGA-II obtains the Pareto-optimal result for the current generation and checks if the fixed maximum generation is exceeded. Repeat the second process if the condition is false.
5. The model terminates with a series of optimized solutions generated under two objective functions at the final generation.

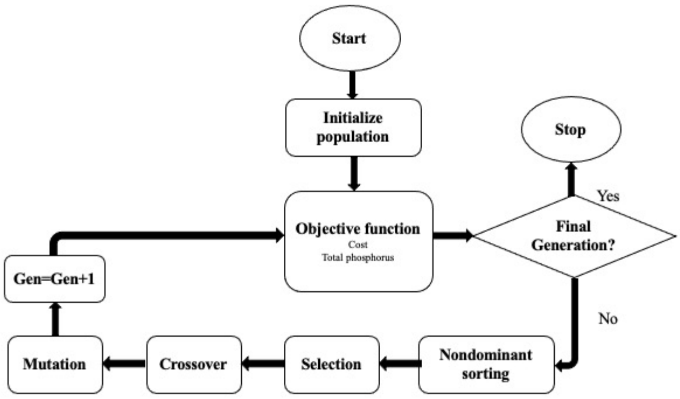

Figure 3-3 The optimization process of NSGA-II

At the beginning, the GA consists of a population of chromosomes (solutions) whose variables are encoded in the form of genes and where each individual carries a different chromosome (Knoak et al., 2006). According to the survival of the fittest, for a given population size, the initial population of chromosomes is randomly generated (Knoak et al., 2006). The objective functions we set in the model are the selection condition, and the model starts running at the first generation. The nondominated sorting procedure is a ranking process that determines the domination of given solutions when evaluating objective functions (Deb et al., 2002). Domination holds when a solution is evaluated better than all other solutions with the same rank under the objective functions (Ercan & Goodall, 206). The process ends when all other solutions in the population have the same ranking, and these individuals are called nondominated individuals. A group of optimal solutions that are nondominated in each generation are called the elite set, and the individuals from the elite set can replace a portion of the population after each generation (Maringanti et al., 2009). The crowding distance is the sum of the side lengths of the rectangles in contact with the adjacent solutions in a non-extreme solution case, and the crowding distance of the extreme solutions is infinite (Coello et al., 2005). NSGA-II uses the crowding distance to assure that optimal solutions produced in each generation are distributed well along the Pareto-optimal front, and the larger the crowding distance, the better the optimal solutions (Maringanti et al., 2011).

In each generation selection process, the available solutions are chosen according to the fitness of each individual; the higher the fitness, the greater chance of being selected in the mating pool (Maringanti et al., 2009). Then the individuals, which are in the mating pool perform crossover and mutation. Crossover and mutation are genetic manipulations. In crossover, better chromosomes (parents) are joined together to produce a new solution (offspring) that is anticipated to inherit good genes (Knoak et al., 2006; Deb et al., 2002). According to the crossover procedure, good genes occur more often in the population and ultimately result in convergence to an overall good solution (Maringanti et al., 2009). The role of mutation is to sustain genetic diversity from one generation of solutions to the next generations (Maringanti et al., 2009). As in nature, by literately selecting better solutions and using them to create new candidates, the solutions improve to adapt to the current optimization problems (Deb et al., 2002). After the last generation, the model stops and generates a series of optimized solutions under two objective functions.

3.4 Cost Calculation

The cost of BMPs we calculated is the partial financial costs, referring to the actual expenditures of each BMP paid to farmers in the RWQP, and this financial cost consists of two parts: a cost sharing part for the one-off investment cost and implementation costs and an annual financial incentive to encourage farmers to adopt the BMP (Formula 1). For example, the cost of buffer strips includes not only eligible costs, such as material and labor costs for buffer strips, and protection and maintenance costs but also incentive payments to landowners to compensate the land taken out of production. Besides, farmers who adopt livestock access restrictions could receive a cost-share reimbursement varying between 50% to 100% of the total implementation costs.

Total costs = one-off investment cost + annual financial incentive (1)

Among a total of eight BMPs, six types of BMPs are selected in this research. Table 3-1 includes assumptions for the six BMPs, which were discussed with experts from the GRCA. We assume that cover crops are an annual project, and that NMP, buffer strips, manure storage, milkhouse waste management, and livestock access restriction all occur over a 25-year period. To calculate annuities for one-off investment costs of the remaining five BMPs, a discount rate of 3.5% is chosen in accordance with HM Treasury Green Book (2020) in this research to make the costs of BMPs comparable throughout time, the annual cost of each project is calculated in 2020 Canadian dollars using the Consumer Price Index published by Statistics Canada from

1998 to 2020. Accordingly, the annual total cost of each project is the sum of the annual investment cost and the annual incentive payment, expressed in 2020 Canadian dollars.

Table 3-1 Main assumptions underlying the cost estimations of the BMPs

Measures	**Definition**	**Assumptions**
Cover Crops	Protect ground by growing conventional crops in rotation, instead of for harvest	Annual project Life time 50 years
Livestock Access Restriction	Restrict livestock access to channels with fencing to protect riverbanks and reduce the input of manure	Life time 25 years Project area 0.172 Discount rate 3.5%
Manure Storage	Preservation of manure runoff and livestock manure in concrete buildings or tanks	Life time 25 years Project area 39.05 Discount rate 3.5%
Milkhouse Waste	Preservation of milkhouse wash water in tanks	Life time 25 years Project area 39.05 Discount rate 3.5%
Nutrient Management Plan	Plans to evaluate fertilizer application rate	Life time 25 years Discount rate 3.5%
Buffer Strips	At least 3 meters wide permanent vegetation strips along one side of waterway	Life time 25 years Discount rate 3.5%

3.5 Objective Functions

In this research, two types of NSGA-II are operated according to two combinations of objective functions—that is, minimization of total costs and maximization of total phosphorus retention, or minimization of total costs and minimization of total phosphorus loading—depending on the type of total phosphorus data. According to the SWAT, the Grand River watershed is delineated into 90 subbasins. These 90 subbasins are variables for searching optimal BMPs to satisfy the objective functions. To evaluate the cost-effectiveness of BMPs, the operation should first meet the objective function: minimization of the total cost of BMPs placement (Formula 2).

$$Min\ f(X) = \frac{\sum_{i=1}^{n}(C\_x_i \times A_i)}{\sum_{i=1}^{n}(A_i)} \tag{2}$$

When analyzing total phosphorus retention, x_i is a BMP indicator for the ith subbasin with a value of 1 for cover crops, 2 for NMP, 3 for buffer strips, 4 for livestock access restriction, 5 for manure storage, 6 for milkhouse waste management, and 0 for no BMP. Since three BMPs and their combinations are considered in SWAT, x ranges from 0 to 7 for BMPs scenarios considered in SWAT: 1 represents cover crops, 2 represents NMP, 3 represents buffer strips, 4 represents combinations of cover crops, NMP, and buffer strips, 5 represents combinations of cover crops and NMP, 6 represents combinations of cover crops and buffer strips, 7 represents combinations of NMP and buffer strips, and 0 represents no BMP. $C(x_i)$is the average cost per unit area ($/ha/yr) of BMP implementation in the ith subbasin, n is the total number of subbasins, which equals 90 in our project. A_i is the area size of the ith subbasin (ha).

Two types of total phosphorus data are selected to use in NSGA-II. One is the total phosphorus retained on the land provided by the GRCA, and the other is the total phosphorus load generated by SWAT, we obtain two objective functions respectively for the total phosphorus data: maximization of total phosphorus retained on land (Formula 3) and minimization of total phosphorus load in water bodies (Formula 4).

$$Max\ g(X) = \frac{\sum_{i=1}^{n}(P\_x_i \times (A_i)}{\sum_{i=1}^{n}(A_i)} \tag{3}$$

$$Min\ h(X) = \frac{\sum_{i=1}^{n}(P\_x_i \times (A_i)}{\sum_{i=1}^{n}(A_i)} \tag{4}$$

For Formula 3, $P(x_i)$ denotes the total phosphorus retention per unit area (kg/ha/yr) for a BMP scenario in the ith subbasin. For Formula 4, $P(x_i)$ denotes the total phosphorus load per unit area (kg/ha/yr) in the ith subbasin. A_i is the area size of the ith subbasin (ha).

3.6 Sensitivity Analysis

Before running NSGA-II, users need to select four GA parameters, namely, population size, generations, crossover probability, and mutation probability, by themselves to assure the efficiency of the optimization procedure and the accuracy of NSGA-II (Hamby, 1995; Maringanti et al., 2011). The population size and number of generations affect the number of optimal solutions and the iteration times, generally starting from 0 to infinity. Whereas crossover and mutation probabilities are critical for selecting the offspring, generally the two sum up to be less than or equal to 1, and hence these parameters are important in NSGA-II. Sensitivity analysis is intended to help users select the best fitting four GA parameters based according to the database they are using to achieve an ideal Pareto-optimal front Pareto-optimal front. The procedure of the sensitivity analysis involves changing the GA parameters one by one to assess each parameter's impact on the Pareto-optimal front (Maringanti et al., 2009). The default and selected GA parameters are presented in Table 1. Default parameters are selected based on the literature review (Maringanti et al., 2011; Chiang et al., 2014; Qi et al., 2020), and sensitivity analysis is performed by the objective functions of total BMPs costs of minimization and total phosphorus load minimization. Figure 3-4 illustrates the Pareto-optimal front according to the changes of GA parameters. Usually, the Pareto-optimal front performs better as the number of generations and population size increase. However, the computation time is greatly affected by the number of generations and population size and can increase from 10 min to 12 h with the parameters increase.

Table 3-2 Selected GA parameters for sensitivity analysis

Order	**Population Size**	**Generations**	**Crossover Probability**	**Mutation Probability**
1	10	100	0.1	0.001
2	50	500	0.3	0.01
3	100	1000	0.5	0.03
4	500	5000	0.7	0.05
5	1000	10000	0.9	0.1
Default	100	1000	0.9	0.1
Optimal	500	5000	0.9	0.01

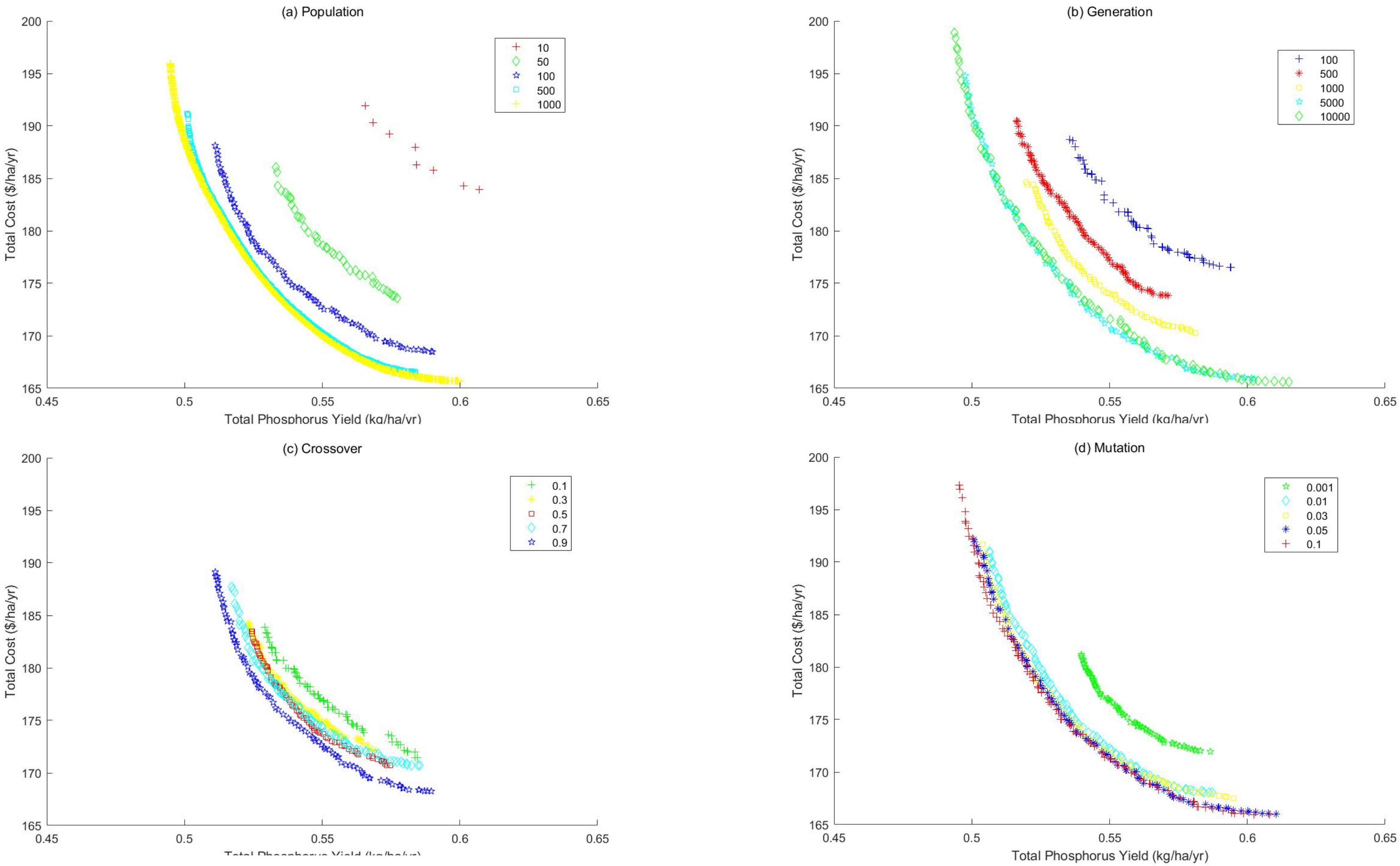

Figure 3-4 GA parameters selection

It is subjective to estimate the goodness of Pareto-optimal front, as the solution becomes better with the front approaches to the origin. It is evident from Figure 3-4a that as the population size increases from 10 to 500, the Pareto-optimal front approached the origin. However, no significant improvement is observed in the front as the population increases from 500 to1,000. This can be explained by the fact that some individuals in the population size of 1,000 have no chance to converge due to setting a fixed number of generations (1,000). Setting a larger number of generations when the population size is 1,000 gives better results, but it may significantly increase the computation time. The shift of the Pareto-optimal front is influenced by the number of generations. Figure 3-4b shows that the larger number of generations, the higher chance of obtaining a set of optimal solutions. However, the change in the Pareto-optimal front between 5,000 and 10,000 generations is unremarkable. When increasing the crossover probability, the shifting pattern of the front is not consistent with the previous movement. Figure 3-4c shows that the Pareto-optimal front moves toward the origin when the crossover probability increases from 0.1 to 0.5, but when it increases to 0.7, the front moves backward and then moves toward the origin again when the crossover probability increases to 0.9. In general, an increase in crossover probability implies a faster convergence. As for the change in mutation probability, the Pareto-optimal front shifts apparently toward the origin in the range from 0.001 to 0.01 (Figure 3-4d). The Pareto-optimal front is insensitive to changes of mutation probability from 0.01 to 0.1, which implies that an excessive mutation rate cannot lead to better convergence. According to the sensitivity analysis and computation time, a population size of 500, 5,000 number of generations, crossover probability of 0.9 and mutation probability of 0.01 are chosen in the NSGA-II.

4 Results

4.1 Maximization of Total Phosphorus Retention

Regarding the total phosphorus data provided by the GRCA, two objective functions are considered: minimization of total costs of BMPs (Formula 2) and maximization of total phosphorus retention on land with BMPs implementation (Formula 3). The aim of NSGA-II is to find the optimal solution to retain the most amount of phosphorus on the land at the least cost. The optimization results from NSGA-II are expressed in Figure 4-1. The Pareto-optimal fronts for all six BMPs are almost linear. The relationship between the effectiveness of BMPs and the cost of BMPs is positive: the economic costs increasing as the amount of phosphorus kept on the land increases. The Pareto-optimal front divides the entire graph into two parts, with the space below the line representing infeasible solutions and the space above the line representing feasible solutions subject to the costs and total phosphorus retention. An optimal solution is represented at each point of the front, preserving the maximum total phosphorus on the land at minimal costs, while also responding to the selected spatial distribution of BMP within the watershed. For example, (1, 193) is selected in Figure 4-1a, which means to achieve a maximum 1 kg/ha of total phosphorus retained on the land each year, the cost for cover crops is $193 per hectare.

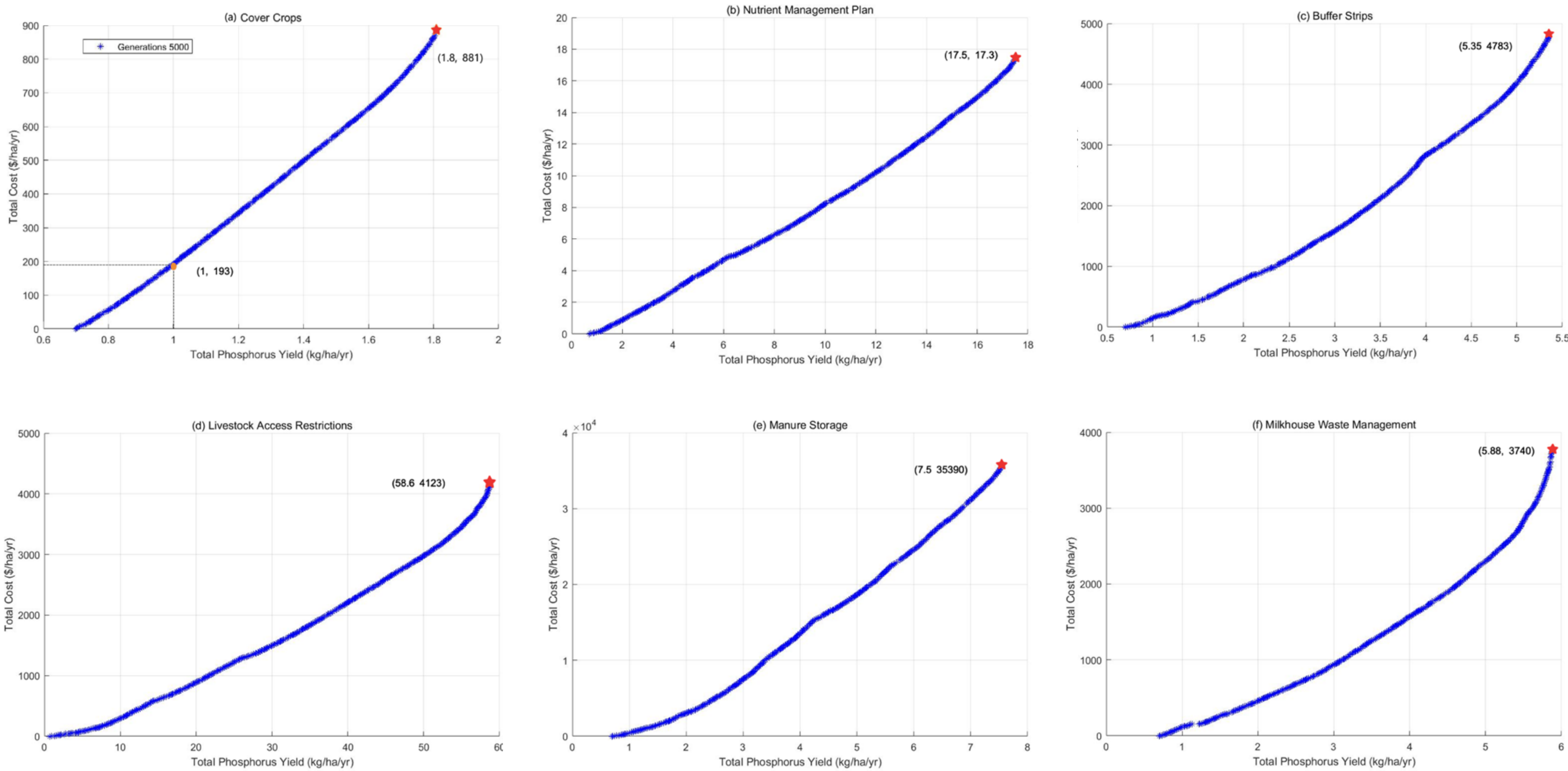

Figure 4-1 Pareto-optimal front between total costs and total phosphorus retention

Figure 4-1(a)–(f) shows that all six Pareto-optimal fronts do not start from the origin, which implies the fact that a certain amount of total phosphorus is retained on the land during the daily activities without BMPs implementation. With BMPs scenarios fully distributed across the Grand River watershed, cover crops can retain a maximum of 1.8 kg/ha of total phosphorus on the land at a minimum cost of $881 per hectare per year. NMP can retain up to 17.5 kg/ha of total phosphorus on the land at a minimum cost of $17.3 per hectare per year. Concerning buffer strips, a maximum of 5.35 kg/ha of total phosphorus can be kept on the land; nevertheless, the cost of implementing buffer strips is a little higher than the first two, at $4,783 per hectare per year. Among all six BMPs, livestock access restrictions can achieve the largest amount of total phosphorus retention, which is 58.6 kg/ha, whereas the lowest total cost of implementation is $4,132 per hectare per year. Manure storage is one of the most expensive BMPs, which can be explained by the expensive construction and maintenance costs, retaining up to 7.5 kg/ha of total phosphorus at a minimum cost of $35,390 per hectare per year. Milkhouse waste management can retain a maximum of 5.88 kg/ha of total phosphorus on the land at a minimum cost of $3,740 per hectare per year. For a more intuitive comparison of the cost-effectiveness of these BMPs, Table 2 presents the minimum unit costs of achieving 1 kg/ha of total phosphorus retention.

Table 4-1 Minimum unit cost of retaining 1kg/ha total phosphorus

BMPs	**Minimum costs of 1kg/ha phosphorus retention(2020C$/ha/yr)**
NMP	0.1
Livestock access restriction	5
Milkhouse waste management	116
Buffer strips	150
Cover crops	193
Manure storage	451

According to Table 2, NMP is the most cost-effective BMP, retaining 1 kg/ha of total phosphorus on the land at a cost of $0.1 per hectare per year. Livestock access restriction are another cost-effective BMP, with a relatively low cost of $5 per hectare per year to retain 1 kg/ha of total phosphorus. Along with NMP, milkhouse waste management and manure storage are major BMPs to address point source pollution in agricultural activities. However, milkhouse waste management is more cost-effective than manure storage, which is the least cost-effective among all six BMPs. Buffer strips are also a cost-effective BMP compared to cover crops and manure storage, with a cost of \$150 per hectare per year to retain 1kg/ha of total phosphorus. The results for cover crops are inconsistent with previous findings. Liu et al. (2016a) posit that cover crops had an effective total phosphorus reduction ability, which was only concluded through the performance of SWAT. In our research, the effectiveness of cover crops is relatively small, with a cost of \$193 per hectare per year to retain 1 kg/ha total phosphorus. However, certain types of cover crops may provide benefits to farmers which may offset the cost of growing cover crops and lead to co-benefits. In this research only incentive payments are considered in the cost calculation and co-benefits are not considered, which may account for the high cost of crop covers in this study. In summary, under NSGA-II, NMP is the most cost-effective BMP, and manure storage is the least cost-effective BMP. However, according to GRCA guidelines, the NMP is only a program to document the application of manure or nutrients by farmers or landowners, there are no specific practices for application on farmland, and there is considerable uncertainty about the actual cost-effectiveness based on farmers' self-reported implementation of the plans. Livestock access restrictions perform better than buffer strips, milkhouse waste management, and cover crops in terms of total phosphorus retention. Cover crops do not perform as cost-effectively as previous studies claim. The reason for comparing the unit costs for the first 1 kg/ha/year is that relative differences in unit costs do not affect the BMP ranking since the graph is linear, meaning that the average unit cost does not vary as more TP is retained on the land; therefore, there are no expected economies of scale. Since only single BMP scenarios are considered in NSGA-II, more accurate analysis of multiple BMPs scenarios and a recommendation of BMPs spatial distribution under phosphorus retention data should be conducted in further studies.

4.2 Minimization of Total Phosphorus Loading

For the total phosphorus data generated by SWAT, two objective functions are considered: minimization of total costs of BMPs (Formula 2) and minimization of total phosphorus load under the implementation of BMPs (Formula 4). Four BMPs scenarios are evaluated in the NSGA-II with the two objective functions described above: a single BMP of cover crops, a single BMP of NMP, a single BMP of buffer strips, and a combination of the three BMPs. The optimal results are expressed in Figure 4-2. The economic cost increases with less phosphorus load in the water, which means that to reduce more total phosphorus, the government will pay more money. The baseline for total phosphorus load generated by SWAT is 0.72 kg/ha. As observed in Figure 4-2, BMPs are more cost-effective in achieving a low total phosphorus reduction rate and less cost-effective in achieving a high phosphorus reduction rate. According to Figure 4-2a, cover crops can reduce total phosphorus load at the outlet of the watershed by up to 18.6% through full application of the BMPs scenarios across the watershed. The points on the Pareto-optimal front represent the optimal solutions for achieving the maximum total phosphorus reduction at the lowest costs. For example, if a 10% total phosphorus reduction target is chosen, the minimum unit cost to be paid is $98 per year based on the NSGA-II results. Compared to cover crops, NMP is much cheaper; however, NMP has less reduction capacity than cover crops (Figure 4-2b). The NMP evaluation for phosphorus reduction is converted in the SWAT scenario simulation to an evaluation of reduced fertilizer application, which included both manure and artificial fertilizers, compared to the NMP analysis for minimized phosphorus retention (see Brouwer et al., forthcoming for more details). The maximum total phosphorus reduction rate of NMP is 12%, with a total cost of $12.4 per hectare per year. Buffer strips are the most expensive BMP and reduced total phosphorus the least of the three. Buffer strips have a maximum total phosphorus reduction rate of 9% but may have a total cost of $534 per hectare per year.

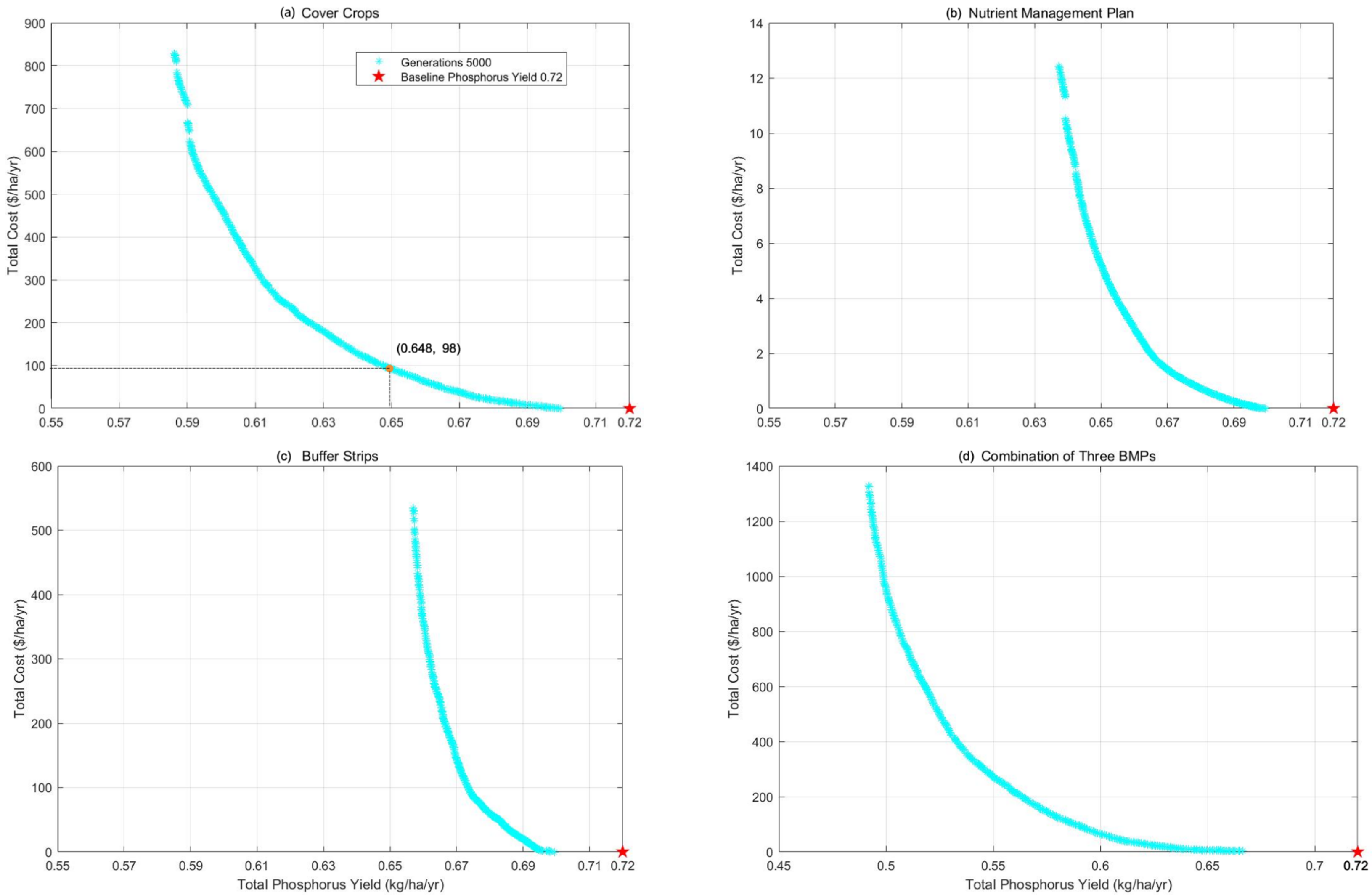

Figure 4-2 Pareto-optimal front between total costs and total phosphorus load

Figure 4-2c illustrates the NSGA-II optimal results for multiple BMPs and their combinations. The Pareto-optimal front yields the optimal solutions—consisting of cover crops, NMP, buffer strips, and their combinations—for total phosphorus reduction at the outlet of the watershed. The results showed that the combined BMPs could achieve 18.6% phosphorus reduction compared to cover crops costing $825 at a cost of $106. Compared to NMP only, BMPs combinations can achieve 12% phosphorus reduction at a cost of $11, which is $1 cheaper than NMP. Compared to buffer strips, BMPs combinations can achieve 9% phosphorus reduction for only $4.5. Therefore, the combinations of BMPs are less costly than the three single BMPs separately. For all three BMPs and their combinations applied throughout the watershed, up to a 32% reduction in total phosphorus can be achieved at a minimum cost of $1,328 per hectare per year (Figure 4-2d), which is the most cost-effective combination compared to single BMP implementation. Although no total phosphorus reduction objective has been set for the Grand River watershed, according to our analysis, none of the single BMPs for cover crops, NMP, and buffer strips could achieve a total phosphorus reduction of greater than 20%. Therefore, implementing a combination of BMPs is a good option for the GRCA. Figure 4-3 depicts the proposed distribution of BMPs generated by NSGA-II with a total phosphorus reduction of 32%. The combination of cover crops and NMP is the most selected BMPs throughout the Grand River watershed and are highly concentrated in areas of agricultural concentration in the upper and central regions due to their outstanding cost-effectiveness ratios. Additionally, BMPs are implemented in nearly every subwatershed to achieve the greatest total phosphorus reduction amount. However, this research simplifies the process by selecting 90 subwatersheds as variables in NSGA-II rather than the hundreds of hydrologic response unit (HRU) in SWAT, which does not subject BMPs distribution to land use types and may cause uncertainties and inaccuracy.

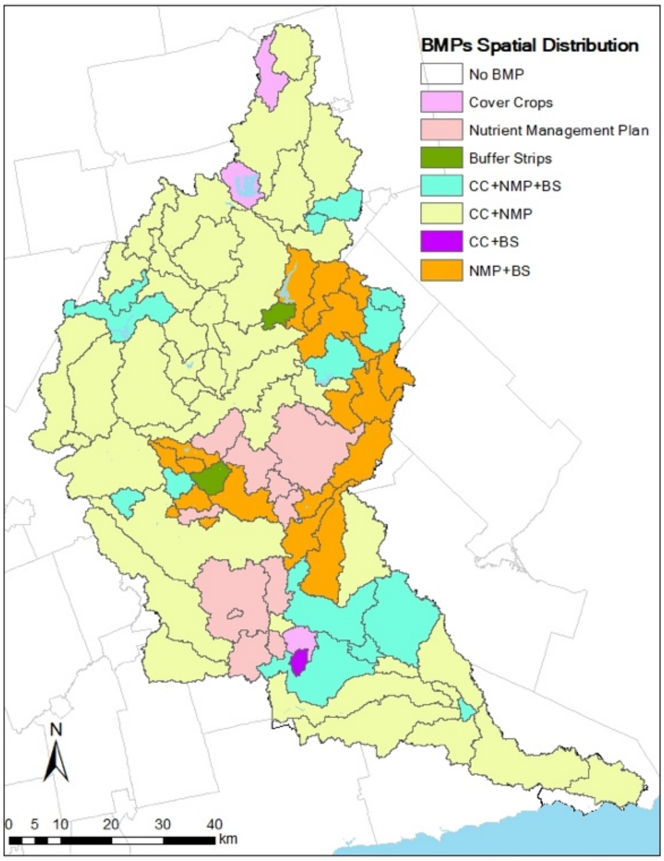

Figure 4-3 Types and distribution of BMPs selection for 32% total phosphorus reduction

5 Conclusions

This research sets out a NSGA-II to evaluate cost-effectiveness of BMPs implemented in the Grand River watershed and finally provides a suggestion for BMPs distribution. Data of BMPs total costs is provided by the GRCA, and two types of total phosphorus data—total phosphorus retention and total phosphorus load—are separately calculated by the GRCA and generated by SWAT. Based on the selected data, two types of NSGA-II are operated according to two combinations of objective functions—that is, minimization of total costs and maximization of total phosphorus retention, or minimization of total costs and minimization of total phosphorus loading. Six types of BMPs—cover crops, NMP, buffer strips, livestock access restriction, manure storage, milkhouse waste management—are selected for maximizing total phosphorus retention. Three BMPs—cover crops, NMP, buffer strips, and their combinations—are selected to minimize total phosphorus loading. Before the optimization procedure, a sensitivity analysis is carried out to ensure the efficiency and accuracy of the optimization. According to the sensitivity analysis, 500 solutions are selected in order to give decision-makers more efficient options to achieve the reduction target.

Regarding the evaluation of the existing BMPs in the Grand River watershed, with maximum retention of total phosphorus, the results indicate that NMP is the most cost-effective BMP and manure storage is the least cost-effective BMP. Livestock access restrictions is another cost-effective BMP, while the cost of retaining 1 kg/ha of total phosphorus is a little higher than NMP. Cover crops are not as cost-effective as the previous studies have shown. This is mainly because the co-benefits of cover crops are not accounted for in the analysis. For minimizing total phosphorus load, cover crops can achieve the greatest reduction in total phosphorus load compared to NMP and buffer strips. However, no single BMP can reduce total phosphorus as much as the BMPs combinations. Based on the optimization of BMPs combinations, a maximum 32% reduction in total phosphorus load can be achieved at a minimum unit cost of \$1,328. In order to improve water quality based on existing BMPs, the spatial distribution of the BMPs combinations is given in NSGA-II subject to the cost minimization and total phosphorus load minimization. The combination of cover crops and NMP is the most recommended BMPs for the entire Grand River watershed.

The results analyzed in this research are practical for farmers, conservation authorities, and policymakers to help establish BMPs schemes, adaptively allocate available funds, and help governments achieve the nutrients reduction objectives. As more research is conducted providing new insights, new polices and phosphorus reduction targets are expected for the eastern basin of Lake Erie in the near future. However, due to the limitation of data collection, assumptions in BMPs characterization, model setup, and financial instead of broader economic cost estimation, a more extensive economic welfare analysis including also the benefits of BMP implementation was not possible in this research. Additionally, the various assumptions reflect substantial uncertainties with respect to the actual cost-effectiveness of BMP implementation. Therefore, more monitoring and additional studies are required to improve the BMPs scenarios in NSGA-II to achieve more reliable optimization results.

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