Simulating Farmer Adoption of Agricultural Best Management Practices in the Upper Medway Creek Subwatershed

by

Liuyi Guo

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Science
in
Geography

Waterloo, Ontario, Canada, 2018

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

In the coupled human-environment system, humans play a central role in creating various environmental problems, and in turn, are impacted by these environmental consequences. In Canada, water quality degradation caused by agricultural activities has become a severe problem for a long time. It has been noted that the application of pesticides, manure and fertilizers have led to an increasing amount of chemicals and other pollutants in surface runoff which eventually converge into surface water bodies and result in water eutrophication. To maintain water quality and develop a sustainable agricultural system, Best Management Practices (BMPs) have been suggested. However, the high complexity of the agriculture system makes it difficult for policymakers and researchers to monitor and evaluate the performance of BMPs across large spatial scales and develop appropriate improvement strategies accordingly. Under these circumstances, agent-based models (ABM) stand out for their ability to deal with the complexities in the agri-environment system.

To better understand the dynamics of farmer's decision-making on BMP application under different socio-economic and environmental situations, an ABM has been developed to simulate the decision-making processes in the Upper Medway Creek subwatershed in this study. The ABM uses an optimizing decision-making structure that relies on choice by highest utility. In addition, the ABM integrates a weighted sum function to evaluate the influences of economic, environmental and social factors on farmers' decision-making. Results from the model pre-test were compared to those obtained from a random generator to examine how does the developed ABM perform against the random generator. Then, a sensitivity analysis has been performed using the one-factor-at-a-time method to examine the impacts of different potential interventions, including government subsidies and educational activities, on farmers' decision-making for certain BMP adoptions.

The results demonstrated that the developed ABM is robust in simulating farmers' decision-making on BMP application within the Upper Medway Creek subwatershed. According to the sensitivity analysis, providing subsidies and improving knowledge level of BMPs have positive effects on the implementations of certain BMPs in general. While comparing to improving knowledge levels of BMPs, providing subsidies makes greater contribution to motivating farmers

to adopt BMPs. For each BMP, a subsidy rate, which indicates the proportion of implementation costs needs to be subsidized to effectively encourage the BMP adoption, has been suggested. The results of this study provide a better understanding of how different socio-economic conditions affect farmers' decision-making on BMP adoptions and offer insights for policymakers to develop effective strategies incentivising farmers' adoptions of BMPs and further preserving water quality in the Upper Medway Creek subwatershed.

Acknowledgements

First and foremost, I would like to express my gratitude to my supervisor, Professor Peter Deadman, for the professional guidance and valuable support during my master's studies. I greatly appreciate all his efforts, time, ideas and funding to make my Master experience wonderful and meaningful. I could not have imagined having a better supervisor for my master's study. I would also thank my committee members Dr. Derek Robinson, Dr. Johanna Wandel, and Dr. Peter Johnson for their time and expert comments. My special thanks are extended to Dr. Merrin Macrae for her assistance in reaching others to support my research.

My sincere thanks go out to the UTRCA (especially Tatianna and Mike) for their support on the field survey and watershed data. I would also thank all survey participants for taking time to participate in the interviews and sharing their experience.

I would like to thank all my friends, Junqian Wang, Yue Zhao, Zhuo Chen, Bo Sun, Yuhao Wu, Yingxuan Qiu, and Lin Shen, who have always been there to support me throughout my study. I would particularly like to thank my friend Dr. Yue Dou for her assistance in providing constructive suggestions. I would like to offer my special thanks to Chen Chen for his help to my writing process. In addition, I am grateful for the joyful time spent with my friends in the Geospatial Innovation Lab.

Finally, I want to express my heartfelt thanks to my mom, dad, and cousin for their endless love and countless support.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Term
ABM	Agent-Based Model
BMP	Best Management Practices
CV	Coefficient of Variance
GIS	Geographic Information System
IR	Implementation Rate
LR	Linear Regression
LUCC	Land Use and Cover Change
OFAT	One-Factor-at-a-Time
Std.	Standard Deviation
WASCoB	Water and Sediment Control Basin

Chapter 1 Introduction

1.1 Background

In the recent years the world has experienced massive unexpected environmental changes and resource losses occurring in the coupled human-environment system which is characterized by the interactions between human system and natural environment across spatial and temporal scales (Filatova et al., 2013; An, 2012; Schlueter et al., 2012; Alberti et al., 2011). In this complex system, humans play a central role in creating various environmental problems (e.g. soil degradation, water eutrophication), and in turn, are impacted by these environmental consequences. Such interactions involve heterogeneity, nonlinearity, uncertainty, cross-scale feedbacks, emergence, and resilience against the adaption, which increases the difficulties for resource managers, policymakers, and researchers to explore and understand the behaviour of the coupled human-environment system (Deadman et al., 2004; Schlueter et al., 2012; Filatova et al., 2013; An, 2012).

Within the coupled human-environment system, agricultural systems have highly exposed to the risks of environmental change. In Canada, water quality and availability are extremely important to the agriculture system (Agriculture and Agri-Food Canada [AAFC], 2016 b). A large amount of freshwater with good quality is required for crop irrigation every year to ensure the food production. However, water flowing from agricultural fields carries soil, chemicals, and other pollutants due to the application of pesticides, and fertilizers including manure (AAFC, 2014). These contaminants, particularly phosphorus and nitrogen (King et al., 2015), are eventually transported into surface water bodies and lead to water problems such as eutrophication (Chardon & Schoumans, 2007; Johnston & Steén, 2000). Accordingly, the declining water quality potentially threatens a variety of human activities including agriculture (AAFC, 2016 c), food production (Kirby et al., 2003), fisheries (Schindler et al., 2008), tourism (King et al., 2015), as well as human drinking water supply system (Davies and Mazumder, 2003).

To maintain good soil and water quality and develop a sustainable agricultural system, Best Management Practices (BMPs) have been suggested. BMPs (e.g. conservation tillage, grassed waterways, windbreaks, riparian buffer strip) refer to a set of practical and affordable practices that farmers can take to protect soil health, enhance water quality and mitigate other adverse environmental impacts of intensive agricultural activities (Ingram, 2008; Feather and Amacher, 1994; Ontario Ministry of Agricultural, Food and rural Affairs [OMAFRA], n.d.). By choosing appropriate BMPs, the adverse consequences of agricultural activities can be reduced and agricultural production can be improved. In order to encourage the implementation of BMPs, various projects and strategies have been developed including the GLASI Priority Subwatershed Project (Ontario Soil and Crop Improvement Association [OSCIA], 2015), Farmland Health Incentive Program (FHIP) (OSCIA, 2016), and Clean Water Act (Government of Ontario, 2006) to provide funds and technical support for farmers. Whereas, human-environment interactions occur in the agricultural system usually involve multiple disciplines and are subject to change depending on the application time and location (An et al., 2005). The implementation of BMPs is limited by the topology, soil characteristics, subsurface conditions, and nutrient requirements of different crops, all of which may vary from location to location (Rudolph et al., 2015). A large amount of effort and time is required for investigating the regional conditions and determine the suitable BMPs. Moreover, the time lag between implementing BMPs and the time their impacts show up is different according to the time, location and the type of BMPs (Rudolph et al., 2015). This further adds challenges to policymakers and researcher to monitor and evaluate the performance of BMPs across large spatial scales and develop appropriate improvement strategies in a short term (Rudolph et al., 2015). Therefore, modelling technique has been suggested to mathematically and logically simulate the processes occurred across a large areal scale in the real world in a small amount of time. A growing number of methods such as statistical and mathematical models (Willock et al., 1999; Schreinemachers, 2005), multi-objective optimization method (Chiang et al., 2014), and conceptual model (Aubry et al., 1998), have been developed to simulate the dynamics in the system and explore the possible outcomes from certain management actions. Among these tools, agent-based models (ABM) stand out for their ability to deal with the complexities in the agri-environment system.

ABM is a useful computational tool that can provide a process-based representation of real world phenomenon embedded in a coupled human-environment system (Bert et al., 2014; Robinson et al., 2007; Parker et al., 2003). They simulate the microscale processes and predict the outcomes of different policies, accounting for the heterogeneity, feedbacks, nonlinearity, as well as temporal and spatial dynamics, without sacrificing large amount of time and budget. Compared to other models (e.g. statistical or mathematical models), ABM puts more attention on the uniqueness of individuals- farmers in the agricultural context (Bert et al., 2014). In an agricultural system, farmers are decision makers who are heterogeneous with regard to their demographic characteristics (e.g. income levels, gender, ages), sizes of their properties, personal experience, and preferences. They decide what BMPs to use and how to implement them to satisfy their needs in response to different social and environmental conditions. ABMs are able to reflect these heterogeneities and incorporate the interactions among farmers and between farmers and their environment into the simulation (Bert et al., 2014; Valbuena et al., 2010; Filatova et al., 2013). Furthermore, ABMs have the ability to incorporate economic factors (e.g. financial benefits), social impacts (e.g. policy, others' behaviours), environmental influences (e.g. climate change), and spatial accessibility (e.g. distance to water body) simultaneously, which can offer a realistic representation of the real-world interactions. These advantages make ABM a powerful tool to explore the process of decision-making in the agricultural management system and evaluate the effectiveness of suggested policies (Kent, 2014).

This study was conducted as part of the Agricultural Water Futures (AWF) project. The AWF project is a seven-year project funded under the umbrella of the Global Water Futures (GWF) project (University of Saskatchewan, n.d.). The project investigates how agriculture and food production systems may change in the future in response to risks and uncertainties brought by different climate stressors and socio-economic drivers (Univerisity of Waterloo, n.d.). By developing improved predictive tools, policy instruments, and governance strategies, it aims to achieve a goal of improving the agricultural water sustainability in Canada (Univerisity of Waterloo, n.d.). The entire project was organized into three work packages. Work package 1 (WP1) intends to calculate and estimate the water use and productivity for agricultural systems, specifically for crop and livestock production system, using a series of innovative models combined with agricultural hydrology models (Macrae et al., n.d.). Work package 2 (WP2) focuses on better understanding the impacts of climate and soil geomorphic factors on water quality through modelling and analysing the existing historical data and literature (Macrae et al., n.d.). Work package 3 (WP3) aims to model the dynamics of the coupled human-environmental system in affecting phosphorus transportation in agricultural watersheds using an ABM approach coupled with a hydrological model (Macrae et al., n.d.). This study contributes to the WP3 of the AWF project. It is a proof of concept study conducted to assess the impacts of different socio-economic and environmental factors on farmers decision-making process of the adoption of BMP. This study was designed to establish a framework for future modelling efforts of the simulation of human-environmental interactions in agricultural system in Canada.

1.2 Goals and Objectives

This study intends to answer the question of how different socio-economic conditions may affect individual farmers' behaviour when adopting BMPs in the Medway Creek subwatershed. The goal of this study is to better understand the dynamics of farmer's decision-making on BMP application under different socio-economic and environmental situations and provide insights for policymakers to develop more effective strategies for water quality preservation. Six BMPs, including the reduced tillage, the no-till system, grassed waterways, riparian buffer strips, Water and Sediment Control Basin (WASCoB), and windbreaks are focused in this study. By using both geographic information system (GIS) based approach and ABM, four objectives has been identified:

(1) Determine the possible BMPs for each agricultural field in the Medway Creek subwatershed;

(2) Develop an ABM which is able to represent the heterogeneities among farmers and their environment in the Upper Medway Creek subwatershed;

(3) Model farmers' behaviours on BMP decision-making using the developed ABM

(4) Examine the impacts of different potential interventions to change farmers' decisions to adopt certain BMPs.

The first objective is achieved by considering the topographic characteristics and spatial accessibility of an agricultural field. The second objective focuses on the internal (e.g. demographic characteristics, preferences) and external (e.g. policies, market price) factors related to farmers' decision-making on BMP application, and provide a tool for addressing the third and fourth objective. The third objective is to examine the outcomes of the developed ABM under a set of initial conditions. The fourth objective is to estimate how farmers' decision-making will change in response to different intervention, including government subsidies or educational activities.

1.3 Thesis Outline

This thesis consists of six chapters. This chapter provides the background knowledge and the overview of this research. Chapter 2 reviews the contributions of previous literature regarding the implementation of BMPs and the application of ABM in the study of human decision-making. Chapter 3 introduces the study area and describes the adopted methodology and the used data. Chapter 4 states the results obtained in this study. Chapter 5 analyses the results of this study and discusses the implications, limitations, and contribution of this study. Chapter 6 summarizes the findings and outlines the possible future work.

Chapter 2 Literature Review

This chapter introduces the required background for this study including BMPs examined in this study, influential factors of BMP adoption, methods for identifying land-use/land-cover change (LUCC) patterns, the application of ABM in simulating human decision-making, the implementation of ABM of LUCC, techniques for model validation, and different approaches for sensitivity analysis. The first section summarizes how each BMP works, what benefits does each BMP have, as well as what requirements need to be met to implement each BMP. In the second section, two methods that have been used by previous literatures to determine the major LUCC change patterns are presented. The third section provides an introduction of the basic structure of the ABM and its advantages in simulating human decision-making processes. Moreover, this section discusses and compares two commonly used decision-making structures. In the last section, the purposes of sensitivity analysis and approaches that can be used to perform the sensitivity analysis depending on the research goals are presented.

2.1 Introduction of Agricultural BMPs

Agricultural Best Management Practices (BMPs) refer to a set of practical and affordable practices that farmers can take to protect soil health, enhance water quality and mitigate other negative environmental impacts of intensive agricultural activities (Ingram, 2008; Feather and Amacher, 1994; OMAFRA, n.d.). By choosing appropriate BMPs, farmers are able to maintain more responsible and sustainable agricultural environments without sacrificing soil and water resources, while improving agricultural production and saving farm management costs (Ingram, 2008; OMAFRA, n.d.). The three most commonly adopted BMPs in the Upper Thames River watershed are discussed in this section, which are erosion control structures, tillage systems, and windbreaks.

2.1.1 Erosion Control Structures

Erosion control structures are constructions used to reduce the erosive force of the runoff and remove the sediments from the water flow (Credit Valley Conservation, n.d.). Depending on the characteristics of farm fields and the types of erosion, different erosion control structures such as grassed waterways, water and sediment control basin (WASCoB), and riparian buffer strips could be implemented.

2.1.1.1 Grassed Waterway

Grassed waterways are permanently vegetated channels constructed for redirecting runoff water to a stable outlet and alleviating soil erosion. The vegetative cover in the waterway increases surface roughness that slows down the water flow and traps the sediment, thus further reducing sediment loading and protecting soil against rill and gully erosion. Generally, grassed waterway channels are designed to follow the natural drainage ways fitting the characteristics of the landscape. According to the Upper Thames River Conservation Authority (UTRCA) (n.d. b), a grassed waterway is recommended to be implemented when a drainage area is greater than 35 acres. When designing a grassed waterway, the dimensions such as width, height, as well as the channel grades, and the shape of waterway are designed depending on the volume of runoff water flow and soil characteristics (Stone and McKague, 2009). A slope greater than 1% has been suggested to prevent out-of-bank flow (United States Department of Agriculture [USDA], 2007). A grassed waterway has a minimum lifespan of ten years (Schroter and Kansas, n.d.).

It has been noted by previous studies that grassed waterways are an effective method against soil erosion. Typically, about 60% to 80% of sediment load can be reduced by implementing grassed waterways (Kansas, 1989). The efficiency of grassed waterways may vary depending on soil characteristics and their design. Comparatively, grassed waterways are more efficient to reduce soil erosion than to control surface runoff (Kansas, 1989). From Mtibaa et al.'s study (2018), grassed waterways reduced sedimentation by 40%, yet surface runoff by only 15.7%.

The grassed waterway is usually combined with other BMPs such as conservation tillage to achieve better effectiveness (Kansas, 1989; UTRCA, n.d. b). Although the effect of grassed waterways on sediment reduction is relatively inferior to buffer strips, the annualized costs (including investment and maintenance costs) for applying grassed waterways are lower than applying buffer strips, which are respectively 18.13 dollars and 40.71 dollars per hectare, respectively (Mtibaa et al., 2018). Additionally, depending on the crop type, topography, and the climate, adopting the grassed waterway could slightly affect the crop yields both positively or negatively (Kansas, 1989).

2.1.1.2 WASCoB

WASCoBs are small embankments constructed to temporarily store the runoff water in order that the sediments can be trapped and collected (UTRCA, n.d. b). After sediments are settled out, the water will be slowly released, thus reducing gully erosion (St. Clair Conservation, n.d.). According to the area of watershed, slope, drainage area, soil characteristics and farm management, the number, size and structure of WASCoBs may vary. First, a single WASCoB is recommended for agricultural field covering an area between 2 acres and 50 acres (NRCS, 2010 b). For those larger than 50 acres, multiple WASCoBs are needed (Maitland Conservation, 2017). Depending on the field slope, broad-based or narrow-based berm can be installed for WASCoB in cross-section. For fields with a slope smaller than 14%, a broad berm is established; while a narrow berm is used if the slope is less than 8% (Maitland Conservation, 2017).

Various studies have been conducted to investigate the sediment removal and nonpoint sources removal efficiencies of the WASCoBs. Yang et al. (2013) found that there was a positive effect on sediment and total phosphorus reduction after implementing new WASCoBs. They found that annual average sediment and total phosphorus loadings were reduced by 559 tons and 334 kilograms, respectively. Because the WASCoBs cannot control soluble phosphorus, its efficiency for phosphorus reduction is somewhat lower than sediment trapping (Kansas, 1989). According to Kansas (1989), WASCoBs can typically remove sediments by 60% to 95% and reduce phosphorus loads by 25% to 50%. They also stated that the sediment removal efficiency could be greater than 90% if it was well designed and maintained. Usually, a typical basin, which is able to serve approximately 5 to 10 acres of croplands, will have ten-year lifespan (Kansas, 1989).

2.1.1.3 Riparian Buffer Strips

Riparian buffer strips are permanent vegetated areas established along rivers, streams or other natural watercourses to reduce the speed of runoff and capture the sediments. Riparian buffer strips serve as barriers between agricultural fields and surface water body that slows down the runoff coming from the fields, reduces sediment and nutrient transport to watercourses, and reduces soil erosion. The effectiveness of buffer strips varies depending on the soil characteristics (e.g. soil texture, slope), vegetation species, as well as the dimension of the buffer strips (e.g. width, length). For example, the effectiveness of a riparian buffer strip is largely reduced if an agricultural field has a slope greater than 15% (Hawes and Smith, 2005; Natural Resources Conservation Service [NRCS], 2010 a).

The documented trapping effectiveness of buffer strips varies widely. Mtibaa et al. (2018) compared the effectiveness of 5-m and 20-m buffer strips, and the results showed that the 20-m buffer strips have greater sediment trapping efficiency of 89%, while 5-m buffer strips only trapped 59% of sediment. According to Borin et al. (2005), a 6-m buffer strip could reduce the sediment by 92% in three years. Generally, as concluded by Liu et al. (2008) from more than 80 studies, the sediment reduction rate for the riparian buffer strips ranges from 45% to 100%. For total phosphorus reduction efficiency, Balana et al. (2012) noted that the total phosphorus loads can be reduced by 27% to 97% by implementing the riparian buffer strips (as cited in Uusi-Kämppä and M Kilpinen, 2000). Different species of vegetative covers play different roles in buffer strip system. For example, grasses are planted to leach and trap the nutrients in the runoff, shrubs and trees with deeper roots are planted to better filter the nutrients and sediments, and also stabilize the stream bank (UTRCA, n.d. a; Walker, 2000).

2.1.2 Tillage System

Soil and water erosion can also be affected by different tillage systems. Depending on the proportion of land surface covered by residues or crop remains, conventional tillage, conservation tillage, and no-till system, are usually applied by farmers.

2.1.2.1 Conventional Tillage

Conventional tillage refers to tillage systems that leave less than 30% of the land surface covered with crop residues or remains (e.g. straw, stubble and leaves) after planting (Gasser, 1993; Hofmann, 2015; UTRCA, n.d. c). Because of the small amount of residue left on the ground, more soil is directly exposed to precipitation and wind, resulting in a higher risk of soil erosion (Gasser, 1993). Moreover, the application of mouldboard system results in higher equipment and labour costs for conventional tillage compared to other tillage systems (UTRCA, n.d. c; Kansas, 1989). Whereas conventional tillage still has some advantages. First of all, the conventional tillage involves the implementation of mouldboard plough which loosen and invert the soil, bury weeds and crop residues under the soil and bring fresh nutrient to the top layer of the soil (Shubham Industries, n.d.). In such a way, the soil porosity can be increased which gives rise to a higher soil microbial activity with conventional tillage (UTRCA, n.d. c). Moreover, conventional tillage requires less herbicides. Kansas (1989) compared and summarized the needs of herbicides for different tillage systems from previous literature, they found that conventional tillage requires approximately 50% or less herbicides compared to no-till systems. Hofmann (2015) also noted that the machinery required for implementing conventional tillage are widely available and familiar to farmers, which therefore, saves the cost for new equipment and reduces learning effort.

2.1.2.2 Conservation Tillage

Different from the conventional tillage, conservation tillage, or reduced tillage system, aims to leave more than 30% crop residues on the soil surface to minimize the disruption of soil (Gasser, 1993; Hofmann, 2015; UTRCA, n.d. c). These crop residues will increase soil surface roughness and increase the organic matter at soil surface, which eventually reduce soil erosion (Gasser, 1993; Devlin et al., 2002). According to previous literature, this tillage can reduce 30% - 60% (or 1 - 12 tons per acre) of soil loss compared to conventional tillage (Kansas, 1989). In addition to soil erosion, reduced tillage also leads to considerable reduction of phosphorus loss from agricultural land. In Yang et al.'s (2013) study, 43.6% of total phosphorus loss was reduced with conservation tillage. This accords with phosphorus reduction rate summarized by Kansas (1989) that 20% to 50% of phosphorus losses can be mitigated with reduced tillage. However, some studies indicate that soluble phosphorus may increase due to the implementation of reduced tillage. For instance, though the particulate phosphorus was reduced by 37%, the soluble phosphorus was about 36% greater after using reduced tillage compared to conventional (AAFC, 2013). Generally, as concluded by Kansas (1989), the loss of total phosphorus can be mitigated by the reduced tillage even though the dissolved phosphorus was greatly increased. Reduced tillage has been identified by many researchers as the most cost-effective method for reducing nonpoint source losses from agricultural land (Kansas, 1989). As previously mentioned, conventional tillage requires more expense in terms of equipment and labour, while reduced tillage requires more pesticides and herbicides (Kansas, 1989; Mtibaa et al., 2018). Whereas the expenses for labour, machinery and fuel are relatively lower than for conventional tillage

(Kansas, 1989; Mtibaa et al., 2018). Data acquired from previous studies indicates that reduced tillage on corn and soybean can save 52% and 58% labour cost, respectively, while machinery-related costs reduced from 54.84 dollars per acre with conventional tillage to 46.10 dollars per acre with reduced tillage (Kansas, 1989).

2.1.2.3 No-till system

Unlike other tillage systems, the no-till system tends to reduce soil erosion by avoiding all tillage techniques and minimizing the disturbance of soil (OMAFRA, n.d.; Hofmann, 2015; Walker, 2000). Due to its effectiveness in reducing soil loss and nonpoint source pollution, the no-till system has been widely adopted by farmers who are concerned with soil and water quality to prevent soil erosion. Mtibaa et al. (2018) reported sediment yields under no-till farming with residue management were 42.46% lower than conventional tillage. Kansas (1989) concluded that no-till farming is able to reduce soil loss by 60% to 90% and phosphorus loads in the runoff by 50% to 80% in general. However, the effectiveness of phosphorus reduction may vary depending on different land characteristics such as slope and soil texture. Liu et al. (2014) investigated and compared the cost-effectiveness for seven BMPs, and the results indicated that no-till implemented on slope less than fifteen degree reduced total phosphorus by 21.93% which is outside the phosphorus reduction range summarized by Kansas (1989). Furthermore, costs for no-till farming are lower than both reduced tillage and conventional tillage (UTRCA, n.d. c). It has been shown by Liu et al. (2014) that costs decrease from conventional tillage by 11.37 dollars per acre annually with no-till farming. Kansas (1989) also summarized that no-till farming saves roughly five to fifteen dollars per acre compared to conventional tillage. This is mainly because of less labour, fewer machinery and less fuel required by no-till system.

2.1.3 Windbreaks

Windbreaks are trees that are planted linearly on an agricultural field to reduce wind speed and redirect wind to protect agricultural fields and livestock. In addition to the main function of reducing wind speed, a well-designed windbreak can also bring many environmental and economic benefits. Windbreaks are able to protect soil from wind erosion and prevent crops and livestock from wind damage. According to fact sheet reported by UTRCA (n.d. d), windbreaks can protect soil within a distance of ten to fifteen times the height of the trees. It has been noted that the declined wind speed improves the soil pollutant filtering ability and decreases plant evaporation rates, which leads to better water quality and higher soil moisture (USDA, 2002; UTRCA, n.d. d). As concluded by Brandle (n.d.), the humidity may be increased by 2% to 4% by applying windbreaks. In the winter, especially in many northern, semi-arid areas, well established windbreak is significant for producing winter wheat due to its ability to capture snow and recharge the melting snow to adjust soil moisture preventing winter desiccation. Meanwhile, the reduced wind speed can also slightly increase the soil temperature within the windbreak sheltered areas (Hodges and Brandle, n.d.; Brandle, n.d.). As a result of all these benefits (include higher soil moisture, better water quality, and warmer temperature), crop yields can be increased by about 5% to 45% (Hodges and Brandle, n.d.; UTRCA, n.d. d; USDA, 2012). It has been stated by previous literatures that the economic return is increased after applying windbreaks (USDA, 2012; Quam et al., n.d.; Brandle, n.d.; USDA, 2002). This is not only because of the improved crop yields, but also attributed to the reduced costs for energy (USDA, 2012; Quam et al., n.d.). Furthermore, windbreaks can also provide shelter and food for wildlife, increase carbon storage, as well as enhance aesthetics of the landscape (USDA, 2012; USDA, 2002; Hodges and Brandle, n.d.).

The efficiency of a windbreak is determined by various factors including height, density, number of rows, species, length, and orientation (Brandle, n.d.; Ontario Woodlot Association, n.d.). For field protection, windbreaks are typically oriented perpendicular to the prevailing wind at the edge of the field to maximize the protected areas. Windbreak density, which is the ratio of the solid portion of the tree barrier to the total planted areas, is another critical factor that affect the effectiveness of the windbreak. It has been summarized that windbreaks with medium density of 40% to 60% contribute to the greatest protection for sheltered fields (Hodges and Brandle, n.d.; Brandle, n.d.; USDA, 2002). Under this circumstance, an area within a distance of approximately ten to thirty times the height of the trees on the downwind side and two to five times on the upwind side, can be protected (Brandle, n.d.; USDA, 2002). At least 20% of wind speed can be reduced, which can effectively improve crop yields and reduce soil erosion (Ontario Woodlot Association, n.d.). In order to take full advantage of windbreaks, the length of a windbreak has to be at least ten times the tree height (Brandle, n.d.).

2.2 Influential Factors of BMP Adoption

BMPs have been widely suggested for reducing non-point source pollution caused by agricultural activities (Ingram, 2008). To effectively improve water quality, it is important to understand how different factors impact the BMP adoption. Factors that influence farmer's BMP adoption can be grouped into seven categories including financial incentives, information and awareness, neighbour's behaviour, locations, farmers' demographics, characteristics of the farm, and farmer's environmental consciousness.

Financial incentives have been shown to have positive impacts on the adoption of BMPs. Läpple and Hennessy (2014) explored the impact of financial rewards on farmers' willingness to participate in agricultural extension programmes. They compared the farm performance of farmers who joined the programme to those who did not join the programme. Results indicate that financial rewards are the main factors influencing famers' willingness to participate in an extension programme that can improve farm performance. Ward et al. (2016) have also conducted a study to explore the impacts of farmer's preferences on adopting agricultural conservation practices. They found that some farmers would not adopt conservation agricultural practices if there was no financial incentive provided. They also indicated that providing subsidies increased the adoption of agricultural conservation practices. According to Tiwari et al.'s study (2008), credits or loans can positively affect the implantation of BMPs. While associated costs can have a negative influence in the BMP adoption. A survey was conducted by Tosakana et al. (2010) to examine how different factors affect the adoption of buffer strips. Results show that maintenance costs were negatively related to the adoption of buffer strips.

Timely access to information related to conservation programs or BMPs plays an important role in BMP adoption. According to D'Emden et al. (2006), the availability and use of technical information are influential to the adoption of conservation tillage. In Rezvanfar et al. investigated how different factors affect the adoption of soil conservation practices using a set of descriptive and inferential statistics (e.g. standard deviation, correlation analysis, and regression analysis). It has been noted that the level of awareness and the availability of information can positively impact the adoption of conservation practices. Interactions with local conservation agencies, extension services, and farm organizations are also correlated with the BMP adoption. Woods et al. (2014) have found that farmers who have frequent interactions with local conservation staff are more likely to adopt conservation practices. Tamini (2011) has studied factors that determine the adoption of BMPs. Through a non-parametric approach, the impacts of agri-environmental extension activities have been analysed. Results show that farmers who participate in an agri-environmental advisory club are more willing to adopt BMPs.

Neighbour's behaviour has been identified as a critical factor in influencing the BMP adoption. According to Wollni and Andersson (2014), who have studied the spatial patterns of organic adoption in response to several influential factors, farmers are more likely to adopt organic farming when it is also be implemented by their neighbours. The similar statement has also been concluded by Turinawe et al. (2015) who have conducted a study to determine influential factors for adopting conservation agriculture. A logistic regression model was performed to build the relationship between influential factors and adoption rates. Results indicate that when other parameters are all fixed, having neighbours implementing conservation technologies can increase the adoption rate by 45% (Turinawe et al., 2015).

Location may have great influence on farmer decision-making regarding BMPs. Agroecological factors such as soil type and precipitation pattern that vary by location can impact farmers decision-making on BMP adoption (D'Emden et al., 2006). Moreover, political views and policies in different locations may also impact the adoption of BMP. Reimer et al. (2013) carried out a study to explore the adoption of conservation practices in response to different agri-environment policies across the United States. A fractional logit model was applied to assess the influence of different factors in adoption rates of conservation practices. It has been found that the adoption rates in fifty states show different values.

It has been found by previous studies that the age, gender, education level, and income are all factors that impact the adoption of BMPs. For both age and gender, mixed results can be found from previous literature. Rahelizatovo and Gillespie's study (2004) has found that younger dairy producers are more willing to adopt BMPs in Louisiana. While in Tiwari et al.'s study (2008), older farmers are more likely to adopt the conservation technology in Nepal. Tiwari et al. (2008) also found that in Nepal, female farmers are more likely to implement conservation technology than male farmers. An opposite conclusion was obtained by Ward et al. (2016). In addition, a farmer's education level will also affect their BMP adoption. AAFC (2012) has summarized factors affect BMP adoption in Quebec. It shows that more educated producers are more likely to adopt the riparian buffer strip, crop rotation, and manure management. While the farmer's education level has no impact to reduce the herbicide use (AAFC, 2012). Farmers income level can also impact the adoption of BMPs. It has been concluded by Vignola et al. (2013) that farmers with low income are more risk-averse and therefore, are less likely to adopt BMPs.

Characteristics of the farm including the land tenure, crop and livestock diversity, and farm size. As concluded by previous literature, renters have a lower probability to adopt BMPs than farm owners because environmental effectiveness brought by BMPs can benefit the owner for a longer period (Parker et al., 2007). In Parker et al.'s study (2007), impacts of land tenure relationships on farmer's conservation behaviours were investigated. They found that farm succession and land tenure are positively related to the adoption of BMPs. However, the opposite conclusion was obtained by Varble et al. (2016) that renters are more likely to adopt an intensive corn rotation and conservation tillage than the owner. To explore the role that crop and livestock diversities play in the cover crop adoption, a study has been conducted by Arbuckle and Roesch-McNally (2015). Results obtained from this study indicate positive relationships between crop and livestock diversity and cover crop adoption. Finally, farm size is also an influencer of BMP adoption. In Baumgart-Getz et al.'s study (2012), it has been discovered that farmers operating small farms are less likely to adopt BMPs. This is because small farms usually don't have sufficient resources and therefore, they need more incentives to operate the farm (Baumgart-Getz et al., 2012).

Farmer's environmental consciousness has been identified as an important factor that influences the BMP adoption. Previous literature has found that farmer's awareness of the environmental benefits of BMPs can result in adoption. Gedikoglu and McCann (2012) have studied the similarities and differences in the factors that affect the adoption of environment-oriented and profit-oriented practices using the probit regression. Results show that the perceived environmental effectiveness and profitability contributed to an increasing trend of the adoption of environment-oriented practices. The same conclusion was also obtained by Tosakana et al. (2010) that the awareness of the environmental benefits of conservation practices can impact the adoption positively. Additionally, farmers' attitudes regarding the land cost and conservation policy were identified as a critical factor for predicting the adoption of the Conservation Reserve Enhancement Program in the New York City watershed.

In summary, financial incentives, information and awareness, neighbour's behaviour, locations, farmers' demographics, characteristics of the farm, and farmer's environmental consciousness have been identified as major factors that influence the adoption of BMP. Financial incentives including government subsidies and financially reward can positively affect BMP adoption. While maintenance costs may reduce the probability of adopting BMPs. Neighbour's behaviour is positively related to BMP adoption. Moreover, BMP adoption will vary depending on the location of the farm. Impacts of farmers' age, gender, and land tenure can be both negative and positive. While education level, income, farm size, and farmer's awareness all have positive relationships with BMP adoption.

2.3 Identify LUCC Patterns

Two methods have been reviewed to identify land use and cover change patterns. Both of the methods are implemented using land use maps from more than two observation years. Wang et al. (2012) have developed a trajectory computing method which uses a set of trajectory codes to express the LUCC change trajectories of the given time series. Because this is a pixel-based study, trajectory code will be calculated for every pixel according to the LUCC classification results using Equation 2.1:

$$T_{ij} = (G1)_{ij} \times 10^{n-1} + (G2)_{ij} \times 10^{n-2} \ldots + (Gn)_{ij} \times 10^{n-n} \qquad \text{Equation 2.1}$$

where T_{ij} is the trajectory code of the pixel at row i and column j in the trajectory layer; n is the number of time nodes which is four in Wang et al.'s study; $(Gn)_{ij}$ is the LUCC class code of the corresponding pixel. Accordingly, trajectory codes consist of four digits each of which represents a corresponding LUCC type at the given observation year. Trajectory codes with same number, such as 1111 and 3333, stand for pixels with no LUCC change overtime; while others with different numbers, like 1234 and 1313, stands for pixels with a series of changes. However, this method is only useful for those images with a maximum of ten LUCC classes as the decimal system is used.

Another approach to identify LUCC change trajectories has been addressed by Swetnam, (2007), which aims to determine change patterns by creating a multi-attribute database. Land-use maps of 23 sites in six time-steps have been used in this study. Every land-use map was converted into raster format and classified to twenty different LUCC types, each of which has been coded with number ranging from one to twenty. In order to represent the LUCC occurred in each site, six land-use maps for a same site were combined into one multi-attribute raster file whose attribute table records both the original value and new values at each location. In the obtained attribute table, each column indicates the LUCC type in a time-step; each row illustrates the LUCC change happened at a given pixel. Nevertheless, researchers have to go through every row in the multi-attribute table to identify the most significant trajectories, which is time-consuming. Thus, this method is not suitable for studies that simulate a large number of LUCC classes or many time nodes.

Although, both of the methods are straightforward and easy to understand, drawbacks exist. As mentioned, the trajectory computing method can only be used to simulate images with a maximum of ten LUCC categories. On the other hand, the Swetnam's method is limited to the raster data with a pixel type of 32-bit floating point or double precision. Comparing the two methods, the trajectory computing method would be more practical than the Swetnam's approach when the number of LUCC types is low. The obtained trajectory codes allow the researcher to identify different LUCC trajectory in a timely manner. In this way, it is easy not only to count the number of each LUCC trajectories occurred in the study area, but also to visualize the results by creating a distribution map.

2.4 Application of ABMs to Simulate Human Decision-making

Agent-based modelling (ABM) is a micro-scale computational modelling approach that can be used to simulate the complex interactions between human and natural systems. It has been applied as a powerful tool to explore the human decision-making and behaviours due to its flexibility and unique capacity (Evans and Kelley, 2004; Mialhe et al., 2012). Unlike other models, ABM provides a more process-based understanding of the interactions, learning, and adaptation of human decision-making (Bert et al., 2014; Robinson et al., 2007). Its capability to incorporate multi-scale processes and multi-disciplinary knowledge also makes it stand out from other models such as mathematical and statistical models (Parker et al., 2003). Moreover, ABM is also able to incorporate the heterogeneity among individuals and their environment during the simulation, which offers a more realistic representation of the processes occurring in the real world (Filatova et al., 2013; Matthews et al., 2007; Robinson et al., 2007).

An ABM usually consists of three components including agents with unique attributes, the environment where agents live, and rules which regulate agent's behaviour. Agents are decision-makers that interact with each other and their environments. They may learn from other agents and adapt to the changing environment to meet a set of goals. An agent's behaviour is specified through a given set of rules or behaviours models (e.g. neural networks) (Macal and North, 2010). The environment offers a space for agents to interact with each other and behave. It is affected by agents' behaviours, and meanwhile, plays an important role in affecting agents' decision-making. In an ABM, all of the interactions, learning and adaptive processes are defined by a set of rules which are grounded in the decision theory. The decision theory is the study of how the decisions are made by agents (Hansson, 2005; Steele and Stefánsson, 2015). Grounding the ABM into established decision theory not only improves the model reusability, but also enables the model application in prediction (Groeneveld et al., 2017). There are four theories that are commonly used in the ABM: (1) expected utility theory (Bernoulli, 1954) that assumes that agents choose the option that will maximise their expected utility based on the perfect and complete knowledge; (2) concept of bounded rationality (Simon, 1956) that assumes that agents with limited knowledge and cognitive capabilities will choose the option that can satisfy their aspiration level instead of the optimal one; (3) stochastic theory (Hey and Orme, 1994) that proposes to incorporate stochastic elements (e.g. a random error term) into the model that agents choose options randomly; (4) the theory of planned behaviour (Ajzen, 1985) that suggests that agents make decisions based on their intentions, beliefs, habits, and perceived social pressure.

Two main decision architectures are used in ABM - the heuristic structure and the optimizing structure - to simulate the human decision-making process.

2.4.1 Heuristic Decision-making Structure

Heuristics refers to a set of relatively simple rules that guide the decision-making process of an individual (Schreinemachers and Berger, 2006). Instead of always making decisions by comparing all the alternatives and selecting the optimum option, the heuristic structure emphasises that decision makers are limited by their cognitive capabilities (Groeneveld et al., 2017; Parker et al., 2003). During the decision-making processes, heuristic agents assess options sequentially and stop once they find an option that can reach their aspiration level. Therefore, setting decision rules with appropriate conditions and correct sequence is important to simulate the heuristic behaviours (Schreinemachers and Berger, 2006). Heuristics are usually used by those who make decisions under the great uncertainties of natural phenomena such as farmers (Schreinemachers and Berger, 2006). For example, the cool-season grass should be seeded 45 days before the estimated date of the first fall frost (PENNINGTON, n.d.). Various methods, including sociological research methods, data-mining techniques, participatory modelling, laboratory experiments, group discussions, or expert opinions (Schreinemachers and Berger, 2006; Groeneveld et al., 2017), can be used to parameterize the decision rules and determine the conditions. For example, Valbuena et al. (2010), who have used the heuristic agents in a regional-scale LUCC model, have determined the thresholds between different options based on both expert knowledge and a field survey. Deadman (1999) has used a series of common-pool experiments to parameterize and develop an ABM to understand individual actions and group performances. In baseline experiments, agents intend to invest tokens in two markets, which the first market have a constant return rate; and the second market offers a return that varies depending on the relationship between total group investment and individual investment. Low-endowment experiments and high-endowment experiments in which 10 tokens and 25 token endowments were given to each agent, respectively, were also run. Castella et al. (2005) has used heuristic agents in an ABM to simulate the LUCC in Vietnam. They have applied group discussions and participatory modelling to identify the relations between the driving factors and their effects (e.g. relations between crop yield and labour).

Generally, the heuristic behaviour is addressed using a decision tree. For instance, Deadman et al. (2004) have developed a LUCITA (Land Use Change in The Amazon) to explore the interactions between farming households and LUCC in the Amazon frontier region using heuristic decision-making strategy. Four key factors including burn quality, annual subsistence requirements, household characteristics (i.e. household capital endowment level, and household composition), and soil quality (i.e. soil pH), have been assessed. For each agent, three decisions may be made as Figure 2-1 shows. The first decision was made by evaluating whether their subsistence requirements have been met. If not, the agent assesses whether the capital and labour requirements have been met for planting annual crops; if yes, the agent then assesses the soil quality and further check if there are enough capital and labour for planting perennials or pasture. Different plants are seeded by following the decision tree (Deadman et al., 2004).

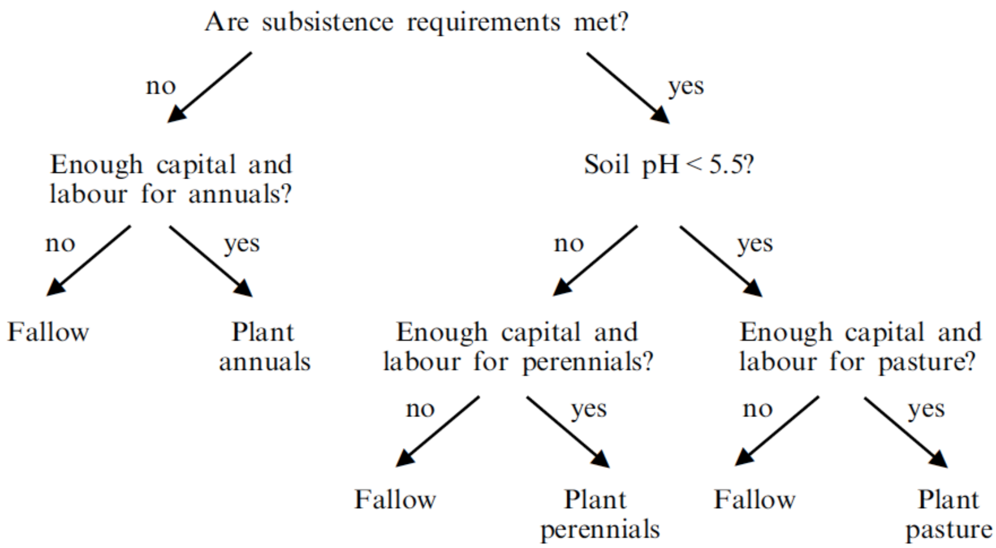


Figure 2-1 Flow of household decision-making in Deadman et al. (2004)

Another example is the CARCHSCAPE model developed by Becu et al. (2003) to understand the effects of upstream irrigation management on downstream agricultural availability in Thailand. The crop decisions are made according to the season, rice production expectation, labour requirements, land-use type, and water availability (i.e. expected average irrigation level). Agents first check the season of planting; if it is in the wet season, the rice production expectation is checked. If the rice production expectation is less than the annual rice needs, rice is planted; while if the needed rice is less than the rice production expectation, land-use type should be checked. If it is in Paddy zone, check the expected level of irrigation and decide the cash crop that will be planted, if it is in Upland zone, the expected irrigation level is automatically identified as high, therefore, particular cash crop is selected. If it is during the dry season, the land-use is first examined. If the land-use is Paddy zone, the agent's expectation of irrigation level is evaluated, and then the cash crop type is determined based on the identified irrigation expectation; if the land-use is Upland irrigated zone, the expected irrigation level is identified as high and the particular cash crop is planted (Becu et al., 2003).

The application of heuristic decision trees also allows the incorporation of agent typology. A typology refers to a system to classify agents to different categories depending on specific criteria (Valbuena et al., 2008). In a heuristic-based decision-making model, agents can be classified into several categories depending on the modelling objectives. Agents in different categories are assigned with different decision trees to guide them through decision-making processes. In Mialhe et al.' s study (2012), heuristic decision-making strategy has been incorporated into the developed CHANOS model to investigate the influences of various variables on farmers decision-making process related to the cropping system. In this study, agents have been divided into three types. According to the level of satisfaction and certainty, agents make decisions following four cognitive strategies: (1) repetition which suggests keeping the current cropping system; (2) social comparison which implies that the agent chooses the majority cropping system among their social network if the currently used one is less than one third of the total; (3) imitation which suggests choosing the most commonly used cropping system; (4) deliberation which proposes to choose the best cropping system depending on the historical salinity records. As shown in Figure 2-2, different decision-making processes may be addressed depending on the agent type. A-type agents make only one decision according to their satisfaction level; B-type agents use two decisions to choose a favourite cropping system according to both satisfactory and certainty level; three decisions were made by C-type agents to decide the cropping system that will be implemented at the next iteration (Mialhe et al., 2012). The agent typology has also been conducted in MameLuke framework by Huigen (2004) to study the interactions between the socioeconomic system and LUCC in Philippine using the heuristic decision-making strategy. In this framework, agents have been divided into categories depending on the theory that a researcher wants to explore. The agent category determines the available options for an agent who then choose these options based on their motivations. The decisions have been made following sequential steps. First, the agent has to check whether the requirements of implementing an option are met by the agent. If the requirements have not been met, move on and check the next option in the list; otherwise, the agent pays the option with its initialisation costs and executes the selected option (Huigen, 2004).

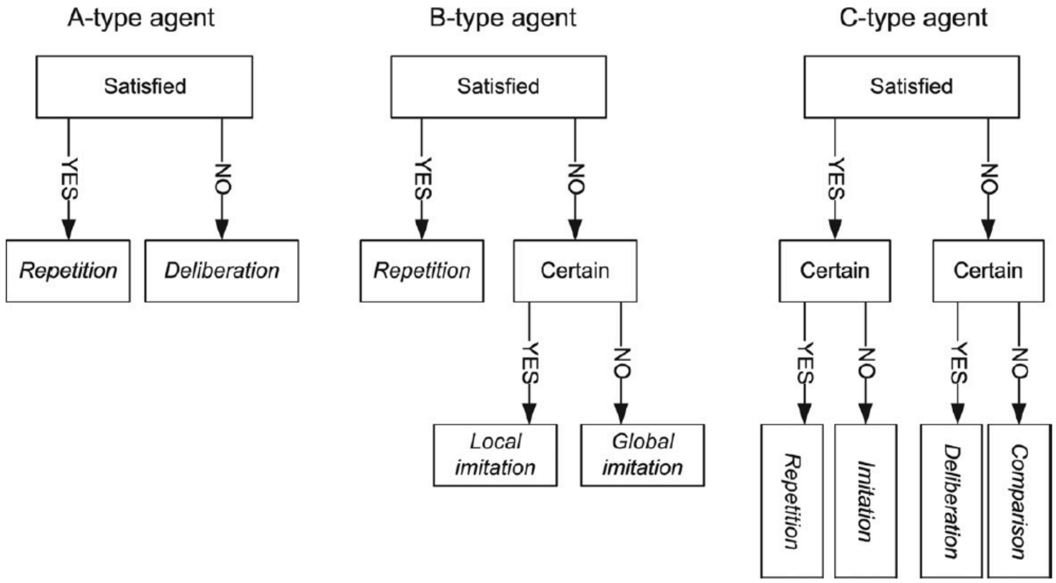


Figure 2-2 Cognitive strategies of all agent types in Mialhe et al.' s research (2012)

As can be seen from previous examples, heuristic decisions are made by independently evaluating each predefined rules and conditions following a specific order. The decision tree is a straightforward graphic representation of heuristic structure depicting how decisions are made step by step.

2.4.2 Optimizing Decision-making Structure

Unlike heuristic strategy, optimizing strategy allows the simultaneous evaluation of decisions by using computational models. The optimization-based approach is built upon the microeconomic theory which assumes that agents will always make rational choices (Schreinemachers and Berger, 2006). It assumes that agents are capable of evaluating all of the available alternatives based on perfect information and cognitive ability and selecting the one that returns the highest utility or profits. Without setting the exact decision rules, the decision is made by specifying an objective function (either linear or nonlinear) to map every option into a scalar value. Equation 2.2 to Equation 2.4 show examples of different utility functions that have been used in Aporia framework developed by Murray-Rust et al. (2014) to model the agricultural land-use change. These utility functions are used to evaluate land-use options for each agent who aims to maximize their economic returns or utility. Equation 2.2 is the function that only takes economic factors into consideration. Equation 2.3 and Equation 2.4 allow the incorporation of both economic factors and non-economic factors; while Equation 2.3 is a linear weighted sum method, and Equation 2.4 offers a non-linear sum function with user-specified slopes and offset values (Murray-Rust et al., 2014).

$$\mathrm{E(R)} = E_{econon}(R) \quad \text{Equation 2.2}$$

$$\mathrm{E(R)} = \frac{1}{n}\sum_{i=1}^{n}\lambda_i\, E_r(R) \quad \text{Equation 2.3}$$

$$\mathrm{E(R)} = \frac{1}{n}\sum_{i=1}^{n}\lambda_i + \delta + (E_i(R)) + \lambda_i - \delta - (E_i(R)) \quad \text{Equation 2.4}$$

Generally, parameters (e.g. weights, offsets) and the form of utility function vary according to the research objective and agent typology. For example, Millington et al. (2008) have presented an ABM to simulate agricultural land-use decision-making. Two types of agents which are commercial and traditional agents, have been determined depending on agents' perspectives. Commercial agents choose options that maximizes their profits, thus, incomes, market values, and conversion costs have been put into a utility function to estimate the potential profits of each option. Traditional agents are those who make decisions based on land size and retirement age rather than economic related factors (Millington et al., 2008). Liu et al. (2006) have developed an optimization-based ABM in which agents of different types use the same linear utility function but with different preference weights for the factors of environmental quality, education benefits, accessibility, land price, and public facilities. In Ligmann-Zielinska's research (2009), a non-linear utility function has been used by three types of agents, each of which use different weights distribution depending on the agent's preferences for different decision criteria. In such a way, the heterogeneity among agents can be clearly represented.

As noted by Schreinemachers and Berger (2006), the application of mathematical utility function offers a straightforward way to represent agents' heterogeneities. Therefore, the optimization ABM is able to be used to investigate the implications of heterogeneities among agents' characteristics, perspectives, and behaviours. Brown and Robinson (2006) presented an ABM to explore how the agents' heterogeneity in resident preferences influences the residential development in an urban system. Two types of the heterogeneities, including the preference variation among the entire population or within an agent type, as well as the heterogeneities across different agent types, have been studied. Five methods have been addressed by Brown and

Robinson (2006) to distribute agents' preference weights to four identified evaluation criteria: (1) preference weights are drawn randomly from a uniform distribution; (2) equal preference weights which is mean value for each criteria drawn from all of the survey sample, are assigned for the entire population; (3) preference weights are drawn randomly from a normal distribution specified by the mean and Std. obtained from the entire survey sample; (4) agents in the same type have equal preference weights of group means; (5) preference weights are drawn randomly from a normal distribution described by the group mean and standard deviation. The magnitude of impacts for different preference setting was examined according to the mean of resident utility value, Gini coefficient value, and the Shannon evenness index. The result shows that the impacts of heterogeneities and variations among agents' preference weights are much greater than the influences of categorization.

As can be seen, optimization model puts more focus on the decision outcomes. Using an objective utility function, all alternatives are evaluated simultaneously, and finally, the optimum option should be selected. In an optimization-based model, all factors are evaluated quantitatively without knowing the exact decision rules. This provides a high level of flexibility to model human behaviour and represents heterogeneity among agents. However, it has been criticized by various studies (e.g. Rounsevell et al., 2012; Filatova et al., 2013) that simulation outcomes from the optimization model are unrealistic as people in the real world do not always make rational decisions.

To better represent human decision-making processes, some studies (references) have carried out a simulation that incorporates heuristic strategies into optimization methods. For instance, Malawska and Topping (2016) have developed an ABM which incorporates both heuristic decision trees and optimizing utility functions to simulate the farmer decision-making on crop choices, as well as the application of fertilizers and pesticides. Agent typology has been created based on agents' goals and motivations toward farming. Depending on the agent type, four decision-making methods, including Imitation, Social comparison, Deliberation, and Repetition, are addressed. If Imitation, Social comparison, or Repetition is used, agents make decisions following a heuristic decision tree; if Deliberation is implemented, crop plan is selected based on the rules of utility optimization (Malawska and Topping, 2016). Another example is the LUDAS presented by Le et al. (2008), which simulates the land-use decision-making processes of household agents by considering household characteristics, environmental and policy information. The decisions are made based on the maximum utilities estimated by a spatial multi-nominal logistic functions nested with heuristic rules.

2.4.3 Methods Comparison

Both optimization and heuristic approaches have been widely applied in the ABM to simulate the processes of human decision-making. Depending on the research questions and the available data, either the optimization approach or the heuristic method, or a combination of both can be selected by the researcher. For example, the heuristic decision tree is more suitable for a study that focuses on the decision process, that is, how decisions are made. Comparatively, the optimization method puts more attention on exploring the impacts of multiple inputs on decision outcomes. As concluded by Schreinemachers and Berger (2006), the heuristic model considers the limited cognitive capacity as the main source of inefficiency, yet the optimization model takes external structural factors as the major source of inefficiency. Therefore, optimization model is more powerful to investigate the impacts of policy intervention (Schreinemachers and Berger, 2006). Furthermore, the optimization approach is able to capture the economic trade-offs due to its ability to make decisions simultaneously (Schreinemachers and Berger, 2006). Comparing to the optimization model, the heuristic model is easier to be calibrated and validated as heuristic agents make decisions using a set of relatively simple rules instead of complex computational models. Whereas the decision-making rules, conditions, and their sequence are extremely significant to realistically represent human behaviours using the heuristic model. Accordingly, accurate and complete data is required to identify and set the important decision and appropriate conditions in the correct sequence. Though some research has questioned the optimization model's capability of realistically representing human behaviour, its ability to include multiple inputs and outputs adds the flexibility to integrate different decision models and offers a straightforward way to represent agent heterogeneity (Schreinemachers and Berger, 2006).

2.5 Application of ABMs to the LUCC in Agricultural Environments

The ABM is a powerful tool in the study of land use change which involves interactions between different entities at different scales and is greatly influenced by human decision-making processes (Mialhe et al., 2012; Evans and Kelley, 2004). In the study of land use change, ABM-based approaches are able to explore how information diffusion and spatial externalities would influence the spatial pattern and composition of land use over time (Evans and Kelley, 2004), and provide a way to explicitly and heterogeneously represent the emergent land use patterns caused by various decision-making process (Matthews et al., 2007; Robinson et al., 2007; Filatova et al., 2013).

The ABM model is superior in three aspects: (1) the ability to capture emergent phenomena (Parker et al., 2003; Castle and Crooks, 2006); (2) the capability of offering natural description of certain systems (Bazghandi, 2012; Bonabeau, 2002); (3) the flexibility (Castle and Crooks, 2006). Emergence is a phenomenon appearing along with unexpected behaviours resulting from the non-linear and discontinuous interactions between individual entities (Castle and Crooks, 2006; Bazghandi, 2012). The ABM is capable of describing these discrete behaviours which are difficult to be represented by using mathematical equations (Bonabeau, 2002; Parker et al., 2003). Moreover, the ABM can provide a better representation of agent typology and heterogeneities (Filatova et al., 2013; Matthews et al., 2007; Parker et al., 2003). Other methods (e.g. equation-based methods), which describe heterogeneities among agent interactions using aggregate equations, smooth out the fluctuations and result in significant deviations from the predicted behaviour (Castle and Crooks, 2006; Bonabeau, 2002). The ABM is able to provide a simulation of a system composed of behavioural entities that are closer to reality (Bazghandi, 2012; Bert et al., 2014; Castle and Crooks, 2006). For instance, describing how people move on the street through ABM is more natural than using a set of equations to govern the dynamics of people density. Finally, the ABM is flexible. First, the ABM can be built for various systems (e.g. building, city, and road networks). Agents in the model can be specified using various mechanisms, and they are allowed to move along different directions in their environment (Castle and Crooks, 2006). Furthermore, interactions among agents can be governed by space, networks, or a combination of structures, which would be more complicated to be explained by mathematics (Castle and Crooks, 2006). Additionally, the ABM allows the coexistence of aggregate agents, subgroups of agents, and single agents with different level of description (Castle and Crooks, 2006; Bazghandi, 2012; Bonabeau, 2002). For all these reasons, the ABM has been applied as a powerful tool to explore the human decision-making and behaviours (Evans and Kelley, 2004; Mialhe et al., 2012; Parker et al., 2003).

To explore how different variables may affect the decision-making processes of farmers on choosing cropping system and further lead to the resulting land use pattern, Mialhe et al. (2012) developed an ABM named CHANOS based on empirical field data. Agent typology was introduced in Mialhe et al.'s research (2012). There are two basic classes of agents in CHANOS, which are farmers who own the farm and investors who "acquire new land in favorable circumstances" (Mialhe et al., 2012). Internal attributes were acquired through a questionnaire survey for farmers including household size, behaviour type, strategies, and outcomes. Some of these attributes are static, while economic attributes may change according to decision-making processes and external economic factors. External factors are the natural, economic, and political factors relevant to the system including market forces, government policies, and environmental and climatic processes such as deltaic land subsidence and typhoon. Thirty runs were first implemented to assess the underlying effects of randomness and uncertainties in the modelling results. After that, twelve scenarios were illustrated by combining the identified three types of farmers' behaviours (rational, collective-minded, and bounded rational) with four environmental dynamics (i.e. no deltaic subsidence, steady subsidence, accelerating subsidence, and subsidence punctuated by external impacts). The results indicate three potential land use change patterns (Mialhe et al., 2012). For agents in different categories, different adaptive abilities were observed.

Valbuena et al. (2010) developed an ABM framework that combines the existing concepts to simulate the diversity of land use decision-making at a regional scale. A case study was conducted to identify how the farmers' views and structural variables contribute to determining the diversification of farming practices (Valbuena et al., 2010). Census data, socio-economic and spatial data were used to describe the attributes of the environment; the farmers' willingness and the ability for farm expansion and farm practices diversification were also addressed to determine the direction and boundaries of the decision-making process (Valbuena et al., 2010). The developed model had been run three times with different set of parameters to identify the influence of internal feedbacks on agents' behaviours and decision-making processes, observe the effects of external factors - adoption of policy of promoting agents to keep their land-on agents' behavior, and the impacts of external factors on the structure of landscape (Valbuena et al., 2010). Finally, additional runs with different random sets of parameters were conducted to observe the uncertainty in the decision-making process (Valbuena et al., 2010). Results indicate that the developed ABM framework is able to explicitly incorporate and represent the diversity of decision-making strategies (Valbuena et al., 2010). This gives it the flexibility to be implemented to simulate different LUCC processes in different regions where heterogeneous individual decision-making is a critical driver of LUCC (Valbuena et al., 2010). Impacts of heterogeneities among agent typology were also examined by Sengupta et al. (2005). An ABM was developed to explore the impacts of policies on affecting farmer land-use decision-making in southern Illinois. In this study, a heuristic decision-tree method was applied. Farmers were classified into three groups: (1) opportunists are commercial farmers who make decisions to maximize their profits; (2) "mixed" agents who are medium-sized farmers; (3) "enrolees" which including small farmers and retirees. Results of this study indicate that the ABM is able to produce a more realistic simulation of land-use decision-making in the Illinois than did a traditional profit-maximization model (Sengupta et al., 2005).

The capability of the ABM to cope with learning and adaptive processes was exhibited in Becu et al.'s study (2003). In Becu et al.'s research (2003), CARCHSCAPE model was developed to explore the individual decision-making of downstream agricultural viability in response to the upstream irrigation management. Four scenarios related to water management were analysed: (1) a baseline scenario in which farmers were forbidden to convert forest into agricultural field; (2) a conflict scenario in which downstream farmers behave under the willingness of upstream managers; (3) a dishonesty scenario in which farmers took more water than was permitted; (4) a water shortage scenario in which the low rainfall situation continued for 10 years. The simulation was based on a heuristic decision-making structure (Becu et al., 2003).

In conclusion, the ABM is an approach that has been commonly used in the study of LUCC due to its ability to couple socio-economic and environmental models, incorporating the micro-level impacts of human decision-making on environmental management, and studying the emergence in response to management policies (Deadman et al., 2004). It provides a dynamic representation of individual decision-making entities taking into account the interaction and heterogeneities among them (Matthews et al., 2007; Millington et al., 2008). Moreover, the capability of incorporate adaptive behaviour at different levels also makes the ABM a powerful tool to explore the existing land use patterns and predict the observable real-world phenomenon at a micro-scale (Mialhe et al., 2012; Evans and Kelley, 2004; Parker et al., 2003).

Based on all advantages discussed above, an ABM is applied in this study for the following reasons. First, heterogeneities (e.g. income level, occupation, preferences, and knowledge level) among agents play a critical role in the decision-making of BMP adoption (Liu et al., 2018). It may lead to the diversity of the individual farmer's decision-making and behaviour (Valbuena et al., 2010). To better understanding the BMP decision-making dynamics, it is important to take into account the local heterogeneity. Compared to other methods such as the equation-based method which represents these heterogeneities using a set of aggregate equations (Bonabeau, 2002), the ABM do not require a numerical or analytical solution to the system (Parker et al., 2003). This highly increases the level of complexity that can be handled by the ABM and makes it become a powerful tool for representing heterogeneous and discrete behaviours (Parker et al., 2003). Second, the decision-making of BMP adoption is also impacted by interactions among farmers (Liu et al., 2018). Although statistical models can reflect the regional heterogeneity to some extent, it lacks the ability to incorporate dynamic interactions and feedbacks in the system, and thus, downplays the decision-making process in the real world (Parker et al., 2003). Nevertheless, the ABM is capable of dynamically describing the impacts of agent interactions on their decision-making (Parker et al., 2003). For all these reasons, an ABM was developed for this study to facilitate the understanding of farmer's decision-making on BMP adoptions.

2.6 Model Validation

More and more researchers have been attracted to apply simulation models to represent phenomena in the real world and solve problems. The models' ability to provide "correct" results is always concerned by the developers, users and other individuals that may be affected by the model results (e.g. policymakers) (Sargent and Smith, 2011). While due to the lack of sufficient data, inadequate model structure, and the variability of real-world entities, uncertainties and errors are raised (Sargent and Smith, 2011; Bert et al., 2014). To ensure that the developed model can represent the behaviours closely enough to reality, model validation should be performed (Rykiel Jr, 1996; Bharathy and Silverman, 2013). Model validation usually refers to implementing a set of techniques and processes to evaluate whether a model can perform as expected (Oreskes et al., 1994). It should be carried out to evaluate whether the developed model can provide an accurate representation of reality and whether the model is acceptable for its intended purpose and use (Bharathy and Silverman, 2013). Accordingly, a model's validity should be determined based on the purpose specified when developing the model (Rykiel Jr, 1996; Sargent and Smith, 2011; Oreskes et al., 1994).

The model validation can be classified into three types: the conceptual validation, the operational validation, and the data validation (Rykiel Jr, 1996). The conceptual validation refers to the process of assessing whether theories and assumptions underlying the model are correct or justifiable (Sargent and Smith, 2011; Bert et al., 2014; Rykiel Jr, 1996). It has to start from the beginning of the model design and development stage (Bert et al., 2014). Two methods can be used to evaluate the conceptual validity of a model. The first one is expert evaluation which includes both experts engaging in model development processes and those independent who did not closely involve in model development processes or with model developers (Bert et al., 2014). Both types of experts are able to provide feedbacks contributing to ABM validation (Bert et al., 2014). The other method for conceptual validation is to assess how the chosen theories and underlying assumptions fit the purpose of a model (Bert et al., 2014). The operational validation is the process to evaluate the model accuracy and adequacy in mimicking the real world (Sargent and Smith, 2011; Bert et al., 2014). Different from the conceptual validation, the operational validation usually starts in the later processes after model verification (Bert et al., 2014). Statistical tests are usually used here to compare the simulated results with real data (Bert et al., 2014). Data validation is performed to identify whether the data used in the model can meet the specified quality standard (Sargent and Smith, 2011; Rykiel Jr, 1996).

A number of techniques have been proposed and implemented for model validation, and both qualitative and quantitative approaches can be performed for model validation. A historical data validation method can be performed when historical data exists. The data is split into two parts, the first part of which is used for building the model, while the second part is used to test whether the model presents a reasonable performance (Sargent and Smith, 2011; Rykiel Jr, 1996). The historical data validation method has been applied in Bert et al.'s study (2011) to validate the developed PM by comparing the predicted outputs with a set of available historical datasets. The results suggested that the simulated land use patterns were consistent with historical development demonstrating the developed PM was able to accurately represent the phenomena and emerging changes in the real world (Bert et al., 2011). Instead of comparing results against the empirical dataset, models can also be validated by comparing outputs to those of other models. In Sengupta et al.'s study (2005), an ABM was developed to simulate the land-use decision-making process in the Illinois based on a heuristic decision-tree method. A traditional profit-maximization model was also implemented of which the outputs were compared to those obtained from the developed ABM. Comparison results indicated that the ABM provided a simulation that is closer to the real world (Sengupta et al., 2005).

While both of the historical data validation method and the comparison to other model method have relatively high data requirements. When there is no historical data nor the data for building another model, the statistical method is suggested. For example, in Zhang and Mahadevan's study (2003), Bayesian hypothesis test has been used to validate the developed state-based reliability prediction model. A Bayes factor, which indicates a good model prediction when it is larger than one, was derived (Zhang and Mahadevan, 2003). Other than the Bayesian test, a quantitative comparison approach has also been suggested by Urbina et al. (2003). In this study, a probability distribution has been created for the model outputs and the reference data. The model prediction can be identified as acceptable when zero is included in the generated probability interval (Urbina et al., 2003).

The model can also be validated using an extreme condition test. By assigning the model with extreme values, the performance of the model in response to behaviours outside of normal conditions can be evaluated (Rykiel Jr, 1996). In Qudrat-Ullah and Seong's study (2010), extreme values have been given to selected parameters to explore whether the model would produce logical results. Results of the extreme condition test were compared to the behaviours of the real system showing that the developed energy policy model is capable of dealing with the extreme conditions and the model is valid (Qudrat-Ullah and Seong, 2010).

A face validity method is one of the conceptual validation techniques that determine whether a model and its behaviours are reasonable by asking individuals who are knowledgeable about the system (Sargent and Smith, 2011; Rykiel Jr, 1996). Bert et al. (2014) implemented a face validity method in a developed Pampas model (PM) to make sure all of the relevant components and processes are included and correctly characterized. The conceptual validation of PM has started from and in parallel with the process of model designing which includes the review of relevant publications and documentation about the theoretical basis of relevant processes or behaviours and ABMs with similar purposes (Bert et al., 2014). Experts, including members and technical staff from Argentina Association of Regional Consortia for Agricultural Experimentation (AACREA)- a civil association for sustainable development of agricultural entrepreneur (Inicio, n.d), and a collaborating farmers' organization, were also involved in the development process of PM and interacted with stakeholders to not only test the correctness of PM's design, but also define the specific processes and parameters for its sub-models (Bert et al., 2014). The results show that the model is able to provide a valid representation of emerging patterns (Bert et al., 2014).

Except for the validation techniques introduced above, sensitivity analysis can also be used in model validation. Sensitivity analysis is a technique that explores model performance by assessing the impacts of a model parameter on model outcomes under given assumptions. Details of the sensitivity analysis were presented in the following section. Depending on model objectives and data availability, different validation techniques may be applied. When the historical data are available, a historical data validation method can be implemented. A face validity technique can be used when relevant knowledge can be inquired from experts easily. The comparison to other modelling methods can be used when data for building another model is available. While when lacking both data and it is difficult to inquire about expert knowledge, statistical validation can be applied.

2.7 Sensitivity Analysis of the ABM

Although ABMs have proved to be a powerful tool in simulating the dynamics of coupled human-environment systems (e.g. Bert et al., 2014; Robinson et al., 2007; Parker et al., 2003), they still face the challenge of verifying and validating the reliability and robustness of the outcomes. Sensitivity analysis is a technique that explores model performance by assessing the impacts of a model parameter on model outcomes under given assumptions. According to Ten Broeke et al. (2016), three major goals of implementing sensitivity analysis in ABM can be identified. First is to understand how emergent patterns in the real-world are generated in the model. By implementing a sensitivity analysis, how changing a parameter may affect the model outcome can be explored. In such a way, researchers are able to gain insights into the model dynamics (e.g. linear, nonlinear) resulting from these impacts. Second, sensitivity analysis is usually used to test the robustness of the model outcomes in regards to changes in the parameter values corresponding to a set of given assumptions. Especially for models which aim to represent a phenomenon that involves a range of situations, proving that the model is robust to parameter changes is very important for indicating the reliability of the model outcomes. The third motivation of conducting sensitivity analysis is to quantify the uncertainty in the model outcomes from the parameter set. This facilitates the identification of parameters that contribute the most to the uncertainty of the model outcomes. Accordingly, it is possible to reduce the model uncertainty by only focusing on the identified parameters.

Various methodologies have been used to carry out the sensitivity analysis. One of the most widely used methods is global sensitivity analysis which explores the uncertainty in the model output by measuring the proportion of the variance explained by the model inputs. A Monte Carlo approach has been used by Schreinemachers (2005) to examine the robustness of the applied model under different parameter settings. The average value of model outcomes obtained from a range of parameter settings have been calculated for each of the identified fifty populations. Std. has been computed for the fifty averages to quantify the variations in the model output. Accordingly, the relative importance for each variable has been defined by comparing the normalized standard deviation. A greater Std. indicates that the model is more sensitive to the corresponding variable. Similarly, the Monte Carlo approach has also been applied by Tsai et al. (2015) in the sensitivity analysis for the developed ABM to investigate the impacts of different socio-economic conditions on land-use change.

However, Parry et al. (2013) pointed out that the Monte Carlo approach may create duplicate information when the output is smooth. Moreover, a great number of runs is required by the Monte Carlo approach to get accurate results. This largely increases the amount of steps and time required for implementing the sensitivity analysis for ABMs that have a large amount of inputs. Therefore, Parry et al. (2013) have conducted a Bayesian Analysis of Computer Code Outputs (BACCO) method to perform sensitivity analysis with greater computational efficiency. An emulator, or meta-model, was constructed to represent the results both qualitatively and quantitatively. The sensitivity has been measured by averaging the model output in regarding to probability distributions on the selected inputs. Sensitivity indices have been used to quantify the uncertainty caused by each input and rank them based on their contributions to uncertainty in model outcomes. Accordingly, parameters that contribute the most to the variation in the model output can be identified. The meta-modeling has also been used by Happe et al. (2006) combining with a statistical technique to measure the variations in the model outcomes that results from the uncertainty in the model parameters. Instead of testing all of the input combinations, major factors that impact agriculture structural change have been selected and simulated in the sensitivity analysis. For every input, factor levels, which indicate the how inputs may be changed based on a set of assumptions, have been assigned. Finally, by using a graphical analysis and meta-models (e.g. regression model), the relationship between structural changes and the effects of factor level change can be statistically analysed. Additionally, the use of DOE (Design of Experiments) techniques provides an insight of the relative importance of model parameters regarding to their contribution to the model variations.

The previous reviewed methods are all model-based which determining model variability based on the individual parameters and their interactions (Zhang et al., 2015). While the sensitivity analysis can also be carried out using model-free methods which is "independent of assumptions about the model structure (Lilburne et al., 2006)". For example, Ten Broeke et al. (2016) has used a Sobol's method to measure model variance caused by different parameter combinations based on the assumption that all model inputs are independent. Keeping all other parameters fixed, sensitivity of a model is indicated by the ratios of the decomposed partial variance of selected (one or multiple) parameters to the total variance in the model output. A bootstrap method has also been addressed to evaluate the accuracy of obtained sensitivity indices. Ligmann-Zielinska et al. (2014) have also performed a model-free sensitivity analysis in which the sensitivity to a factor is represented using the ratios of the contribution of each parameter to the total model variance. A greater ratio indicates that the model is more sensitive to the examined parameter.

Another method to perform sensitivity analysis is the One-factor-at-a-time (OFAT). In this method, one parameter is changed at a time while keeping all other parameters at their baseline values. This adds the comparability of the results, which makes it stands out in investigating how parameter changes affect the model output (Ten Broeke et al., 2016). Ten Broeke et al. (2016) has implemented the OFAT to examine the effects of all parameters to model output. Dot graph was used to represent the change of model outcomes based on the minimum, mean, and maximum value among ten replicates. In this way, tipping points have been easily identified, which indicates the model dynamics responding to the change of a particular parameter. However, the OFAT method cannot provide an accurate measurement of the variance of combined parameters (Ligmann-Zielinska et al., 2014).

To sum up, different methodologies may be used to perform the sensitivity analysis depending on the research goals. The OFAT provides a simplest way to qualitatively represent the relationships between model inputs and outputs. It can be applied to explore model dynamics with respect to changes of an input parameter, and assess the robustness of the model in regarding to the variance of a model input. Unfortunately, it presents a limited ability in explaining the effects of combined parameters on model behaviours (Ligmann-Zielinska et al., 2014). Comparatively, the global sensitivity analysis approaches allow the simulation of the combined impacts of multiple variables and offer quantitative representation of the variance in the model output. Whereas as noted by Ligmann-Zielinska et al. (2014), the computational costs for global sensitivity analysis approaches are higher than the OFAT approach.

2.8 Chapter Summary

This chapter first introduces the BMPs that are examined in this study and their potential benefits. It shows that all discussed BMPs are able to improve soil health, enhance water quality and facilitate the development of sustainable agricultural system. Depending on the location, crop type, topography and climate, different BMPs or combinations of BMPs may be adopted. While for each BMP, the effectiveness is highly determined by the construction dimensions such as width, height, channel grades, as well as the shape. Then methods for identifying primary LUCC change patterns are summarized. Two methods were presented, which are the trajectory computing method suggested by Wang et al. (2012) and Swetnam's method (2007) which determines the LUCC change patterns by creating a multi-attribute database. Comparing to the Swetnam's method, the trajectory computing method would be more practical than the Swetnam's approach when the number of LUCC types is less than ten. Moreover, the trajectory computing method allows the researcher not only to identify different LUCC trajectory without taking a lot of time, but also to visualize the results by creating a distribution map. In the third section, two decision-making structures that have been widely applied in the ABM are discussed. The choice between these two methods should be based on the research questions and the available data. Although the heuristic decision tree is able to provide a sequential representation of how decisions are made step by step, the optimization model, which is built upon the microeconomic theory, is more suitable for exploring the influences of policy intervention since it takes external structural factors as the major source of inefficiency (Schreinemachers and Berger, 2006). Furthermore, the ability of the optimization model to include multiple inputs and outputs offers a straightforward way to represent agent heterogeneity (Schreinemachers and Berger, 2006). Finally, approaches for performing the sensitivity analysis are summarized. Different methodologies may be used to perform the sensitivity analysis depending on the research goals. Both of the global sensitivity analysis and Sobol's method are able to simulate the impacts of interactions between the parameters, or inputs, and offer quantitative representation of the variance in the model outputs. However, comparing to the OFAT, the computational costs of these two methods are much higher. On the contrary, the OFAT could qualitatively demonstrate the relationships between model inputs and outputs in a simplest way. By changing exactly one factor at a time, the OFAT is more powerful in study the impacts of changing model parameters on model outputs.

Chapter 3 Data and Methodology

3.1 Study Area

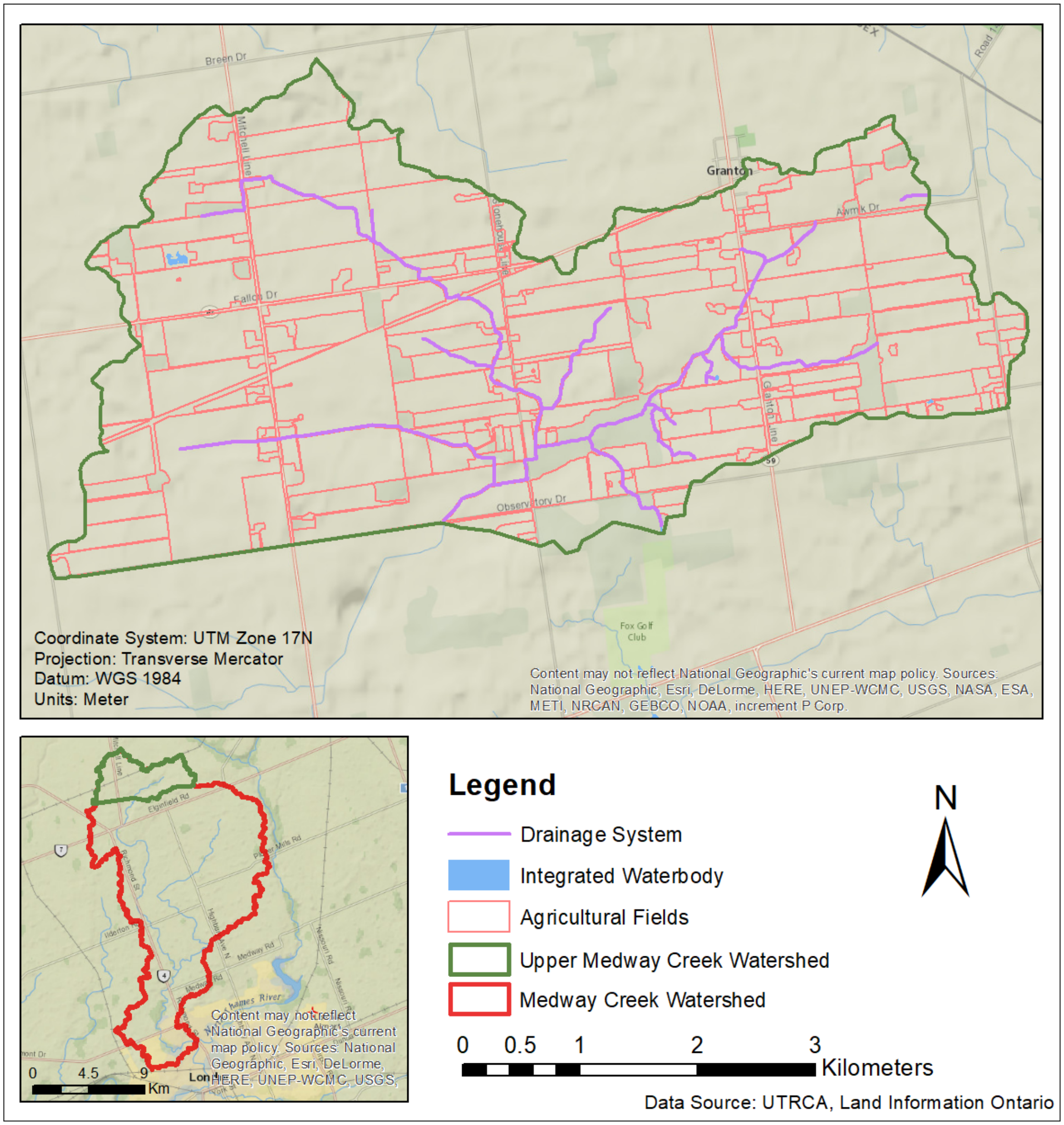


Figure 3-1 Study area of the Upper Medway Creek subwatershed

The Medway Creek subwatershed is one of the 28 subwatersheds in the Upper Thames River Watershed in Ontario, Canada (Medway Creek, n.d.; 2017 Watershed Report Card, 2017; UTRCA, n.d. c). It covers $205km^2$, taking up 6% of the entire Upper Thames River watershed. The Medway Creek subwatershed sits along the western edge of the Upper Thames River basin, it spans the northwest part of London, the Middlesex Centre, Thames Centre, and Lucan-Biddulph. As a tributary of the Thames River, the Medway Creek is 218 km long, originating from the north of Elginfield road and flows to the North Thames River near the Western University in London. About 66% of the Medway Creek watershed has agricultural field tile and 6% of the watershed has urban drainage (2017 Watershed Report Card, 2017). The dominant soil types in the Upper Medway subwatershed are clay loam and silty loam which cover about 33% and 32% of the subwatershed, respectively (2017 Watershed Report Card, 2017). The current prevailing land use type in the Medway Creek subwatershed is the agricultural land which covers 82% of the total land throughout the entire region (2017 Watershed Report Card, 2017).

The Medway Creek subwatershed has been suffering from a severe surface water quality problem for more than ten years (UTRCA, n.d. c; 2017 Watershed Report Card, 2017). In 2007, it was identified as a region that are highly requisite for the environmental improvement (UTRCA, n.d. c). According to the 2017 Watershed Report Card (2017), the overall water quality in the Medway Creek subwatershed has remained a grade of D over the past ten years. The concentration of Phosphorus, one of the major elements that affect surface water quality, is two times as high as the provincial aquatic life guideline having an overall grade of B in the Medway Creek subwatershed (2017 Watershed Report Card, 2017). It has been noted by the UTRCA in the 2017 Watershed Report Card (2017) that the poor water quality of the subwatershed is closely related to the regional agricultural activities. The application of fertilizer and manure increases the nutrient loadings in the surface runoff which further flows into the surface waterbodies in the end and causes eutrophication (UTRCA, n.d. c). In order to control soil erosion and reduce nutrient losses from farm land, Best Management Practices (BMPs) including conservation tillage, no-till system, grassed waterways, buffer strips, Water and Sediment Control Basin (WASCoB), and windbreaks are used in the Medway Creek subwatershed (Medway Creek, n.d.).

Throughout the subwatershed, the upper region has higher soil erodability and poorer surface water quality (UTRCA, n.d. c.; 2017 Watershed Report Card, 2017). Little research has been addressed to investigate the agri-environment system, specifically farmers' agricultural decision-making process, in this region. Therefore, the Upper Medway Creek subwatershed was selected as the study area. The Upper Medway Creek subwatershed locates at the north of the Medway Creek subwatershed and extends to the Observator Drive and south of Granton to the South. It has an area of $21.55km^2$ which covers 10.51% of the entire Medway Creek subwatershed. As calculated, about 83.71% of the land in the Upper Medway Creek subwatershed is used for agriculture. As estimated by the UTRCA, there are approximately forty farmers operating in the Upper Medway Creek subwatershed. In 2015, the Upper Medway Creek was selected as a priority subwatershed project by the UTRCA and OMAFRA (2017 Watershed Report Card, 2017). The project encourages the application of BMPs and assesses its effects to mitigate soil and phosphorus losses from agricultural land into surface runoff (2017 Watershed Report Card, 2017). Refer to Figure 3-1 to see the location and boundary of the study area.

3.2 Social Field Survey

A survey is a widely used method to collect quantitative or qualitative information from a particular group of people. It can be conducted by phone, mail, internet, or a face-to-face interview (De Leeuw, 2008). Among these methods, a face-to-face interview is one of the oldest and common, implemented by direct communication with target respondents (De Leeuw, 2008). Although doing a face-to-face survey can be costly and time-consuming, there are still many advantages that make it an appropriate survey method for this study (De Leeuw, 2008). First, a face-to-face interview allows the use of visual aids and body language, which help farmers who are not familiar with BMPs to understand survey questions related to the BMP adoption (De Leeuw, 2008). Moreover, the interviewer can discuss with interviewee during the interview so that get more in-depth understanding regarding why a farmer implements BMPs (De Leeuw, 2008). Compared to a structured interview, a semi-structured interview is preferred in this study as it allows respondents to express new idea and views toward factors affect their BMP adoption (De Leeuw, 2008). Therefore, a semi-structured interview was conducted with the farmers in the Upper Medway Creek subwatershed to capture the decision-making dynamics of the BMP adoption.

This survey was developed for the WP3 of AWF. It is a modified version from the survey, “Sustainability in Agriculture: Southwestern Ontario”, under the Early Researcher Awards (ERA) program for Dr. Derek Robinson. The Sustainability in Agriculture: Southwestern Ontario survey consists of four parts. The first part collects information related to agricultural practices, including farm characteristics (i.e. farm size and farmland type), crop rotations, what agricultural practices are being adopted, and the initiatives or programs a farmer participates in. The second part focuses on factors that influence farmer’s decision-making. The third part focuses on information dissemination and social network that may influence farmer’s decision-making. Questions such as “how important are the listing sources of information to your land use decisions on your farm?” and “from what source have you heard of drone technology for application in agriculture?” have been asked in this part. In the fourth part, farmer’s general information, including the year of birth, gender, farm succession and inheritance, weekly farm/off-farm working hours and the proportion of farm/off-farm income. Therefore, based on influential factors of the BMP adoption discussed in Section 2.2, questions including “what BMPs are you using?”, “what motivate you to adopt BMPs”, “what are the main concern of adopting BMPs”, and “do you participate in any BMP-related support or incentives from any programs or organizations?” have been added to the Sustainability in Agriculture: Southwestern Ontario survey.

The modified survey was designed in collaboration with the UTRCA. I’ve also participated in designing parts of the survey. It was composed of three parts to elicit the factors that may influence farmers’ decision-making, the motivation for applying for agricultural BMPs, as well as general information about farmers and their farmlands. In the first part, information related to the agricultural practices has been collected, which includes crop rotations that are followed by farmers, factors that affect farmers’ agricultural decision-making in terms of economic, environmental and social aspects, as well as the proportion of a farmer’s agricultural decision-making that is affected by each of the three factors (i.e. economic, environmental and social factors). Questions such as “how many years have you been farming?”, “how much environmental factors affect your crop rotation/livestock choices?”, “what percent of your agricultural decision-making is affected by economic, environmental, and social factors, respectively?”, and “what farming practices most influence water quality?” were asked in this part. The second part of the survey focuses on motivations and barriers, especially the finical concerns, of BMPs adoption, BMPs that are currently utilized by farmers and farmers' satisfaction level of implementing these BMPs. Except for BMP-related questions introduced in the previous paragraph, questions such as "what is your satisfaction level for currently used BMPs?" and "are you considering implementing any new BMPs?" were also asked in the second part. Part 3 intends to collect general information of the purpose of adopting farming practices, farmer, such as the age, the proportion of average weekly on-farm working hour, the percentage of income that comes from farming activities and whether the farmer has an off-farm occupation. Questions such as "was your farm inherited?" and "what proportion of your weekly labour is spent on farming?" were asked in here. Additionally, this section generates the sources of agriculture-related information preferred by the farmer. For example, "how often do you search for information on the following media", and "what form of information do you prefer?".

The survey participants were recruited by the UTRCA staffs. Before the interview, farmers were first contacted by the UTRCA staff to get their willingness of participation and their available time for taking the interview. Only farmers who present their willingness of participation were interviewed by UTRCA staffs. This survey has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#21913).

3.3 Identifying Prominent Land-cover Changes

3.3.1 Data

3.3.1.1 Boundary Data

The Medway Creek boundary data used in this study is one of the quaternary subwatershed divisions obtained from the Land Information Ontario. The quaternary divisions were created based on the Water Resources Index Inventory Filing System which is also known as federal 'Drainage Area' reporting framework (Land Information Ontario, 2010). The boundaries of each division were determined based on drainage area, and all land mass and waters within this drainage area was included in the polygon (Land Information Ontario, 2010). The boundary of the Upper Medway Creek subwatershed was digitized manually based on both of the Medway Creek boundary data and the Upper Medway base map (see Appendix A) provided by the UTRCA. The boundary data for agricultural fields was created by manually digitizing according to the world imagery base map with a spatial resolution of 1m (Esri, 2018) embedded in the

ArcMap. The digitization was performed at scales ranging from 1:3,000 to 1:1,000. Satellite images and street views in Google Maps were taken as the reference data for digitizing. The field borders were identified by the non-crop strip or the strip of shrubby. Furthermore, the field borders were also determined where the adjacent area are coloured differently. Drainage systems and watercourse running through the middle of fields were all excluded from the field parcel. As the boundary of the Upper Medway subwatershed was determined by the drainage area, it goes through the middle of some agricultural fields, which makes parts of these fields sit outside of the subwatershed. However, as parts of the fields are still within the Upper Medway subwatershed boundary, instead of only taking areas within the boundary, the whole fields were digitized. Finally, 176 polygons were obtained.

3.3.1.2 Land-cover Data

The Annual Crop Inventory data from 2011 to 2015 obtained from the Agriculture and Agri-Food Canada (AAFC) were used as land-cover data in this study. It is a set of raster data that shows the distribution of different crop types in Canada at a spatial resolution of 30m. Different crop types were classified using a Decision Tree based method based on the combination of multi-temporal optical data (e.g. Landsat images, RADARSAT-2 data, and AWiFS imagery), annual crop insurance data and ground-truth information (Agriculture and Agri-food Canada, 2016 a). Finally, 66 categories of land-cover types in total were classified with an overall accuracy of at least 85% (Agriculture and Agri-food Canada, 2016 a). For the Ontario region, the overall target accuracy of all crop classes is higher than 82% except for images in 2012 which have a target accuracy of 76% (Agriculture and Agri-food Canada, 2016 a). Depending on the availability of spectral data and training sites, some classes such as Cereal class were further divided to sets of sub-categories.

3.3.2 Identifying Prominent Land-cover Change Patterns

The Annual Crop Inventory data from 2011 to 2015 obtained from the AAFC was used here to identify the prominent crop rotations within the Upper Medway Creek subwatershed. To begin with, raster-based land-cover dataset was first summarized by agricultural field boundary spatially. The land-cover type of each agricultural field was determined by the pixel that occurs most often in the same parcel. As a result, eight land-cover types, including Beans, Wheat, Cereal, Corn, Mixedwood, Pasture and Forage, Soybean, and Barley, were obtained. Because Wheat is one of the subcategories of Cereal (Agriculture and Agri-food Canada, 2016 a), it was reclassified to the class of Cereal. Furthermore, according to UTRCA (n.d. c), major cereal grown in the Upper Medway Creek subwatershed is winter wheat and most of the pasture and forage area are planted with hay. Therefore, Cereal and Pasture and Forages classes were renamed to Winter Wheat and Hay, respectively. The existence of Mixed Wood class may be because of the misclassification in the original crop inventory data.

A trajectory computing method, which represents the land-cover change pattern of the examined time series using a set of trajectory codes, developed by Wang et al. (2012) was conducted to represent the land-cover change from 2011 to 2015 in the Upper Medway Creek subwatershed on a parcel-based level. To address the trajectory computing analysis, land-cover codes ranging from 1 to 7 were assigned to each land-cover class (refer to Table 3-2). In such a way, a code could be identified for each parcel to represent the land-cover type it has at particular time node. Next, Equation 3.1 (Wang et al., 2012) was used to combine the five land-cover maps and calculate the trajectory code for each parcel.

$$T_i = (G1)_i \times 10^{n-1} + (G2)_i \times 10^{n-2} \ldots + (Gn)_i \times 10^{n-n} \qquad \text{Equation 3.1}$$

where, T_i is the trajectory code for parcel *i*, *n* is the number of time nodes (5 in this case), and $(Gn)_i$ is the land-cover code of the given parcel at time node *n* (Wang et al., 2012). The calculation takes all of the five years into consideration simultaneously.

As a result, the land-cover change code consists of five digits, which describes the pattern of land-cover change on a field parcel for five years. From left side to right side, every digit indicates the land-cover for a giver year on the given parcel from 2011 to 2015, respectively. If all the digits in the code are the same number (e.g. 11111 and 55555), it suggests that there was no land-cover change that occurred on the parcel over the examined five years. Moreover, the crop rotation implemented on a specific field was also indicated by a trajectory code presenting a certain pattern (e.g. 23232 and 36236). Trajectory codes without any pattern would also exist. Finally, the prominent land-cover changes happened in the Upper Medway Creek subwatershed were determined based on the number of each land-cover change pattern that occurred in the study area. However, one land use change pattern could be indicated by different codes. For instance, both code 36363 and 63636 indicate a two-year crop rotation of corn and soybeans; similarly, code 23623, 36236 and 62362 indicate a three-year rotation from winter wheat to corn and to soybean. Thus, the numbers of trajectory codes which represent the same change pattern will be summed up when counting the occurrence of each land-cover change pattern. The identified prominent land-cover change patterns will become the choices for farmers to decide the crop rotation adopted on each agricultural field in the developed ABM.

3.4 Determining Possible BMPs

3.4.1 Data

3.4.1.1 Hydrology and Soil Data

The hydrology data used in this study, including enhanced watercourse and integrated water body data, were derived from the Ontario integrated hydrology data produced by the Ministry of Natural Resources and Forestry. The enhanced watercourse dataset comprises all connected watercourse features in the Ontario hydrologic network. Similarly, the integrated waterbody dataset includes all of the on-network water bodies in the Ontario. The digital elevation model (DEM) data was obtained from the Ministry of Natural Resources and Forestry, Southwestern Ontario Orthophotography Project (SWOOP) 2015 Digital Elevation Model. It is a set of raster graphics with a spatial resolution of 2m that represents the elevation of earth's surface. The SWOOP 2015 DEM has been processed using a "steam rolling" algorithm to reduce the impacts of raised surface features and make it closer to "bare-earth" elevations (Ministry of Natural Resources and Forestry, 2016). The drainage system was manually digitized according to the Upper Medway Creek base map provided by the UTRCA (shown in Appendix A). The soil type data was obtained from the Soil Survey Complex dataset provided by the Agriculture Food and Rural Affairs. The Soil Survey Complex data was collected by a number of soil surveyors between 1929 and 2002. It consists of a set of soil polygons, each of which indicates one to three soil components.

3.4.1.2 BMP Installation Data

The criteria and requirements for installing each BMP were acquired from government publications. To effectively control the erosion and reduce the nutrient losses, the slope of the grassed waterway has to be steep enough to minimize the deposition of sediments, but cannot be too steep to mitigate the soil erosion (Alberta Agriculture and Forestry, 2007; USDA, 2007). According to USDA (2007), it is recommended to have a grassed waterway with a slope that is higher than 1%, as the contributing area may suffer the out-of-bank flow if the slope of grassed waterways is lower than 1%. Therefore, a minimum slope of 1% is required for the grassed waterway. While with the help of a permanent erosion mat, a grassed waterway is able to have a slope of up to 15% (Alberta Agriculture and Forestry, 2007). Thus, to effectively reduce soil erosion, the grassed waterway has to be designed with a slope lower than 15%. For the riparian buffer strip, the effectiveness would be largely reduced when the slope is steeper than certain level. According to NRCS (2010 a), the maximum slope for a riparian buffer strip varies between 10% and 30% depending on the topology and climate. While Hawes and Smith (2005) have recommended that the slope of the riparian buffer strip has to be smaller than 15% in general, which is also the average of the steep slope suggested by NRCS (2010 a). Therefore, field slopes that are lower 15% has been set as one of the installation requirements of the riparian buffer strips in this study. Moreover, the riparian buffer strip shows little effectiveness when it is installed on soil that composed mostly of sand (Hawes and Smith, 2005). The implementation of WASCoB is recommended for fields that cover an area of more than two acres (NRCS, 2010 b), yet not exceed fifty acres (Maitland Conservation, 2017). In general, the slope of a field cannot exceed 14% to implement the WASCoB. When the slope is lower than 8%, a broad berm should be adopted; while when the slope is between 8% and 14%, a narrow berm may be established (Maitland Conservation, 2017). In the light of Brandle (n.d.), the length of the windbreak has to be at least ten times the tree height. As one of the most commonly used tree species for the windbreak in the Upper Thames River watershed (Roberts, 2017), the white cedar has the average height of 15m (Government of Ontario, 2018). Hence, the minimum length of the windbreak is 150m in this study. The summarization of these requirements and their sources are shown in Table 3-1.

Table 3-1 Data source of crop products related data

BMP	Requirements	Sources
Grassed Waterway	• Area > 35 acres • 1% < Slope < 15% • Upon drainage ways	UTRCA (n.d. b) USDA (2007) Alberta Agriculture and Forestry (2007)
Riparian Buffer Strip	• Slope < 15% • Not on soil composed mostly of sand • Adjacent to water body and drainage ways	Hawes and Smith (2005) NRCS (2010 a)
WASCoB	• 2 acres < Area < 50 acres • Slope < 14%	NRCS (2010 b) Maitland Conservation (2017)
Windbreak	• Installation length < 150m	Brandle (n.d.) Government of Ontario (2018) Roberts (2017)

3.4.2 Determining Suitable BMPs on Each Agricultural Field

The availability of BMPs on each agricultural field were determined according to the area, slope, soil type, land-cover type, drainage systems, water accessibility, and the edge length of each field. A heuristic decision tree was applied to determine whether a field is suitable for particular BMP. In the lights of government documentation files, criteria and requirements for installing an effective BMP were summarized as a set of rules (refer to Table 3-1).

Average slope of each field polygon was calculated in degrees using the DEM data. Because the geometry of soil type data and field boundary data are different, a field polygon may include more than one types of soil. Four types of soil, including sandy loam, loam, silt loam, and silt clay loam, were identified within the Upper Medway Creek subwatershed. According to the soil texture triangle created by USDA (n.d.), sandy soil is the only one that is predominantly sand. Moreover, riparian buffer strips would be less effective if it is installed on soil that composed mostly of sand (Hawes and Smith, 2005). Therefore, fields that contain sandy soil were considered as not suitable for installing the riparian buffer strip. To identify the fields that are adjacent to drainage system and water body, a 10m buffer was established for all drainage system and water body. Fields that intersect with buffered area were identified as adjacent to drainage system and water body. According to Klock et al. (2002), the prevailing winds in Ontario come from the southwest in the summer while northwest in the winter. Moreover, as noted by the Arbor Day Foundation (n.d.), windbreaks should be installed on the northern side of the field. Additionally, an L-shaped windbreak is recommended to increase the protected area (Brandle, n.d.). For all these reasons, the windbreak should be installed at northern and western sides of the field to protect the field from the wind. Because most of the fields are rectangular shaped parcels, we assume that the length of windbreaks equals to the length of northern and western sides of the field to be installed, half of the entire edge length. If half of a parcel's edge length is less than 150m, this field is determined to be not suitable for installing a windbreak. The availability of each BMP was determined by the VBA function in the Field Calculator in ArcGIS using "IF...THEN...ELSE" statements. The agricultural fields that are suitable for particular BMP were assigned a value of 1, others were assigned a value of 0. The obtained availability of certain BMP on each field will be used as input data in the developed ABM.

3.5 Modelling BMP application Decision-makings Process

3.5.1 Data

To estimate annual profits a farmer can obtain after adopting each BMP, farmers' average off-farm income, average annual crop yields and market price, as well as the costs of different crops and BMPs were collected from previous literatures and government documentations.

3.5.1.1 Farmer Income Data

The Ontario minimum hourly off-farm wages and the proportion of operators' average weekly hours of off-farm work were collected. The minimum hourly off-farm wages from 2015 to 2019 (refer to Table B-2 in Appendix B) was obtained from the Government of Canada (n.d.). An increasing trend with an average growth rate of 0.07 was calculated with the minimum hourly off-farm wages from 2015 to 2019 as shown in Table B-1 in Appendix B. The proportion of operators' average weekly hours of off-farm work in 2010 (as shown in Appendix Table B-1) were obtained from the Snapshot of Canadian Agriculture reported by Statistical Canada (2012).

3.5.1.2 Crop Products Related Data

The input costs, market prices and yields for soybeans, hay, winter wheat, and corn were collected to estimate the costs and gross income of planting certain crops. The input costs of each crop (in dollars per acre) were obtained from the 2017 FIELD CROP BUDGETS reported by the Ontario Ministry of Agricultural, Food and rural Affairs [OMAFRA] (2016). It estimated the expenses, including seeding, herbicide, machinery, labour and other relevant costs for the selected field crops in 2017 based on field surveys and other government documentations. The input costs for different field crops are summarized in Table D-1 in Appendix D. The market prices from 2008 to 2015 (see Table D-3 in Appendix D) were obtained from OMAFRA which summarized the historical provincial estimates of the harvested area, production, yield, and market price by crop from 1981 to 2016 (OMAFRA, 2018 a). The yield data from 2012 to 2017 (see Table D-2 in Appendix D) was obtained from OMAFRA (2018 b). The unit, source, and timespan of all data are summarized in Table 3-2.

Table 3-2 Data source of crop Products related data

Data	Unit	Timespan	Source
Annual Input Price	\$/Acre	2017	OMAFRA (2016)
Annual Average Yields	tonnes/Acre	2012 - 2017	OMAFRA (2018 a)
Annual Market Price	\$/tonne	2008 - 2015	OMAFRA (2018 b)

3.5.1.3 BMP Related Data

Data on the annual costs of implementing each BMP including labour, machinery, operation and installation expense, were derived from previous literature as a set of ranges (refer to Appendix D, Table D-1). The costs data was recorded in dollars per acre of field. Similarly, the environmental effectiveness of each BMP including sediment removal, P loss reduction, and soil/wind erosion control were also summarized from previous literature as a set of ranges due to their variability regarding the soil and climate characteristics (e.g. soil type, slope, precipitation, and temperature). The effectiveness of sediment removal was expressed in percentage of decrease, which is calculated from the amount of sediments in tons that have been reduced per acre of field. The P loss reduction efficiency was also expressed in percentage, which is derived from the amount of P in pounds that have been reduced per acre. While the effectiveness of soil erosion control was the proportion of decreased soil losses expressed in percentage. The data sources of collected BMP costs and environmental effectiveness data are summarized in Table 3-3. As the summarized costs of the grassed waterway and the riparian buffer strip do not fit the condition of the upper Medway Creek subwatershed, their annual costs of implementation in the study area were calculated according to the data obtained from Kansas (1989) and Tourte et al.'s (2003) research. The annual costs of adopting the riparian buffer strip were computed using the costs data summarized by Mtibaa et al. (2018) and the buffer width data presented by UTRCA (n.d. a). The details of the calculation were elaborated in Section 3.5.2.1. As can be seen, most of the data are obtained from Kansas's study (1989) which summarizes the cost-effectiveness of some of the most commonly used BMPs in reducing P losses from previous literatures. Though this literature is very old, several reasons can be given for using it. First, Kansas's study area is the great lakes basin in the United States, the climate and topographic of which are very close to Ontario. Second, this study was backed by the US Environmental Protection Agency, an independent agency for the United States federal government, which adds the credibility to the data provided by this study. Third, because data about the costs and the environmental effectiveness of BMPs are very limited, reference data that fits my study most.

Table 3-3 Data source of BMP costs and environmental effectiveness data

Data	Source (Costs)	Source (Env. Effectiveness)
Conventional Tillage	OMAFRA (2016)	NA
Reduced Tillage	Kansas (1989)	Kansas (1989)
No-till	Kansas (1989)	Kansas (1989)
Grassed Waterways	Kansas (1989) Tourte et al. (2003)	Kansas (1989)
Riparian Buffer Strips	Mtibaa et al. (2018) UTRCA (n.d. a)	Hawes and Smith (2005)
WASCoB	Kansas (1989) UTRCA (n.d. a)	Kansas (1989)
Windbreak	Roberts (2017) Kansas (1989) Howmuch (n.d.).	López et al. (2017) Dafa-Alla and Al-Amin (2011)

3.5.2 Agent Based Model Development

In order to simulate the farmers' decision-making related to the adoption and use of BMP applications, an agent-based model (ABM) was developed on a parcel-based manner. The ABM was built using the Java-based modelling system embedded in the Repast Simphony 2.5. The model was built on the Aporia framework developed by Murray-Rust et al. (2014). The idea that agents will calculate a score for each influential factor embedded in the Aporia (Murray-Rust et al., 2014) was inherited by this study. The linear weighted sum multi-criteria utility function suggested in the Aporia (Murray-Rust et al., 2014) was used in this study to modelling farmers' decision-making processes. Similar to Murray-Rust et al.'s study (2014), drivers of decision-making were grouped into economic, environmental, and social factors each of which has assigned a multi-criteria preference.

In the ABM developed in this study, farmers in the Upper Medway Creek subwatershed are taken as agents, while the environment is represented as a set of manually digitized agricultural field parcels. The choice of BMP applications was determined based on the Expected Utility Theory (Groeneveld et al., 2017) assuming that land manager will choose the BMP scenario with the highest utility. The utility is calculated using a weighted sum function suggested by Murray-Rust et al. (2014) (Equation 3.2) which is defined by evaluating the influence of economic (e.g. income, cost, and subsidies), social (e.g. neighbours' behaviour and knowledge level) and environmental (e.g. sediment, nutrients, and soil erosion reduction efficiency) factors that influence farmer BMP decision-making (Murray-Rust et al., 2014).

$$U_{BMP} = w_{eco} * S_{eco} + w_{env} * S_{env} + w_{soc} * S_{soc} \qquad \text{Equation 3.2}$$

where, U_{BMP} is the utility score for the specified BMP, w_{eco}, w_{env}, and w_{soc} are the preference weights assigned to economic (S_{eco}), environmental (S_{env}), and social (S_{soc}) criteria, respectively (Murray-Rust et al., 2014). The economic, environmental, and social score will be normalized before feeding it into the utility function (Equation 3.2).

In the model, each farmer has unique information about their knowledge level towards each BMP, whether they have an off-farm employment, the weekly off-farm working hours, and their preference weights on the economic, environmental, and social criteria. Each parcel contains unique information about land-cover type, land manager, land-cover change scenario, a list of suitable BMP scenarios on this parcel, the currently implemented BMP scenario, and a list of their neighbours. Land-cover type suggests the crop that is currently growing on the field such as "Wheat", "Hay" or "Soybeans". Land manager is the farmer that manages this parcel. They are responsible for choosing a BMP scenario that will be conducted to an parcel. Land-cover change scenario indicates the crop rotation that is being followed by a specific parcel. The BMP scenarios refers to the application of a single BMP, as well as those of combinations of multiple BMPs summarized from local government publications and field surveys. A total of eleven BMP scenarios, including the conventional tillage (S_{CT}), the reduced tillage (S_{RT}), the no-till system (S_{NT}), the grassed waterway (S_{GW}), the riparian buffer strip (S_{BS}), the WASCoB (S_{WA}), the windbreak (S_{WI}), the combination of the reduced tillage and the riparian buffer strip (S_{RB}), the combination of the no-till system and the riparian buffer strip (S_{NB}), the combination of the reduced tillage, the riparian buffer strip, and the windbreak (S_{RBW}), as well as the combination of the no-till system, the riparian buffer strip, and the windbreak (S_{NBW}) have been examined in this study. Each of the BMP scenarios has a lifespan which indicates the minimum required time period of implementation with proper maintenance. The list of suitable BMPs on a parcel indicate a set of available multi-year BMP scenarios determined based on the soil type, area, slope, land-cover type, the accessibility to drainage system and water body, as well as the edge length of each parcel (refer to Section 3.4.2 for details).

The decision-making was simulated following a year-incremented loop. Stochastic process was also incorporated in the model where both random factors and systematic factors were included. The details of these stochastic processes are discussed in the following section. Meanwhile, the developed ABM does not consider any adaptation process among the decision makers. Farmers are always aiming to maximize their utility, and their preferences towards the three factors would never change during the simulation. Figure 3-2 shows the overall workflow of the developed ABM.

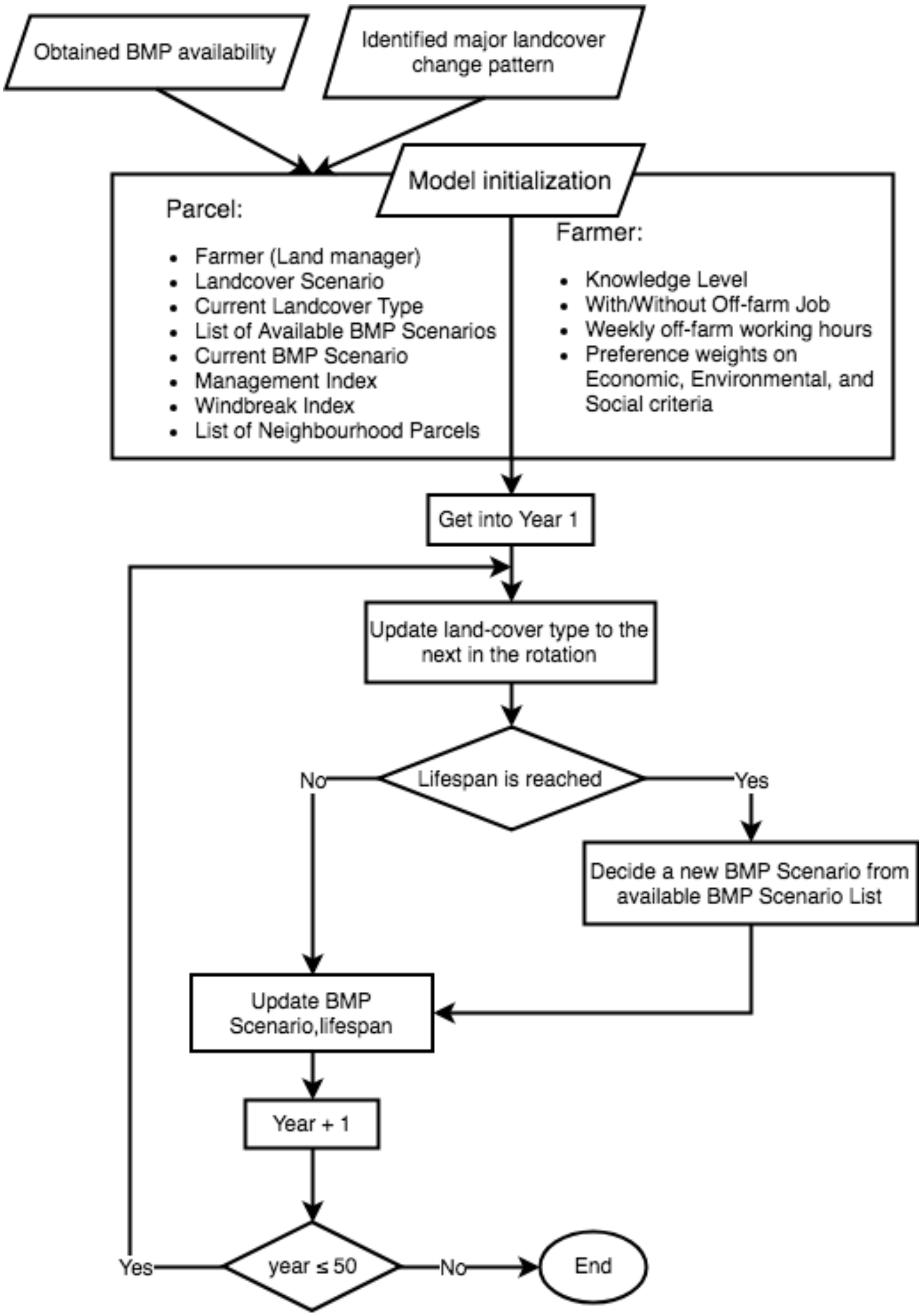


Figure 3-2 Overall workflow of the developed ABM

3.5.2.1 Economic Submodel

The economic score (Murray-Rust et al., 2014), which estimates the average annual profits, was obtained based on the costs of crop seeding, pesticides expenses, planting and harvesting expenses, BMP installation and maintenance costs, labour expenses, gross income of crop products, off-farm income, as well as government subsidies or cost-share program. The economic score can be obtained through Equation 3.3:

$$S_{eco} = \frac{\sum_{i=1}^{Y} I_{crop} + I_{off-farm} \times Y - TC_{BMP} - \sum_{i=1}^{Y} C_{input} + S}{Y} \quad \text{Equation 3.3}$$

where, S_{eco} is the economic score of specified BMP, I_{crop} and $I_{off-farm}$ are the gross income of crop products in year *i* and the annual gross off-farm income, respectively, *Y* is the lifespan of the simulated BMP scenario, TC_{BMP} stands for the total cost of implementing a BMP; C_{input} refers to the total input costs for planting the selected crop in year *i*; and *S* is the subsidies provided by government, it is calculated as Equation 3.4 shows. Notably, the income and the input costs of crop products were estimated following the crop rotation conducted on the corresponding field.

$$S = TC_{BMP} * S_{rate} \quad \text{Equation 3.4}$$

where *S* is the total amount of subsidies offered by government, TC_{BMP} stands for the total cost of implementing a BMP, S_{rate} is the subsidy rate which indicates the proportion of implementation costs of a BMP that is subsidized. The input costs of growing a crop estimated by OMAFRA (2016), including the expenses of seeding, fertilizing, planting, harvesting and other machinery costs which are fixed value estimated from agricultural engineering formulas and Ontario average custom rates by OMAFRA (2016), were used to estimate the costs of growing certain crop (refer to Appendix C for Table C-1). Because there is no archive data indicating the trends or changing rate of the crop input price, an assumption is made that the crop input price keeps the same during the simulation. It was computed using Equation 3.5:

$$C_{crop} = P_{input} \times A_i \quad \text{Equation 3.5}$$

where, C_{crop} is the total input price for the selected crop, P_{input} refers to the unit input costs (in dollar/acre) of a certain crop, and A_i stands for the field area for field i.

The gross income of crop products was calculated using yields and crop market price data. According to the annual average yields data from 2012 to 2017 (refer to Table C-2 in Appendix C), a normal distribution that models the yields was created for each of the crop type based on the standard deviation and the mean of yields in the six years. Similarly, a normal distribution was also created for each field crop to model its market price from 2008 to 2015 (refer to Table C-3 in Appendix C). During the simulation, the yields and market price of the specific crop will be drawn randomly from the defined normal distribution. The seeded and harvested areas are assumed to be consistent with the area of a field parcel. Therefore, the gross income of crop products can be calculated by using Equation 3.6:

$$I_{crop} = Y_i \times (1 + R_{BMP}) \times A_i \times MK_i \qquad \text{Equation 3.6}$$

where, I_{crop} is the gross income of crop products; Y, A and MK refers to the annual yields, harvested area and market prices of crop i, respectively; and R_{BMP} is the percentage of increase/decrease of crop yields caused by BMP.

According to the total number of operators in Canada and the proportion of operators' average weekly hours of off-farm work (refer to Appendix B, Table B-1) reported in the Snapshot of Canadian Agriculture (Statistical Canada, 2012), the range of overall average hours of off-farm work per week can be computed. The result shows that a farmer spends about 27 to 38 hours per week on his (or her) off-farm employment on average. Because data about off-farm wage is scarce, the minimum wage for off-farm work was used. Accordingly, the off-farm income is computed by Equation 3.7:

$$I_{off-farm} = W \times (1 + r) \times \frac{T}{7} \times D \qquad \text{Equation 3.7}$$

where, $I_{off-farm}$ is the annual off-farm income, W is the minimum wage (in dollars per hour) of farmer *i*'s off-farm employment which is fourteen dollars per hour with an interest rate r of 0.07, T is the hours per week of off-farm work, and D is the total number of days in a year which is 365. Notably, r was obtained by calculating the average yearly increasing rate of the minimum general wage provided by the Government of Ontario (n.d.) from 2015 to 2019.

The calculation of BMP costs varies with different BMPs. Data of the costs of implementing BMPs were summarized as a set of ranges (refer to Table E-1 in Appendix E) because the costs of the BMPs are site-specific. The expense of implementing particular BMP is estimated through randomly selecting a value within its cost range specified in Table E-1. The values within the specified range are uniformly distributed, and thus each value has an equal possibility to be picked.

(1) Tillage. The annual expenses of implementing conventional tillage were summarized from the 2017 FIELD CROP BUDGETS report (OMAFRA, 2016) which suggests that the cost ranges from \$50/acre to \$83/acre. Therefore, the initial expense of the conventional tillage for every parcel was randomly selected from the cost range (refer to Table E-1 in Appendix E) at the beginning of the simulation. When a reduced tillage practice was used, its expenses were computed based on the costs of conventional tillage. As the costs of reduced tillage and no-till system decrease from conventional tillage by about 3% and 7%, respectively (Kansas, 1989), the expenses of using reduced tillage system were computed through multiplying the costs of conventional tillage by 97%, while the expenses of applying no-till system were calculated by multiplying the conventional tillage expenses by 93%.

(2) Grassed waterways. As Kansas (1989) noted, one acre of grassed waterway is able to serve about 75 acres of cropland on average. Thus, to convert the costs for grassed waterways into dollars per acre of cropland, Equation 3.8 is used:

$$\begin{cases} Upper\ Bound: C_{upB} = \frac{C_{up}}{A_{unit}} \times \frac{1}{75} \\ Lower\ Bound: C_{lowB} = \frac{C_{low}}{A_{unit}} \times \frac{1}{75} \end{cases} \qquad \text{Equation 3.8}$$

where, C_{upB} and C_{lowB} refer to the upper and lower bound of the costs for grassed waterways per acre of cropland, C_{up} and C_{low} are the estimated maximum and minimum costs, A_{unit} stands for the area unit used by Tourte et al. (2003). The results of implementing Equation 3.6 indicate that the minimum and maximum costs of grassed waterways are \$1.57 and \$44.46 per acre of croplands, respectively. Furthermore, grassed waterways may increase or decrease crop yields by +/- 10% (Kansas, 1989). Hence, a percentage value from -10% to 10% was randomly drawn and added to or deduced from the generated yields, so that the impacts of changed yields on economic returns could be considered.

(3) Riparian buffer strips. According to UTRCA (n.d. a), the width of the buffer strips established for sediment removal should be between 10m and 30m. However, there is no data indicating the costs for a 30-m buffer strip. Therefore, the annual costs of the 5-m and 20-m buffer strips, which are \$3.16/acre and \$12.65/acre, respectively, reported by Mtibaa et al. (2018) will be used to estimate the costs of the 10-m and 30-m buffer strips. First, the unit change in price is calculated to indicate the costs for increasing 1m of buffer width. Then, the costs for a 10-m and 30-m buffer strip can be estimated using Equation 3.9:

$$\begin{cases} C_{10m} = C_{5m} + \left(\frac{C_{20m} - C_{5m}}{15}\right) \times (10 - 5) \\ C_{30m} = C_{5m} + \left(\frac{C_{20m} - C_{5m}}{15}\right) \times (30 - 5) \end{cases} \qquad \text{Equation 3.9}$$

where, C_{5m}, C_{10m}, C_{20m} and C_{30m} are the costs for the 5-m, 10-m, 20-m and 30-m buffer strips, respectively. As a result, the costs for a 10-m buffer strip is \$6.32/acre, and the expenses for a 30-m buffer strip is \$18.98/acre. Accordingly, the costs of buffer strips for sediment removal range from \$6.32/acre to \$18.98/acre annually.

(4) WASCoB. The annual costs of WASCoBs are summarized by Kansas (1989), which range from \$26.3/acre to \$78.8/acre of croplands. Therefore, the annual cost per acre of implementing the WASCoB would be drawn randomly from \$26.3/acre to \$78.8/acre.

(5) Windbreaks. The planting and maintenance expenses of windbreaks are estimated separately. First, to be eligible to apply for the cost-share program, minimum 500 trees need to be planted for the windbreak (Roberts, 2017). Therefore, expenses for planting 500 trees will be used to evaluate the minimum economic criteria for windbreak. The planting costs of coniferous tree were used in this study as they are the most common tree species used for windbreaks in the Upper Medway Creek subwatershed. Planting windbreaks without plastic matting costs least while planting into plastic matting costs most. Accordingly, the costs of planting a 1km windbreak with 500 trees range from \$961 to \$2819.25. The average labour expense for planting windbreaks is 106 dollars per tree (Howmuch, n.d.). The cost-share rate is 75% for the Upper Medway Creek region (Roberts, 2017), which means 75% of the installation costs could be covered by the government. The maximum windbreak length is half of the entire edge length of a parcel as previously mentioned. As for the maintenance costs of windbreaks, an assumption was made that the maintenance expenses of a windbreak were in the same proportion as the

maintenance costs of implementing the grassed waterways, which is 5% of the installation investment (Kansas, 1989). This is because both of them required the use of pesticide, fertilizers, and weed-control efforts (UTRCA, n.d. a; Stange and Brandle, n.d.). The expenses for installing windbreaks are computed as Equation 3.10 shows:

$$C_{install} = (C_{plant} \times l + No._{tree} \times l \times C_{lab}) \times (1 - 75\%) \quad \text{Equation 3.10}$$

where, C_{plant} is the 1km windbreak planting cost drawn randomly from the provided range, l is the length of the windbreak, $No._{tree}$ is the number of trees per kilometre which is 500 in this case, and C_{lab} refers to the average labour cost for planting one tree.

The total costs of implementing the grassed waterways, buffer strips, WASCoB and tillage system are calculated using Equation 3.11:

$$TC_{BMP} = A_j \times Y \times C_{BMP} \quad \text{Equation 3.11}$$

where, TC_{BMP} is the total costs of implementing certain BMP, A_j refers to the area of the field where BMP is applied, Y is the lifespan of a BMP, C_{BMP} stands for the annual cost per acre of a BMP. The total cost of windbreak is computed as Equation 3.12 shows:

$$M_{WB} = C_{install} \times Y \times 0.05 \quad \text{Equation 3.12}$$

where, TC_{WB} is the maintenance cost of implementing windbreaks, Y refers to the number of years a windbreak can be applied, $C_{install}$ is the installation expenses of the windbreak. Meanwhile, the increased yields by windbreaks will be drawn randomly from 8% to 25% and used for calculating the gross income of crop products.

3.5.2.2 Environmental Submodel

The efficiencies of sediment removal, P loss reduction and soil/wind erosion control were considered as three environmental indicators in the environmental submodel. Sediment removal means capturing runoff water to trap and settle sediment in the water (Credit Valley Conservation, n.d.). While erosion control refers to the activities that can stabilize the soil and prevent soil from detaching from the surface and being transported elsewhere (OMAFRA, 2015). The sediment removal, P loss reduction, and soil/wind erosion control efficiencies for each BMP were selected randomly from their corresponding ranges (refer to Table E-2 in Appendix E). The default value for each indicator is zero when the data values are not available (shown as NA in table 6). In order to get an environmental score for each BMP, a weighted sum function, which is similar to the one suggested by Murray-Rust et al. (2014), was used to combine the three environmental indicators. To weight the three indicators, they were first ranked in ascending order depending on their importance (Flitter et al., 2013). Since this study puts more attention on the effects of BMPs on mitigating p loading in the freshwater, the efficiency of P loss reduction was given rank 1. Moreover, rank 1 was also assigned to soil/wind erosion control efficiency as it was identified as an essential concern by all survey participants. The efficiency of sediment removal was given a rank of 2. Then a rank sum method was used to calculate the relative importance for each environmental indicator as Equation 3.13 shows:

$$I = n - r + 1 \qquad \text{Equation 3.13}$$

where, *I* is the relative importance for each of the sediment removal, P loss reduction and soil/wind erosion control indicators , *n* is the total number of indicator which is three in this case, and *r* refers to the rank of an environmental indicator. The weights assigned to each of the environmental indicators are calculated by normalizing the obtained relative importance (Equation 3.14) (Flitter et al., 2013).

$$w_{env-indi} = \frac{I_{env-indi}}{I_{sedi} + I_{Ploss} + I_{ero}} \qquad \text{Equation 3.14}$$

where, $w_{env-indi}$ is the weights assigned to an environmental indicator, $I_{env-indi}$ is the relative importance of the that environmental indicator, I_{sedi}, I_{Ploss}, and I_{ero} are the relative importance for the the sediment removal, P loss reduction and soil/wind erosion control indicators, respectively.

Eventually, the weights for sediment removal, P loss reduction and soil/wind erosion control effectiveness are 0.375, 0.25 and 0.375, respectively. Accordingly, the environmental score was calculated by Equation 3.15:

$$S_{env} = w_p * I_p + w_{sed} * I_{sed} + w_{ero} * I_{ero} \qquad \text{Equation 3.15}$$

where, S_{env} is the environmental score, w_{sed}, w_p, and w_{ero} are the weights for sediment removal, P loss reduction, and soil/wind erosion control efficiencies, respectively, I_{sed}, I_p and I_{ero} are the total efficiencies of sediment removal, P loss reduction, and soil/wind erosion control of the examined BMP scenario.

3.5.2.3 Social Submodel

Two aspects were included in the social submodel, which are farmers' knowledge level regarding different BMPs and the impacts of their neighbours on their BMP decision-making. The knowledge level indicates the degree of how familiar a farmer is with certain BMPs. It considers the farmer's personal experience and the information a farmer obtains from various social media. From Very Unfamiliar to Very Familiar, the knowledge level score ranges from one to ten. The knowledge level for each of the BMP scenario is the average value of the knowledge level of all BMPs it contains. The value of neighbours' behaviours indicates the number of a parcel's neighbours which are applying each BMP Scenario. For each parcel, its neighbour is defined by parcels within a 30m buffer which is the maximum distance measured between two parcels in the Upper Medway Creek region. Therefore, the social score was calculated using Equation 3.16:

$$S_{soc} = KL + NB \qquad \text{Equation 3.16}$$

where, S_{soc} refers to the social score of each BMP, *KL* represents the knowledge level of a farmer, and *NB* stands for the value of Neighbourhoods' behaviour. Neighbourhood parcels belonging to the same farmers were not counted.

To ensure that any of the economic, environmental, and social score value would not greatly overpower the other factors, a normalization process has been conducted for each of factors respectively. Taking the economic factor as an example, the normalization process (refers to Equation 3.17) was carried out after the economic scores for all of the possible BMP scenarios that can be adopted on a parcel were calculated.

$$N_{eco,i} = \frac{S_{eco,i}}{\sum_{i=1}^{n} S_{eco,i}} \qquad \text{Equation 3.17}$$

where, $\mathrm{N_{eco}}$ is the normalized economic score for the *i*th BMP scenario in the list of suitable BMP scenarios for a parcel; $\mathrm{S_{eco,i}}$ refers to the original economic score for the *i*th BMP scenario in the list; *n* is the total number of BMP scenarios in the list.

3.5.2.4 Model Initialization

Before running the model, each agent and parcel was initialized. First, a farmer's knowledge level regarding each BMP was initialized by randomly assigning a score between one (Very Unfamiliar) and ten (Very Familiar). While as a widely used tillage system, the knowledge level of conventional tillage is always ten. Preference weights toward economic, environmental, and social criteria (Murray-Rust et al., 2014) were also initialized for each agent to indicate farms' preference on each factor. Although data related to farmers' preferences assigned to each of the economic, environmental, and social factors have been collected in a field survey, assuming that all of the forty agents in the Upper Medway Creek region have the same preferences with the five responses would be very unrealistic. Moreover, as there is no data to explain how farmers balance their preferences among the three factors, agent's preference weights were randomly picked from a uniform distribution. To ensure that the preference weights assigned to an agent should always sum to one, randomly selected preference weights for an agent were normalized using the Equation 3.18.

$$w_f = \frac{I_f}{I_{eco} + I_{env} + I_{soc}} \qquad \text{Equation 3.18}$$

where, w_f is the normalized preference weight to a factor (i.e. one of the economic, environmental, and social factor); I_f is the preference weight for the same factor, which is randomly selected before normalization; I_{eco}, I_{env}, and I_{soc}, are the randomly picked preference weights for economic, environmental, and social factors, respectively.

According to Ikerd (2001), the farm management system is experiencing a transition from conventional farm economics to a sustainable farm economics. Instead of always focusing on the profit maximization, farmers also dedicate resources to balancing their economic, ecological and social objectives (Ikerd, 2001). Therefore, the preference weight assigned to the economic factor is always the highest (greater or equal to preference weights of other factors). Then, 46.8%, which is identical with the proportion of farm operators with off-farm employment in Canada summarized by Statistics Canada (2012), of total farmers within the Upper Medway Creek subwatershed were randomly selected as those who hold an off-farm employment. For each of them, the number of average weekly working hours was generated randomly from the range of average weekly off-farm working hours provided by Statistics Canada (2012).

Each parcel was initialized with a set of attributes including land managers, land-cover types, land-cover change scenarios, and currently adopted BMPs. The land manager which indicates the farmer who is managing the parcel, is drawn randomly from the forty farmers. One farmer could be assigned to different parcels, while each parcel has exactly one farmer. The land-cover change scenario that indicate the crop rotation followed by a parcel, is selected randomly from the three prominent rotation patterns, including the Corn-Soybean rotation, the Corn-Soybean-Wheat rotation, and the one-crop system of hay, observed in the Upper Medway Creek subwatershed. Then, the initial land-cover type for each parcel was randomly picked from the crop types involved in the selected land-cover change scenario. Once the crop rotation pattern on a field parcel has been determined, it will remain unchanged during the entire simulation. The BMP scenario implemented on each parcel was also determined by randomly selecting from the available BMP scenarios list obtained in Section 3.3.2. When a BMP scenario is selected, a management index was generated randomly between one and the lifespan of the selected BMP scenario to indicate the age of the selected BMP scenario. The management index was. Additionally, if windbreaks were used, a windbreak index would be also given to indicate the age of windbreak. As mentioned by Hodges and Brandle (n.d.), a windbreak is able to live at least fifty years. Therefore, the windbreak index was drawn randomly from one to fifty.

3.5.2.5 Decision-making process

The simulation was carried out year by year iteratively. At the beginning of the simulation, the model would first look at its management index to identify the age of the BMP scenario that is currently applied. If the BMP scenario applied on a field parcel has not finished, that is, the management index has not reached the last year in its timespan, the particular parcel would keep implementing the current BMP scenario in the next year. While if the BMP Scenario has finished, new BMP scenario has to be determined.

To determine the new BMP scenario, the windbreak index was checked to determine whether the windbreak reaches its lifespan during the period of conducting new BMP scenario. If yes, both maintenance and planting costs of implementing a windbreak would be considered, otherwise, only maintenance expense should be included. For each field parcel, BMP scenario with the highest utility score would be selected. After all parcels make their decisions, agents' perceptions would be updated and move on to the next year simulation. Farmers are always aiming to maximize their utility, and their preferences towards the three factors would never change in a simulation. Referring to Figure 3-3 for the workflow of the decision-making process.

A pre-test has been conducted to examine the effects of stochastic elements embedded in the model. In the lights of pervious literatures (Tuite et al., 2017; Garbey et al., 2017), at least fifteen replicate runs are required to account for the stochasticity in the model. Moreover, as this model contains many random processes, the simulation was carried out with twenty replicates to evaluate the model variance caused by the random elements in the model. The number of parcels implemented with each BMP scenario at every time-step is counted and recorded for each run.

A random number generator was also used to evaluate the performance of the model. Instead of choosing the BMP scenario with the highest utility, the decisions were made by randomly selecting a BMP scenario from the list of possible BMPs for a parcel. When a BMP scenario's lifespan has reached and a new decision has to be made, each BMP scenario in the list is chosen entirely by chance and has an equal probability of being selected. The random generator was run 100 times at a fifty-year time scale. To compare the results of the developed ABM with those generated from the random generator, another eighty runs were carried out for the developed ABM at a fifty-year time scale.

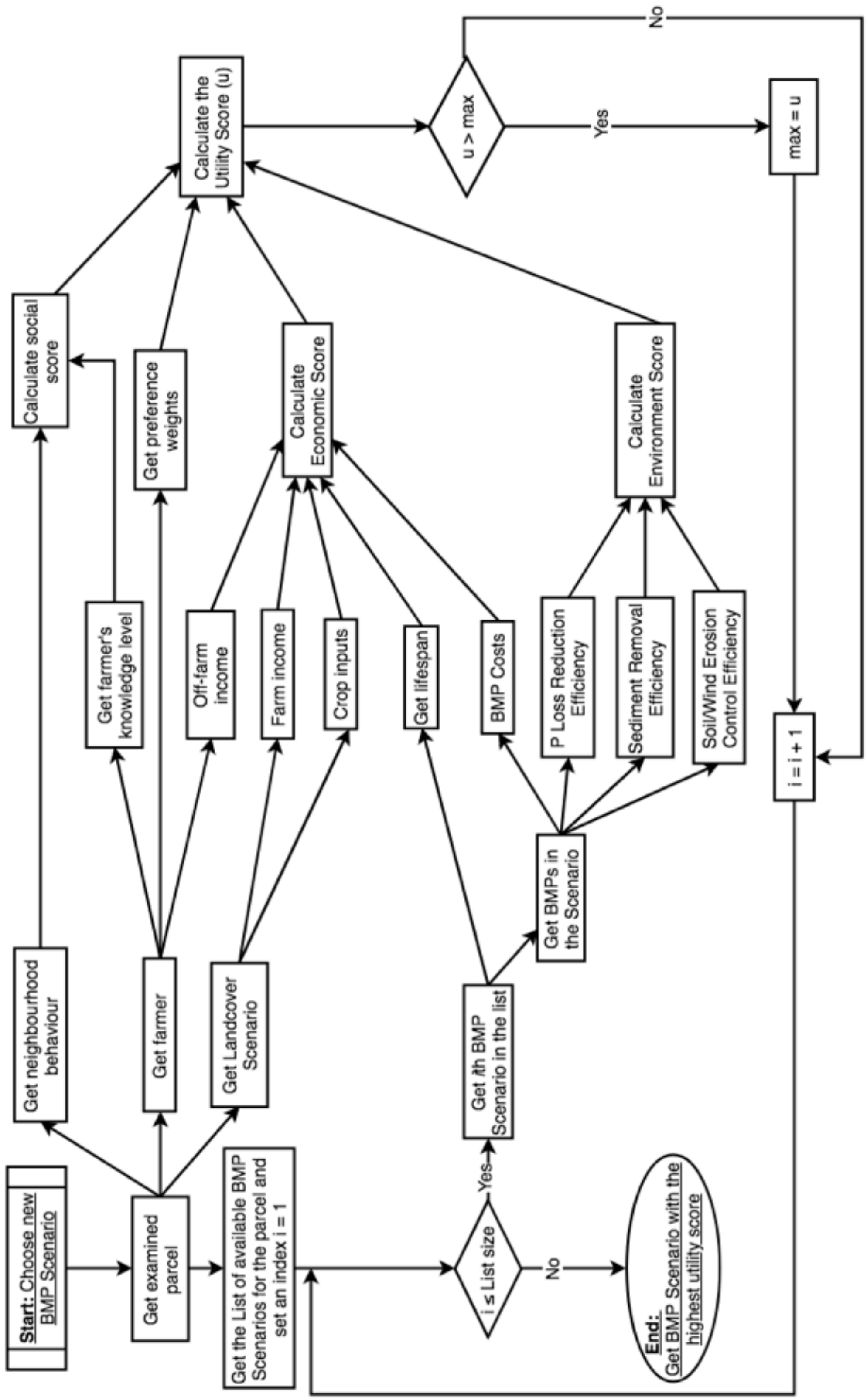


Figure 3-3 Workflow for decision-making process in the ABM

3.6 Sensitivity Analysis

Sensitivity analysis was implemented to explore agents' decisions on adopting certain BMPs in response to different interventions. In the view of UTRCA (n.d. c), the fact that management actions implemented in the Upper Medway Creek subwatershed mainly focus on providing funding support and educational activities (e.g. workshops, presentations, seminars). These actions intend to encourage the BMP application by influencing farmers' economic condition and knowledge level regarding BMPs. Thus, parameters changed in the sensitivity analysis are the amount of subsides in the economic submodel and the farmers' knowledge level regarding each BMP in the social submodel.

The OFAT method (Ten Broeke et al., 2016) was addressed to investigate how increasing subsidies and farmers' knowledge levels to each BMP may affect model results. All model parameters introduced in Section 1.4 were included as input for the sensitivity analysis. The impacts of different subsides were explored by changing the subsidy rate individually for each BMP. The subsidy rate indicates the proportion of a BMPs' implementation costs that would be covered by subsidies. Beginning with 20% of the implementation costs of a BMP, 20% was incremented every time a new subsidy rate was carried out for each BMP except for the windbreak. Because the cost of windbreaks has been subsidized by the cost-share program, it was excluded from this analysis. Other parameters keep unchanged during the simulation. Accordingly, for each of the five BMPs (reduced tillage, no-till, grassed waterway, riparian buffer strip, and WASCoB), five experiments were carried out, each of which was given a specific subsidy rate as shown in Table 3-4.

Table 3-4 Subsidy rates assigned to each experiment for each of the five BMPs

Experiments	Subsidy Rates (in %)
1	20
2	40
3	60
4	80
5	100

For the changing BMP knowledge level, we assumed that farmers' knowledge level regarding a BMP would increase after attending an educational activity. The impacts of the growing agents' knowledge level were investigated by adding a farmer's original knowledge level towards a particular BMP by two every time a new experiment was addressed. The increment would stop once a famer's knowledge level has reached ten which is the upper bound of farmers' knowledge level. All other parameters remain unchanged during the simulation. In such a way, five experiments, each of which was given a specific subsidy rate as shown in Table 3-5, were addressed for each of the examined BMPs (reduced tillage, no-till, grassed waterway, riparian buffer strip, WASCoB, windbreak).

Table 3-5 The value of increment of farmers' knowledge level in each experiment for each of the six BMPs

Experiments	Increased Value of Knowledge Level
1	+2
2	+4
3	+6
4	+8
5	+10

As mentioned by Ten Broeke et al. (2016), the time-step used for the sensitivity analysis should be time when the model output does not largely change, instead, it fluctuation randomly around a mean. Outputs of the pre-test conducted in Section 3.4.2.5 shows that the number of parcels adopting each BMP scenario does not strongly fluctuant when the time-step has reached fifty. Furthermore, at least ten replicate runs are needed for each parameter setting to evaluate how results spread (Ten Broeke et al., 2016). Therefore, twenty replicates were run per parameter setting at a fifty-year time scale. The outputs of the per-test at the time-step of fifty are used as the comparison standard for the sensitivity analysis. The number of fields implemented with each BMP scenario was considered as the output of interest for the sensitivity analysis.

A linear regression (LR) was performed at 95% confidence intervals to explore the significance of the impacts of defined subsidy rates and knowledge levels on adopting agricultural BMPs. In the LR, the IRs of a BMP scenario derived from twenty replicate runs have been taken as the dependent variables; the defined subsidy rates and increased knowledge levels have been considered as the independent variables. The p-value of the LR, which indicates a statistically significant influence when it is smaller than 0.05, is examined. Additionally, variable importance has been measured to compare the relative contribution each defined subsidy rate or increased knowledge level makes to the BMP adoption. The larger the value of variable importance, the greater the influence of the increased knowledge level on facilitating the BMP adoption. The LR and variable importance have been performed using RStudio version 1.1.453. The influences of increasing subsidies and knowledge levels on BMP adoption have been examined separately.

3.7 Chapter Summary

This chapter summarizes the study area, data and methodologies used in this research. A field survey was conducted to farmers in the Upper Medway Creek subwatershed to collect information about the BMPs utilized by farmers and the factors that influence farmers' agricultural decision-making. A trajectory computing method developed by Wang et al. (2012) has been addressed to observe the prominent land-cover change patterns in the study area. In order to determine the suitability of BMPs to be implemented on every agricultural field, area, slope, soil type, land-cover type, drainage systems, water accessibility, and the edge length of each agricultural field have been obtained and analysed. An ABM was developed based on the Expected Utility Theory using a weighted sum function to evaluate the influence of economic, environmental, and social factors and simulate farmers' decision-making on the adoption of different BMPs. Finally, a OFAT method has been carried out to perform a sensitivity analysis to investigate the impacts of government subsidies and educational activities on encouraging farmers to adopt certain BMPs.

Chapter 4 Results

4.1 Field Survey

A total of five responses were collected. The five participants comprise both full-time and part-time farmers. These farmers work land ranging in size from 80 to 1600 acres, including fields that are both rented and owned. The survey collects information about the agricultural practices and factors influencing farmers' agricultural decision-making. Two prominent land-cover change patterns were identified from survey responses: (1) the "corn-soybean-winter wheat" rotation; (2) the one-crop system of hay. According to the responses, participants consider economic factors to be of primary importance in agricultural decision-making. There are three economic factors have been identified that play essential roles in affecting farmers' agricultural decision-making, the costs of new equipment and technology, commodity prices and market values of crops, and crop yields. Respondents indicated that at least 55% of their agricultural decision-making was impacted by these economic factors. Environmental factors were rated as the second most important influencer on farmers' agricultural decision-making, with farmers giving this factor a 20% to 30% weighting. The environmental factors that have major impacts are soil and wind erosion, nutrient runoff/loss, and soil health. Social factors have the least impacts on farmers' agricultural decision-making. Three out of five participants responded that social factors have no effect on their agricultural decision-making, while the other two responses indicated that social factors have the same contribution as environmental factors. The wind direction and speed must be considered when applying herbicides so as not to upset the neighbours. Four out of five respondents think implementing conservation tillage is one of the best management practices to improve regional water quality. Additionally, all five participants indicated that their fields are suffering problems of soil and nutrient losses.

The second part of the survey aims to obtain information related to the BMPs utilized by farmers in the Upper Medway Creek region and their motivations and satisfactions of using these BMPs. In general, the adoption of agricultural BMPs is motivated by a desire for soil/wind erosion reduction, profit maximization, and sustaining the land for future use. Nevertheless, financial costs have also been identified as the greatest barrier to applying BMPs. There are two financial concerns of adopting BMPs including the high costs versus low benefits and the availability of financial incentives. No-till, riparian buffer strip, and cover crops are the most commonly used BMPs. Among these BMPs, the satisfaction level for implementing cover crops is the highest followed by the adoption of conservation tillage, no-till, and riparian buffer strips which are all medium high. Other BMPs such as manure storage, nutrient management, windbreaks, WASCoB, and other erosion control structures (e.g. berm, rock chutes) have also been adopted by the farmers. Both windbreaks and WASCoB have received a satisfaction levels of medium high; while nutrient management is given a satisfaction level of high. Refer to Table 4-1 for the summarized motivations and satisfaction levels of implementing different BMPs.

Table 4-1 Summary of motivation and satisfaction level of adopting different BMPs

BMP Name	Motivation	Satisfaction Level
Conservation Tillage/No-till	• Less time • Economic & environmental motivations • Soil erosion reduction	High
Cover Crop	• Erosion reduction • Build organic matter • Improve soil health • Pushed by UTRCA staff • Avoid non-growing periods	Very High
Manure Storage	• Suggested by the Environmental Farm Plan (EFP)	NA
Nutrient Management	• Suggested by the EFP	Very High
Riparian Buffer Strip	• Recreational benefits • Soil erosion control • Hilly geography • Improve water quality	High
WASCoB	• Soil erosion and loss control • Strip cropping	Medium high
Windbreaks	• Wind and soil erosion reduction • Wildlife habitat • Reforestation	Medium high
Other: Blind Inlets, Berms, Hicken bottoms, Rock chutes	• Erosion reduction • Drainage management	High

Farmers reported that their own experience and knowledge, government organizations and farmers' associations (e.g. OSCI, AAFC, OMAFRA), friends and neighbourhood farmers, university researchers, as well as online documents are the main sources of information that influence farmers' agricultural decision-making. Websites are the most popular medium for farmers to acquire agriculture-related information. Other preferred sources of information include magazines/newsletters, government publication, workshops, and presentations. Moreover, it has been shown that for all of the participants, at least 50% of household income comes from their farming. For farmers who have off-farm employments, no more than 50% of their weekly labour would be spent on farming.

4.2 Primary Land-cover Change Patterns

After summarizing the raster-based AAFC land-cover dataset by agricultural field boundary, seven land-cover types, including Beans, Wheat/Cereal, Corn, Mixedwood, Pasture and Forage, Soybean, and Barley, were obtained. As can be seen from Figure 4-1, corn, soybeans, wheat or cereals, as well as pasture and forages are the primary crop types growing in the Upper Medway Creek subwatershed. It could be observed in 2012 that eight out of 167 agricultural fields were planted with beans. In both 2012 and 2014, only one out of 167 fields was classified to Mixedwood class. The barley class appears in 2015, in which exactly one agricultural field was identified to be covered with barley. In the end, the Wheat or Cereal and Pasture or Forage classes have been renamed to Wheat and Hay, respectively since the major cereal growing in this subwatershed is wheat and the major pasture and forages area are planted with hay (UTRCA, n.d. c).

A total of 77 different trajectory codes have been identified after addressing the trajectory computing method (refer to section 3.2 for details). Based on the number of agricultural fields that have trajectory codes representing the same land-cover change pattern (e.g. 23623 and 36236), three major land-cover change patterns have been determined: 1) Corn-Soybean rotation; 2) Corn-Soybean-Wheat rotation; 3) Hay with no change over time. These three primary land-cover change patterns cover 103 fields, which is about 62% of the total agricultural fields (see Figure 4-2). Among these 103 fields, 31 fields implement Corn-Soybean rotation, thirty fields follow a Corn-Soybean-Wheat rotation, and another 42 fields show land-cover change pattern of

Hay with no change over time. For the other trajectory codes, no more than ten agricultural fields have been identified for each of them. Therefore, they are excluded from the major land-cover change patterns. Among the three major land-cover change patterns, the Corn-Soybean rotation and the one-crop system of hay are also shown as the major land-cover change patterns in the field survey.

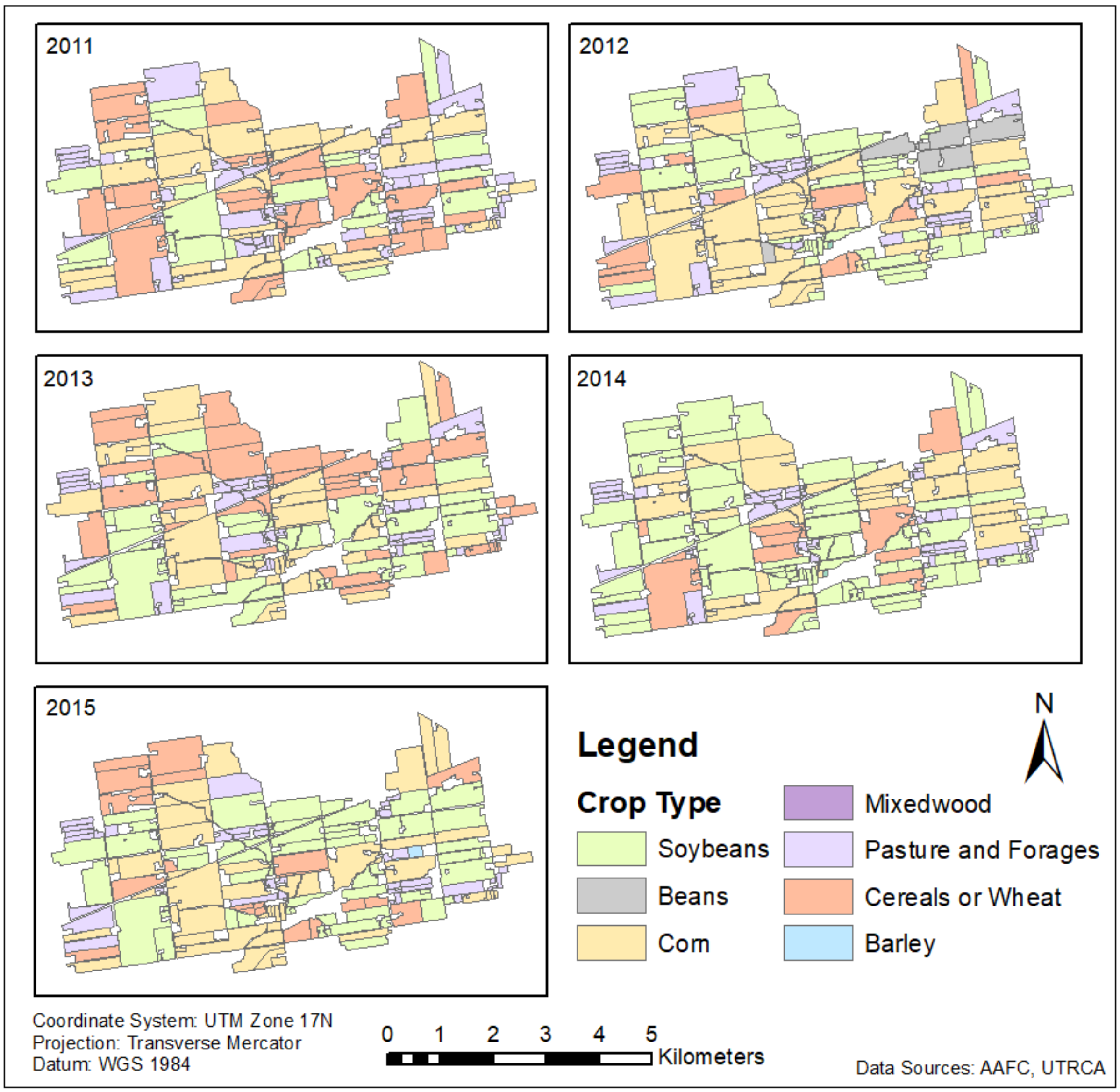


Figure 4-1 Land-cover on each agricultural field from 2011 to 2015 in the Upper Medway Creek subwatershed in different years

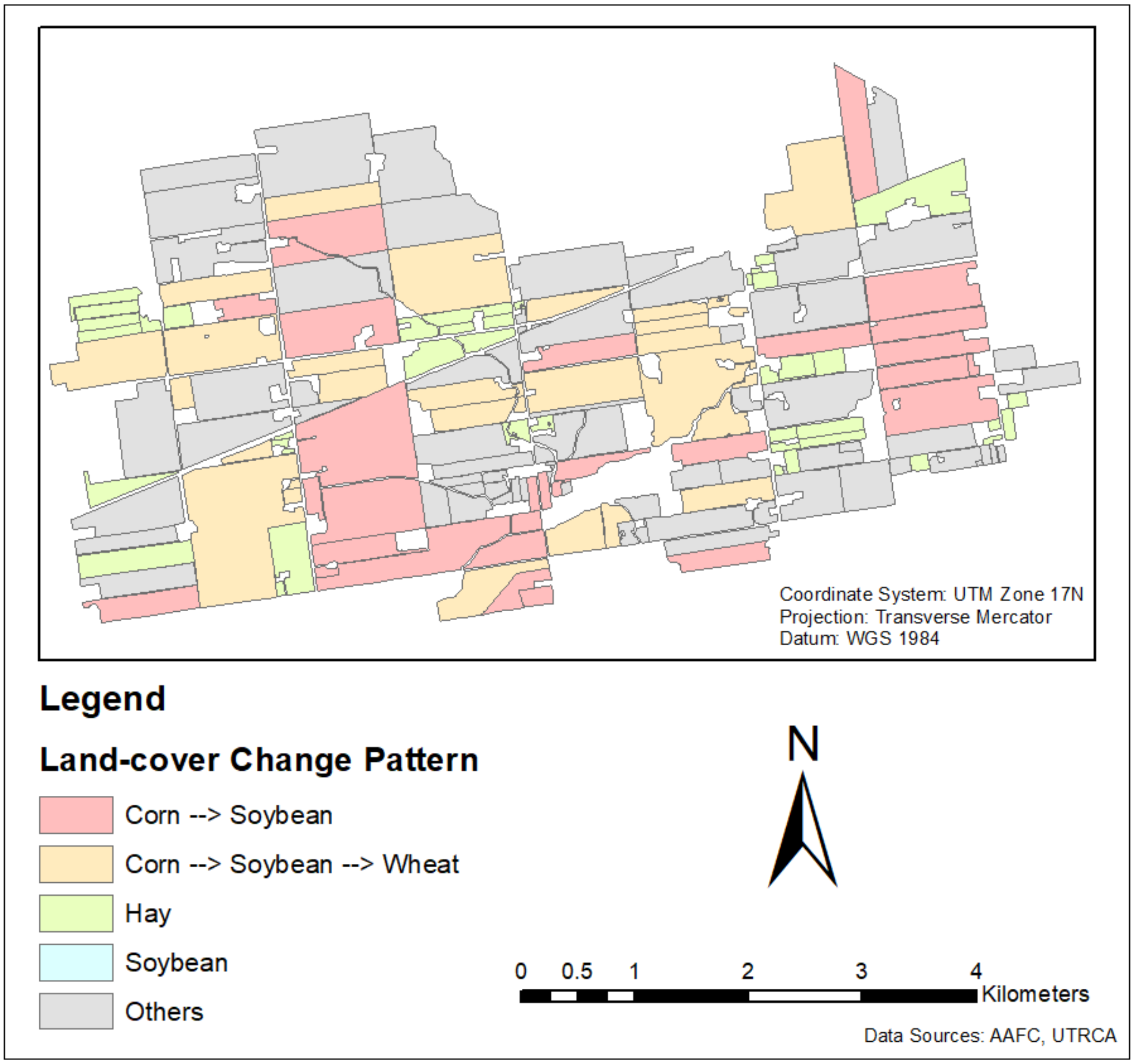


Figure 4-2 Major rotations and land-cover change patterns in the Upper Medway Creek subwatershed from 2011 to 2015

4.3 Determining Possible BMP on Each Agricultural Field

The availability of different BMPs on each agricultural field is determined according to the area, slope, soil type, land-cover type, drainage systems, water accessibility, and field's edge length. Generally, conservation tillage and no-till systems are able to be implemented to all fields. As can be seen from Figure 4-3-a, agricultural fields that are suitable for installing grassed waterways are least prevalent in the Upper Medway Creek subwatershed. Among the total 167 agricultural fields, only 25 fields can be implemented with grassed waterways. The number of agricultural fields that are suitable for riparian buffer strips is about twice the number of fields suitable for grassed waterways. Approximately 68% of the agricultural fields can accommodate a WASCoB. A majority of agricultural fields are suitable for adopting windbreaks as Figure 4-3-d shows. Windbreaks is able to be planted on a total of 159 fields, about 95% of all agricultural fields in the entire Upper Medway Creek region. Given these points, the number of agricultural fields that are suitable for S_{RB}, S_{NB}, S_{RBW}, and S_{NBW} is 52, 52, 50, and 50 respectively. Though many other factors may also have impacts on the suitability of a particular BMP on a field, this study only considers the above factors, and further investigations can be implemented in the future.

Figure 4-3 The suitability of agricultural fields for grassed waterways, riparian buffer strips, WASCoBs and windbreaks, respectively

4.4 Pre-test of the ABM

To evaluate the model variance caused by the random elements in the model, a pre-test has been conducted with twenty replicate runs. The number of agricultural fields implementing each BMP Scenario after fifty time-step has been counted for each of the twenty runs. The result shows that S_{WI} is always the predominant BMP scenario in the Upper Medway Creek subwatershed followed by S_{NT} and S_{WA}. However, nearly no farmer would like to implement S_{GW}, S_{RB}, and S_{RBW} after fifty years.

In order to get the insight of the overall situations of BMP implementations, the average value of the number of agricultural fields using each BMP scenario after twenty runs has been calculated (Table 4-2). As mentioned in Section 3.4.2, the number of fields suitable for each BMP scenario varies according to the topography, soil characteristics, water accessibility, as well as the field size. This makes it unreasonable to directly compare the number of fields using each BMP scenario. Therefore, the implementation rates (IR), which is the ratio of the number of fields adopted with each BMP scenario to the total number of fields that are suitable for each BMP scenario, is calculated and expressed as a percentage to improve the comparability of the results between different BMP scenarios. As can be seen from Table 4-2, the proportion of agricultural fields implemented with S_{WI} is the largest, as more than half of the available agricultural fields would choose to apply S_{WI}. Though a few number of agricultural fields is implemented with S_{NBW}, the small data size of available agricultural fields for S_{NBW} make it becomes the second highest among the eleven BMP scenarios. Among the three examined tillage system, no-till is the most popular tillage technique whose IR is about ten times the IR for either the conventional tillage or the reduced tillage system. The average IR of the grassed waterway demonstrates that nearly no farmer would adopt grassed waterways after fifty years. Additionally, the proportions of agricultural fields implemented with S_{RB} and S_{RBW} stay low.

Table 4-2 Statistics of the results of model pre-test at a fifty-year time scale

Scenario	S_{CT}	S_{RT}	S_{NT}	S_{GW}	S_{BS}	S_{WA}	S_{WI}	S_{RB}	S_{NB}	S_{RBW}	S_{NBW}
Total No. of fields*	167	167	167	25	52	113	159	52	52	50	50
Avg.**	2.79	2.16	26.00	0.16	7.63	19.05	89.21	0.79	6.26	1.21	11.74
Avg. IR (in %)	1.67	1.29	15.57	0.63	14.68	16.86	56.11	1.58	12.04	2.33	23.47
Std.***	2.34	1.79	7.31	0.37	4.82	8.56	8.69	1.37	2.96	1.31	5.85
CV****	0.85	0.83	0.28	2.44	0.60	0.44	0.10	1.83	0.47	1.14	0.51

* The total number of agricultural fields suitable for each BMP scenario
** Mean value of the number of agricultural fields using each BMP scenario after 20 runs
*** Standard deviation of the number of agricultural fields using each BMP scenario after 20 runs
**** Coefficient of variation = Std. / Avg.

The results obtained from running the model twenty times are used to determine the degree of variation of the model. Here, the coefficient of variance (CV) is calculated to indicate the relative variability of the model on simulating the BMP implementation decision-making under the impacts of the randomness embedded in the model. As shown in Table 4-2, ten out of eleven BMP scenarios have a CV that is smaller than one, which indicates a relatively low variation in the outputs (Brown, 2012). The highest value of CV is computed for S_{GW}. Though the values of CV for both S_{RB} and S_{RBW} are lower than S_{GW}, they are still relatively higher than other BMP scenarios, the CV of which is greater than one. This indicates a relatively high variability in the datasets of S_{GW}, S_{RB}, and S_{RBW}.

4.5 Random Generator

Table 4-3 Statistics of the results of the 100 model runs at a fifty-year time scale

Scenario	S_{CT}	S_{RT}	S_{NT}	S_{GW}	S_{BS}	S_{WA}	S_{WI}	S_{RB}	S_{NB}	S_{RBW}	S_{NBW}
Total No. of fields*	167	167	167	25	52	113	159	52	52	50	50
Avg.**	2.92	2.13	28.79	0.41	6.74	18.32	85.95	0.95	5.76	0.79	14.24
Avg. IR (in %)	1.75	1.28	17.24	1.64	12.96	16.21	54.06	1.83	11.08	1.58	28.48
Std.***	2.59	1.39	11.01	0.55	5.72	10.98	9.93	1.15	4.70	1.18	10.65
CV****	0.89	0.65	0.38	1.34	0.85	0.60	0.12	1.21	0.82	1.50	0.75

* The total number of agricultural fields suitable for each BMP scenario
** Mean value of the number of agricultural fields using each BMP scenario after 20 runs
*** Standard deviation of the number of agricultural fields using each BMP scenario after 20 runs
**** Coefficient of variation = Std. / Avg.

Table 4-3 shows the result obtained from 100 times running of the developed ABM. Similar results were obtained as the model pre-test. That is, S_{WI} is the most prevalent BMP scenario in the Upper Medway Creek subwatershed while S_{GW} is the least predominant BMP scenario in the Upper Medway Creek subwatershed after fifty years. According to values of CV, a relatively low variability can be identified for S_{CT}, S_{RT}, S_{NT}, S_{BS}, S_{WA}, S_{WI}, S_{NB}, and S_{NBW}; while relatively high variation has been observed for the datasets of S_{GW}, S_{RB}, and S_{RBW}.

Table 4-4 Statistics of the results of the random generator at a fifty-year time scale

Scenario	S_{CT}	S_{RT}	S_{NT}	S_{GW}	S_{BS}	S_{WA}	S_{WI}	S_{RB}	S_{NB}	S_{RBW}	S_{NBW}
Total No. of fields*	167	167	167	25	52	113	159	52	52	50	50
Avg.**	4.15	4.24	4.13	1.39	4.61	15.17	109.92	4.43	7.03	5.44	6.51
Avg. IR (in %)	2.49	2.54	2.47	5.56	8.87	13.42	69.13	8.52	13.52	10.88	13.02
Std.***	2.27	1.67	1.82	1.21	1.88	3.45	5.74	2.20	2.61	2.97	2.50
CV****	0.55	0.39	0.44	0.87	0.41	0.23	0.05	0.50	0.37	0.55	0.38

* The total number of agricultural fields suitable for each BMP scenario
** Mean value of the number of agricultural fields using each BMP scenario after 20 runs
*** Standard deviation of the number of agricultural fields using each BMP scenario after 20 runs
**** Coefficient of variation = Std. / Avg.

Results of the random generator are presented in Table 4-4. As shown, the IR of S_{WI} is significantly greater than other BMP scenarios. S_{CT}, S_{RT}, and S_{NT} show relatively low values of IR. The CV was also calculated to assess the degree of variation generated by the random generator. As can be seen, none of the BMP scenarios has a value of CV that is greater than one, which indicates a relatively low variation in all of the datasets.

4.6 Sensitivity Analysis

The results introduced in Section 4.4 are taken as the baseline in the entire sensitivity analysis. The average value of the number of agricultural fields implemented with each BMP scenario and their IRs derived from twenty replicate runs is computed for each BMP scenario.

4.6.1 Impacts of Increasing Subsidies

In this section, the influence of adding subsidies on the adoption of a particular BMP (both individually or combining with other BMPs) has been explored first. The IR for a particular BMP is the ratio of the total number of agricultural fields adopting that BMP (both individually and combined with other BMPs) to the number of fields available for that BMP expressed in percentage. For example, the IR of no-till system should be calculated by dividing the sum of fields implemented with S_{NT}, S_{NB}, and S_{NBW} by the number of fields available for the no-till system.

Generally, an increasing trend for all of the examined BMPs is observed when more subsidies are provided. The impact of adding subsidies on encouraging the implementation of BMPs is the greatest for the no-till system and WASCoB. According to Figure 4-4, the IR of no-till system would increase about 12%-18% when 20% of the subsidy rate is added each time after the subsidy rate has reached 20%. For the WASCoB, a drastic increment can be found when the subsidy rate increases from 40% to 60%. Similarly, the IR of the riparian buffer strip has increased the most when subsidies change from 40% of the implementation expenses to 60%. However, the impact of increasing subsidies on the implementation of the riparian buffer strip is not as evident as the influence on the WASCoB. Figure 4-4 shows that the increasing subsidy rate would not strongly impact the implementation of reduced tillage until it is at least 60% of implementation costs of the reduced tillage. Nevertheless, adding subsidies could barely affect the implementation of grassed waterways in the Upper Medway Creek subwatershed.

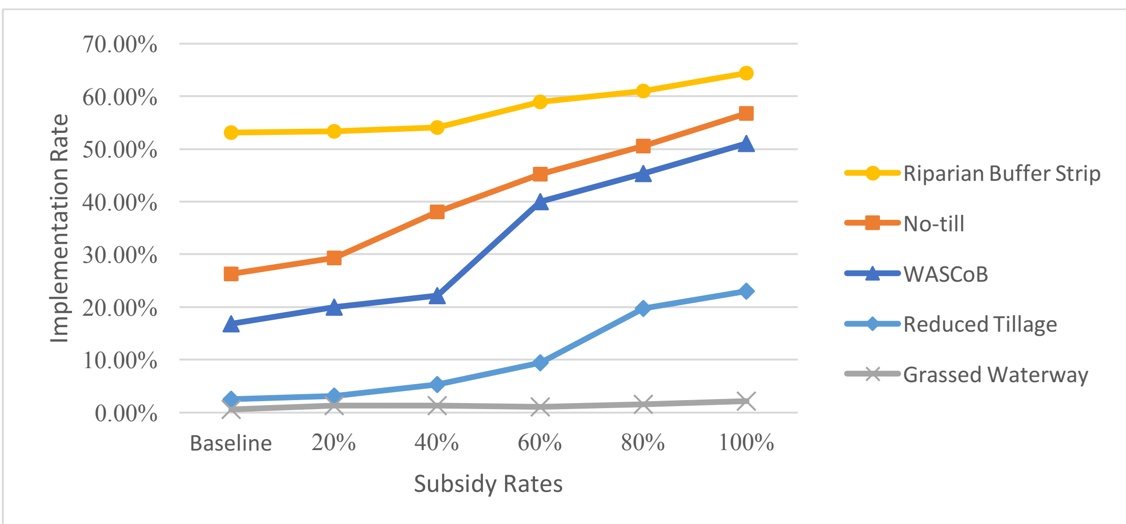


Figure 4-4 Changes of the number of agricultural fields adopting each BMP in regard to the increasing subsidies

Table 4-5 and Table 4-6 summarises the p-value and variable importance of LR built from the defined subsidy rates and the number of fields adopting each BMP except windbreaks. The p-values of the reduced tillage and the no-till become lower than 0.05 after the subsidy rate has reached 40%, which indicates that the influences of subsidy rates on increasing the IR of the reduced tillage and the no-till system are statistically significant when it has reached 40%. Whereas for the reduced tillage system, values of the variable importance of subsidy rates that are higher than 80% are almost three times the subsidy rates that are lower than 80% (refer to Table 4-6). Thus, subsidy rates higher than 80% make a greater contribution to increasing the application of reduced tillage. Moreover, the IR of the reduced tillage first exceeds the IR of the WASCoB when the subsidy rate of the reduced tillage has reached 80%. For both the riparian buffer strip and the WASCoB, statistically significant increases of IR have been identified when the subsidy rates are higher than 60%. Furthermore, there are a sudden increases of the variable importance for both the riparian buffer strip and the WASCoB when the subsidies increase from 40% to 60% as shown in Table 4-6. This demonstrates that subsidy rates that are higher than 60% have a much stronger impact on encouraging the adoption of riparian buffer strips and WASCoBs. Comparatively, there is no statistically significant impact of growing subsidies on the implementation of grassed waterways as the p-values of the grassed waterway under all defined subsidy rates are greater than 0.05. According to Table 4-6, the contributions made by each defined subsidy rate to changes of IR of the grassed waterway are about the same. Therefore, increasing subsidies to installing grassed waterways could hardly encourage the adoption of grassed waterways.

Table 4-5 The p-value of LR between defined subsidy rates and the number of fields adopting each BMP (except windbreaks)

	LR p-value				
Subsidy Rate	**Reduced Tillage**	**No-till**	**Grassed Waterway**	**Riparian Buffer Strip**	**WASCoB**
20%	0.568	0.286	0.384	0.991	0.634
40%	0.008	0.000	0.384	0.991	0.136
60%	0.000	0.000	0.579	0.043	0.000
80%	0.000	0.000	0.236	0.048	0.000
100%	0.000	0.000	0.071	0.017	0.000

Table 4-6 Variable importance of defined subsidy rates to the number of fields adopting each BMP (except windbreaks)

	Variable Importance				
Subsidy Rate	**Reduced Tillage**	**No-till**	**Grassed Waterway**	**Riparian Buffer Strip**	**WASCoB**
20%	0.573	1.074	0.875	0.012	0.478
40%	<u>2.700</u>	<u>4.018</u>	0.875	0.012	1.505
60%	<u>5.790</u>	<u>6.449</u>	0.557	<u>2.050</u>	<u>6.950</u>
80%	<u>14.396</u>	<u>8.258</u>	1.193	<u>2.003</u>	<u>8.591</u>
100%	<u>17.120</u>	<u>10.352</u>	1.830	<u>2.424</u>	<u>10.321</u>

To obtain a better understanding of how giving different subsidy rates could affect the implementation of different BMPs, the eleven BMP scenarios are examined in detail respectively. The change of IRs with respect to increasing subsidies to the reduced tillage can be seen in Figure 4-5-A. The IR of S_{RT} increases when more subsidies are offered. For S_{RB} and S_{RBW}, the IRs are slightly reduced when the subsidy rate is 20% of the implementation costs of the reduced tillage. However, p-values for both S_{RB} and S_{RBW} are greater than 0.05 when the subsidy rate is 20% (refer to Table 4-7), which means that the impact of adding subsidies of 20% implementation costs on these reductions is not statistically significant. The impact of adding subsidies on adopting reduced tillage individually becomes statistically significant when the subsidy rate has reached 40%. For BMP scenarios that combine the reduced tillage with other BMPs (S_{RB} and S_{RBW}), the influences of subsidy rates are statistically significant when it is higher than 80%. Moreover, a drastic increase of IR for all of the three BMP scenarios is observed when the subsidy rate increases from 60% to 80%. Accordingly, the effects of adding subsidies of 80% implementation costs are statistically significant to the increment of implementing S_{RT}, S_{RB}, and S_{RBW}. For all of the three BMP scenarios implementing reduced tillage, a drastic increase can be identified for the values of variable importance when the subsidy rate changes from 60% to 80% (refer to Table 4-7).

Table 4-7 The p-value and variable importance of defined subsidy rates to the IRs of BMP scenarios adopting reduced tillage

	LR p-value			Variable Importance		
Subsidy Rate	**S_{RT}**	**S_{RB}**	**S_{RBW}**	**S_{RT}**	**S_{RB}**	**S_{RBW}**
20%	0.204	0.584	0.468	1.281	0.549	0.729
40%	<u>0.024</u>	0.421	0.248	<u>2.290</u>	1.020	1.163
60%	<u>0.000</u>	0.286	0.090	<u>5.638</u>	1.333	1.714
80%	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>11.932</u>	<u>4.336</u>	<u>7.547</u>
100%	<u>0.000</u>	<u>0.000</u>	<u>0.000</u>	<u>13.869</u>	<u>5.307</u>	<u>9.517</u>

According to Figure 4-5-B, the IRs of all of the three BMP scenarios adopting a no-till system present an increasing trend with the increase of subsidies. While the IR of S_{NT} and S_{NBW} have a greater increase from a subsidy rate of 0% (the baseline) to 100% compared to S_{NB}. Results of the LR and variable importance performed for the impacts of different subsidy rates on the IR of BMP scenarios that implement no-till system are provided in Table 4-8. The p-value of LR for S_{NT} indicates that the influence of subsidies on the no-till adoption becomes statistically significant when it is 40% of the implementation expenses of no-till system. A statistically significant influence is observed for S_{NB} when the subsidy rate is 100% of the implementation costs of no-till system. For S_{NBW}, which combines no-till with riparian buffer strips and windbreaks, the p-value becomes lower than 0.05 when the subsidies are higher than 80% of the no-till implementation costs. Furthermore, the variable importance reveals that subsidy rates higher than 60% make a great contribution to the growth of adopting no-till individually. Subsidy rate of 100% is identified that plays a critical role in affecting the adoption of S_{NB}. Subsidy rates higher than 80% present a relatively high importance to increasing the IR of S_{NBW}.

Table 4-8 The p-value and variable importance of defined subsidy rates to the IRs of BMP scenarios adopting no-till

	LR p-value			Variable Importance		
Subsidy Rate	S_{NT}	S_{NB}	S_{NBW}	S_{NT}	S_{NB}	S_{NBW}
20%	0.393	0.344	0.956	0.858	0.950	0.056
40%	0.000	0.175	0.264	3.710	1.366	1.125
60%	0.000	0.147	0.115	6.543	1.462	1.593
80%	0.000	0.139	0.019	8.305	1.494	2.395
100%	0.000	0.028	0.001	9.976	2.228	3.286

Though there is an increasing trend of the adoption of grassed waterways when more subsidies of implementation costs are provided except increasing the subsidy rates from 40% to 60% (refer to Figure 4-5-C), the p-value for all defined subsidy rates are higher than 0.05 as shown in Table 4-9. This indicates that the influence of increasing subsidies for installing grassed waterways on the growing IR is not statistically significant. The variable importance (refer to Table 4-9) also indicates that the contribution each defined subsidy rate makes in changing the IR of S_{GW} is not evidently different with each other.

Table 4-9 The p-value and variable importance of defined subsidy rates to the IRs of BMP scenarios adopting grassed waterways

	LR p-value	Variable Importance
Subsidy Rate	S_{GW}	S_{GW}
20%	0.384	0.875
40%	0.384	0.875
60%	0.579	0.557
80%	0.236	1.193
100%	0.071	1.183

The changes of IR of BMP scenarios incorporating riparian buffer strips are visualized in Figure 4-5-D. The IR of S_{BS} remains the same as baseline when the subsidy rate is only 20%; while it keeps increasing when the subsidies are higher than 20% of the implementation costs of riparian buffer strips. According to Table 4-10, the p-values of S_{BS} indicate that the influence of the defined subsidy rates on the IR is statistically significant when the subsidies are at least 60% of the riparian buffer strips implementation expenses. In addition, the variable importance reflects that subsidy rates of 60%, 80%, and 100% make a relatively large contribution in improving the implementation of S_{BS}. As can be seen from Figure 4-5-D, the change of IRs of S_{RB} caused by the increased subsidies represent a decreasing trend except when the subsidy rate is between 20% and 40%. However, the p-values of the subsidy rates that are smaller than 100% are all greater than 0.05, which indicates that the influences of these subsidy rates on adopting riparian buffer strips are not statistically significant. It has been also proved by the value of variable importance that the subsidy rate of 100% plays a more important role than other defined subsidy rates in facilitating the adoption of S_{RB}. Although increasing subsidies can somehow impact the implementation of S_{NB} to S_{NBW}, their p-values have shown that these influences are not statistically significant.

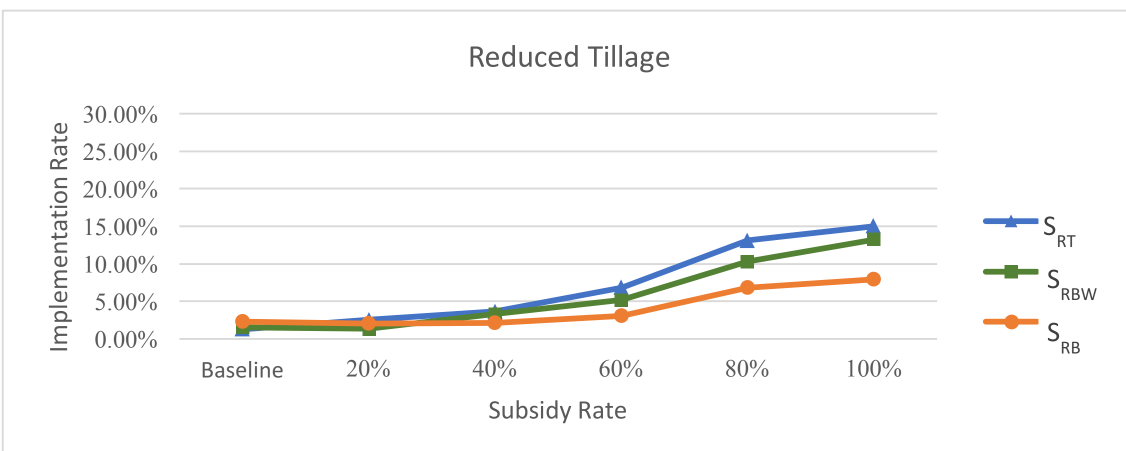
Table 4-10 The p-value and variable importance of defined subsidy rates to the IRs of BMP scenarios adopting riparian buffer strips

	LR p-value					Variable Importance				
Subsidy Rate	S_{BS}	S_{RB}	S_{NB}	S_{RBW}	S_{NBW}	S_{BS}	S_{RB}	S_{NB}	S_{RBW}	S_{NBW}
20%	0.924	0.159	0.917	0.051	0.561	0.096	1.419	0.105	1.978	0.584
40%	0.340	0.255	0.078	0.078	0.255	0.959	1.419	1.783	1.785	1.222
60%	<u>0.030</u>	0.610	0.126	0.314	0.470	<u>2.205</u>	1.511	1.543	1.013	0.726
80%	<u>0.002</u>	0.385	0.264	0.231	0.333	<u>3.211</u>	2.101	1.124	1.206	0.974
100%	<u>0.000</u>	<u>0.123</u>	0.643	<u>0.004</u>	0.791	<u>3.738</u>	<u>2.555</u>	0.464	<u>2.942</u>	0.266

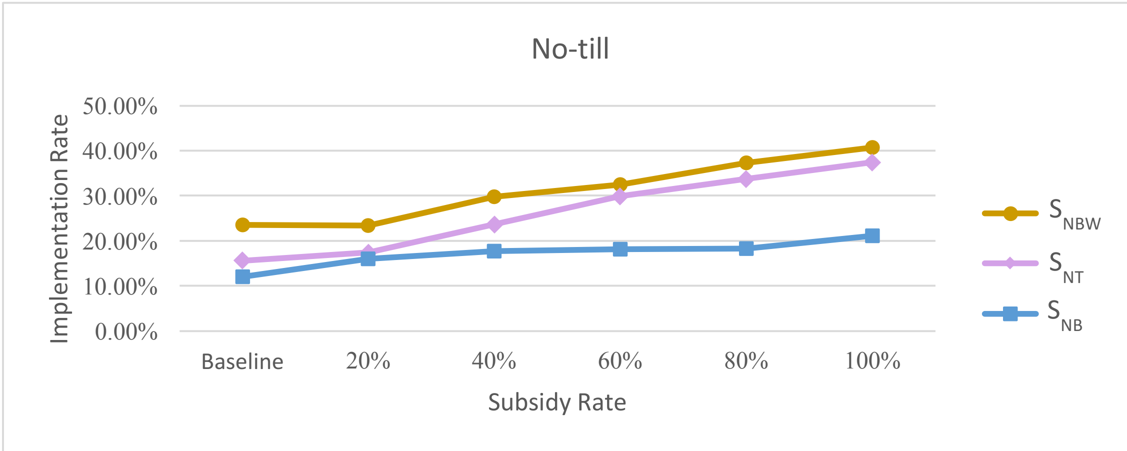
As shown in Figure 4-5-E, the IR of S_{WA} increases with the growth of subsidy rates. There is a sudden rise of IR when the subsidies increase from 40% of WASCoB implementation costs to 60%. When the subsidy rate is at least 80% of the WASCoB implementation costs, the IR of adopting WASCoB individually has exceeded the IR of S_{WI} which adopts windbreaks individually. By examining the p-value obtained from the LR (refer to Table 4-11), it can be concluded that the impacts of increased subsidy rates on the IR of S_{WA} become statistically significant when the subsidies are at least 60% of the WASCoB implementation expenses. Moreover, subsidy rates of 60%, 80%, and 100% play an important role in improving the implantation rate of the WASCoB.

Table 4-11 The p-value and variable importance of defined subsidy rates to the IRs of BMP scenarios adopting WASCoB

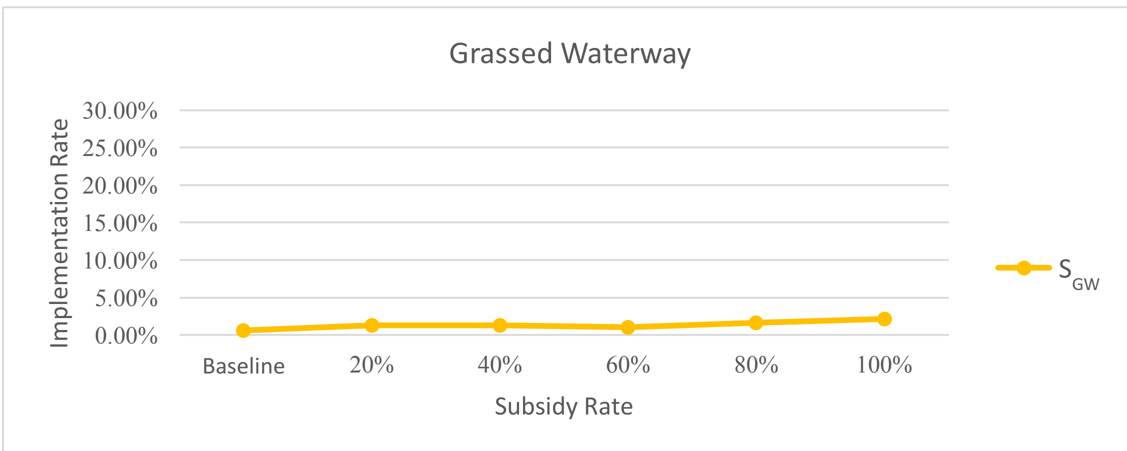
	LR p-value	Variable Importance
Subsidy Rate	S_{WA}	S_{WA}
20%	0.634	0.478
40%	0.136	1.505
60%	0.000	6.950
80%	0.000	8.591
100%	0.000	10.321



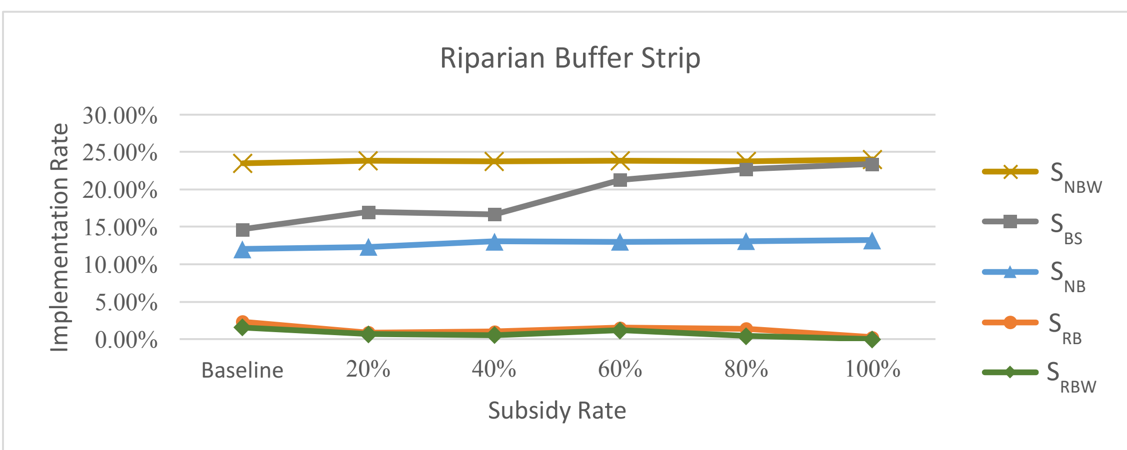
A


No-till
Implementation Rate
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Baseline
20%
40%
60%
80%
100%
Subsidy Rate
S NBW
S NT
S NB

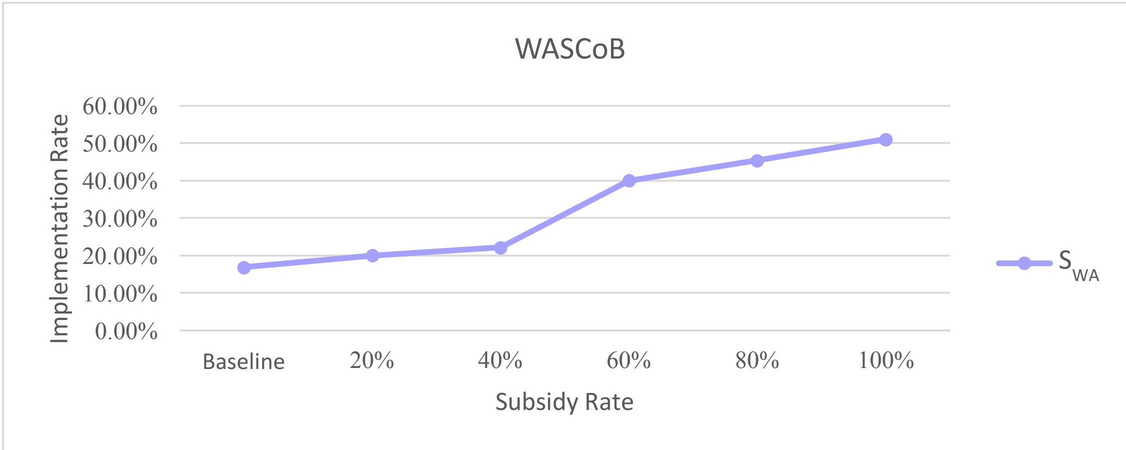
B


Grassed Waterway
Implementation Rate
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Baseline
20%
40%
60%
80%
100%
Subsidy Rate
S GW

C


Riparian Buffer Strip
Implementation Rate
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Baseline
20%
40%
60%
80%
100%
Subsidy Rate
S NBW
S BS
S NB
S RB
S RBW

D



E

Figure 4-5 Changes of the IR for BMP scenarios in regard to different subsidy rates

Because the implementation of windbreaks has been subsidized by a cost-share program which covers 75% of the windbreak installation expenses, this information was compared with results of sensitivity analysis for windbreaks to examine the performance of the model in simulating the impacts of different subsidy rates on encouraging the implementation of BMPs. Beginning with 15% of the installation costs of windbreaks, 15% was incremented every time a new subsidy rate was given until the subsidy rate reached 75% which is equal to the proportion of expenses subsidized by the cost-share program. A total of five experiments, each with twenty replicate runs, were carried out. The results show that the IR of windbreaks would increase with growing subsidies (refer to Figure 4-6). However, according to the p-value derived from the LR (refer to Table 4-12), the impact of increasing subsidies on the adoption of a windbreak is statistically significant when the subsidy rate has reached 75%. Moreover, the value of variable importance shows a drastic increase when the subsidy rate changes from 60% to 75%. This demonstrates that the subsidy has the strongest influence on facilitating the windbreak implementation when it is 75% of the installation costs of the windbreak.

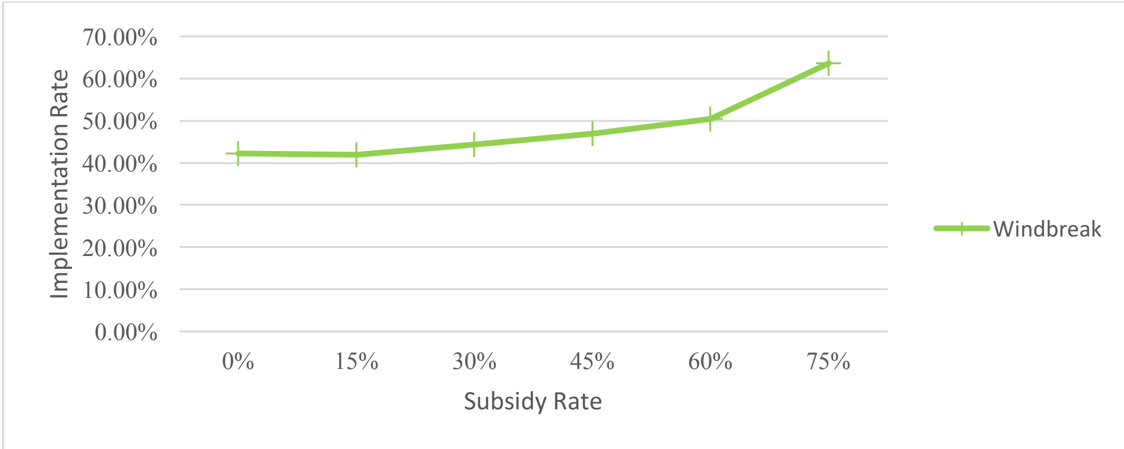


Figure 4-6 Changes of the IR for the windbreaks in regard to different subsidy rates

Table 4-12 The p-value of LR model between defined subsidy rates and the number of fields adopted with windbreaks

	LR p-value	**Variable Importance**
Subsidy Rate	**Windbreak**	**Windbreak**
15%	0.643	0.466
30%	0.948	0.065
45%	0.308	1.025
60%	0.073	1.816
75%	0.000	5.074

4.6.2 Impacts of Increasing Farmers' Knowledge Levels

Figure 4-6 shows how the IR changes with respect to the increasing knowledge level of a particular BMP. Similar to investigating the impacts of increasing subsidies, the average IR for a particular BMP, obtained from twenty replicate runs, was used to explore the influence of growing farmers' knowledge level on the adoption of this BMP (both individually or combining with other BMPs). The results demonstrate that with the increase of farmers' knowledge level to each BMP, the IR presents an increasing trend. However, no evident growth has been identified for all of the examined BMPs every time the knowledge level of a BMP has been added with two units. In general, the degree of increment of IR caused by the growing farmers' knowledge level is smaller compared to the increases that resulted from increasing subsidies (refer to Figure 4-4). However, for the grassed waterway, increasing the farmers' knowledge level seems to have a greater impact.

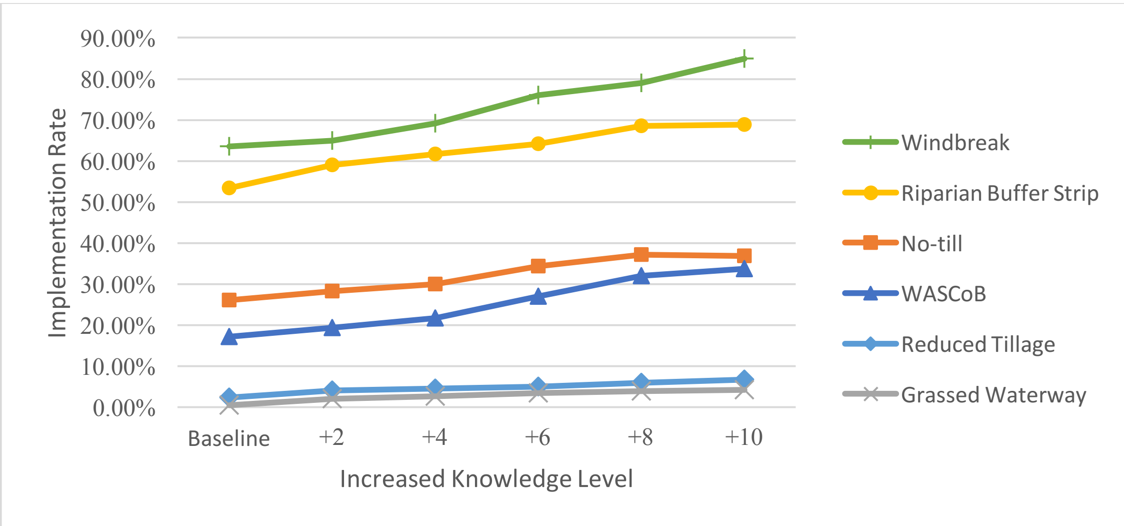


Figure 4-7 Changes of the number of agricultural fields adopted with each BMPs in regard to the increasing the knowledge level

Table 4-13 and Table 4-14 summarises the p-value and variable importance of LR models built from the increasing knowledge level and the number of fields adopted with each BMP. For both the reduced tillage and the windbreak, p-values indicate that the influence of increased knowledge levels on the IRs become statistically significant when four or more units have been added to the farmers' knowledge level towards these two BMPs. According to Table 4-14, the increasing knowledge level for the reduced tillage system accounts for the substantial part of the contribution to increasing the application of reduced tillage when eight or more have been added. A statistically significant impact of growing knowledge level has been found for the no-till system and the WASCoB when farmers' knowledge level toward these two BMPs has increased by at least six. For both the no-till system and the WASCoB, the values of variable importance when the added knowledge level is equal to or higher than six is two times greater than those when the increased knowledge level is lower than six. Thus a greater influence of the growing knowledge level can be identified when at least six have been added to the original farmers' knowledge level towards the no-till system and the WASCoB. As shown in Table 4-13, p-values of the grassed waterway are all smaller than 0.05 after adding at least six to the farmers' knowledge level. This indicates that the increase of IR of the grassed waterway is statistically significant when six or more have been added to farmers' knowledge level. There are little differences among the variable importance of the grassed waterway under different increased knowledge level, which indicates that each increased knowledge level makes the similar contribution to facilitating the adoption of grassed waterways. The growth of the IR for riparian buffer strips caused by the increasing knowledge level is statistically significant for all of the experiments.

Table 4-13 The p-value of LR model between the increased knowledge level and the number of fields adopted with each BMP

	LR p-value					
Increased Knowledge Level	**Reduced Tillage**	**No-till**	**Grassed Waterway**	**Riparian Buffer Strip**	**WASCoB**	**Windbreak**
+2	0.078	0.439	0.190	0.040	0.396	0.606
+4	0.028	0.161	0.079	0.004	0.078	0.035
+6	0.010	0.003	0.015	0.000	0.000	0.000
+8	0.001	0.000	0.004	0.000	0.000	0.000
+10	0.000	0.000	0.003	0.000	0.000	0.000

Table 4-14 Variable importance of the increased knowledge level to the number of fields adopted with each BMP

	Variable Importance					
Increased Knowledge Level	**Reduced Tillage**	**No-till**	**Grassed Waterway**	**Riparian Buffer Strip**	**WASCoB**	**Windbreak**
+2	1.786	0.777	1.321	2.070	0.852	0.518
+4	2.229	1.413	1.780	2.995	1.786	2.142
+6	2.633	3.070	2.469	3.919	3.887	4.737
+8	3.601	4.076	2.928	5.446	5.872	5.868
+10	4.368	3.957	3.158	5.584	6.549	8.081

4.7 Chapter Summary

This chapter summarizes the results of field survey, land-cover change pattern analysis, and the sensitivity analysis of the developed ABM. Results from the field survey show that contributions made by economic factors to farmers' agricultural decision-making are always the highest among the economic, environmental, and social factors. Reducing the soil/wind erosion and maximizing profits are the most common motivations for BMP adoption. Among the BMPs that are implemented by the five survey participants, cover crops, the manure storage, the reduced tillage/no-till system, as well as riparian buffer strip have been given the highest satisfaction level. Moreover, the five responses demonstrate that farmers would like to obtain agricultural information through attending presentations or workshops and reading newsletters or government publications. According to the land-cover change pattern analysis, three major land-cover change patterns have been observed in the Upper Medway Creek region, which are the Corn-Soybean rotation, the Corn-Soybean-Wheat rotation, and the one-crop system of hay. For the developed ABM, the values of CV computed for the eleven BMP scenarios indicate a low variability of the model on simulating the decision-making of BMP adoption under impacts of the randomness embedded in the model. The sensitivity analysis shows that increasing subsidies and farmers' knowledge level to a particular BPM would facilitate the implementation of that BMP. However, not all of these impacts are statistically significant. In most of the cases, a threshold can be determined to indicate the minimum requirement for subsidy rates to lead to statistically significant increases of the implementation of a specific BMP.

Chapter 5 Discussion

5.1 Pre-test of the ABM

According to the values of CV for all of the BMP scenarios (refer to Table 4-2), most of them indicate that there is a relatively low variation in the model outputs. However, a relatively high variation could be identified for S_{GW}, S_{RB}, and S_{RBW} whose CVs are greater than one. This is because that, as mentioned in Section 4.4, more than half of the data obtained for S_{GW}, S_{RB} and S_{RBW} have a values of zero, which results in a small mean value and a high value of standard deviation. Accordingly, a greater value of CV could be obtained. Moreover, as reported by Heckert and Filliben (2003), the CV is sensitive to the subtle changes in the mean value when the mean value is close to zero. As can be seen from Table 4-2, the mean value of S_{GW}, S_{RB}, and S_{RBW} are all very close to zero, which would lead to a great change of the value of CV for these three BMP scenarios when more replication runs are performed. Consequently, the developed model could be considered as a robust model in simulating farmers' decision-making on BMP application within the Upper Medway Creek subwatershed since it presents a low variability on most of outputs.

Because the preference weights on the economic factors are always the highest, BMPs with lower implantation costs are more preferred by agents in general. Although the cost of installing the windbreak is the highest among all of the BMPs, the cost-share program covers 75% of its installation which greatly reduces the expenses of implementing the windbreak. Because the windbreak has long lifespan, low maintenance expense, as well as higher improvement percentage of crop yields, applying windbreaks may bring higher economic benefits. Furthermore, the higher implementation rate could also contribute to the higher wind erosion reduction efficiency, which has the greatest weight in the environmental submodel, of the windbreak. The relatively high implementation rate for S_{NBW} can be explained by the relative high economic return and environmental effectiveness. Though the expense of S_{NBW} has to cover the installation costs of three BMPs (i.e. no-till, riparian buffer strip and windbreak), the adoption of windbreaks improves the crop yields and therefore, increases the agricultural income. Moreover, due to the high environmental effectiveness brought by the three BMPs in S_{NBW}, the environmental score for S_{NBW} is at a relatively high level among all of the BMP scenarios. As a result, a higher IR is attained by S_{NBW}.

Among the three tillage systems (S_{CT}, S_{RT}, and S_{NT}) which have the same data size of available agricultural fields, the no-till system is the most commonly used technique due to its lower implementation expense and higher environmental efficiency. This was confirmed by the responses of farmers in the field survey. The implementation rate for S_{GW} is extremely low. This is identical with the responds of our field survey which shows that none of the five participants have installed a grassed waterway. One of the most important reasons is that the number of available agricultural fields for S_{GW} is very small. Only 25 out of 167 agricultural fields in the entire Upper Medway Creek subwatershed satisfy the requirements for installing the grassed waterway. Another reason that the implementation rate of S_{GW} is low is that the impacts of installing the grassed waterway on crop yields could be negative (refer to Section 3.5.2.1). Though installing the grassed waterway may also lead to 10% increment of crop yields, this number is much smaller than the improvement percentage brought by windbreaks.

5.2 Random Generator

Comparing outputs of the random generator with those obtained from running the ABM, different distribution of IRs for BMP scenarios can be identified. This indicates that instead of making decisions randomly, the developed model is making rational decisions. Results obtained from the random generator show that S_{WI} is still the predominant BMP scenario; while S_{CT}, S_{RT}, and S_{NT} has become the least prevalent BMP scenarios. This can be explained by the long time period of the lifespan for S_{WI}. In this study, the simulation was run at a fifty-year time scale which is identical to the lifespan for S_{WI}. Therefore, a new decision would not be made during the simulation once the parcels have decided to implement S_{WI}. However, for other parcels implemented with other BMP scenarios with a shorter lifespan, S_{WI} is still an alternative choice for their new decisions. As a result, the number of fields implemented with S_{WI} keeps increasing during the fifty-year simulation. For S_{CT}, S_{RT}, and S_{NT}, which have a lifespan of one year, a new decision has to be made at the beginning of every year. However, the probability of choosing other BMP scenarios (about 70%) is higher than that of any of them. Accordingly, a lower IR was obtained for S_{CT}, S_{RT}, and S_{NT}.

According to values of CV, outputs of the random generator have relatively lower variability than those obtained from the developed ABM. This is because the probability of selection for each BMP scenario varies in the ABM depending on a set of randomly selected parameters. In the developed ABM, parameters such as BMP annual costs and the P loss reduction efficiency are randomly drawn from a predefined range. When a larger value is drawn, the BMP scenario will get a higher probability to be selected, vice versa. Thus, the probability of selection of a BMP scenario is fluctuant according to the randomly selected values of parameters. The fluctuation of the probability of selection will further impact the decision-making. For example, the number of fields implemented with that BMP scenario would become larger when the probability of selection for a BMP scenario is high. In that case, a higher value of IR can be obtained. Accordingly, the value of IR for each BMP scenario will fluctuate with the changing parameters and lead to a higher variability. While for the random generator, every BMP scenario has an equal probability of selection. Hence, a lower value of CV can be observed for outputs of the random generator.

Though the value of CV for the ABM are higher than those for the random generator, a relatively high variation can only be observed for S_{GW}, S_{RB}, and S_{RBW} as Table 4-3 shows. This is mainly because for S_{GW}, the small sample size (i.e. the number of fields that is suitable for S_{GW}) and low environmental effectiveness make it less competitive than other BMP scenarios; while for S_{RB} and S_{RBW}, the lower economic and environmental benefits than S_{NB}, and S_{NBW} reduces its probability of selection. In that case, other BMP scenarios are more preferred, which have led to a lot of values of zero in outputs of S_{GW}, S_{RB}, and S_{RBW}. Consequently, a small mean value was obtained for the three datasets. Because the CV measures the variation in the dataset relative to the mean (Heckert and Filliben, 2003), a lower mean value would result in a higher value of CV which indicates relatively high variation. To reduce the variance exists in model outputs, more data about BMP and crop are required. If more accurate estimates of BMP costs and environmental effectiveness can be provided, the variability of the probability of selection caused by randomly selected parameters can be reduced. Accordingly, variance in the model outputs can be reduced.

5.3 Sensitivity Analysis

Generally, providing subsidies is a favourable way to encourage farmers to adopt the promoted BMP. However, a threshold has to be met to significantly increase the implementation of a specific BMP. This is identical to the conclusion obtained in Kent's study (2014), which demonstrates that the impacts of cost shares on increasing the adoption of watershed-specific BMPs are effective when the subsidy has reached a threshold. Compared to this study, ABM developed in Kent's research has some advantages. Frist of all, the SWAT (Soil and Water Assessment Tool) model has been embedded in the ABM developed by Kent (2014), which enables more accurate estimates of crop yield changes and the environmental effectiveness of adopting a BMP. In such a way, learning and adaptation processes (i.e. update farmers' perspective towards each BMP based on the environmental and economic feedbacks, and make yearly crop decisions instead of consistently following one crop rotation) have been included in Kent's study (2014) to produce more realistic simulation. Second, the ABM developed by Kent also includes community agents to incorporate the influence of enforced community policies (e.g. tax). However, the ABM built by Kent (2014) did not include farmers with off-farm employment, which is taken into account in this study. Furthermore, the developed ABM in this study examines more types of BMP and allows farmers to adopt multiple BMPs simultaneously. In Kent's study (2014), simulation of BMP decision-making has been carried out at a yearly scale, which is impractical for simulating BMPs that have a minimum required time period of implementation that is longer than one year such as the grassed waterway, WASCoB, and riparian buffer strip. Unlike Kent's ABM, the developed ABM in this study is capable to evaluate and compare BMPs or BMP scenarios with different lifespans. Comparatively, more detailed data of community policies, topography and hydrological characteristics are required for the Kent's ABM. This makes it difficult to be used for studies that are highly limited by data availability, for example this study.

Results of the sensitivity analysis have been examined by LRs. According to the p-values and the variable importance (refer to Table 4-6 to Table 4-14), it is not surprising to see that higher subsidies make a greater contribution to the change in the implementation rate of a BMP. This is because farmers' economic motivations to adopt certain BMP scenarios generally increase with the growth of subsidies. The sensitivity analysis for the windbreak indicates that 75% of the installation expenses have to be subsidized to effectively increase the implementation of the windbreak (refer to Table 4-12). This is identical to the amount of subsidies provided by the windbreak cost-share program, which indicate that the estimated subsidy rates for BMPs are capable to provide insights for further explorations. According to responses of the field survey which identify the high costs and the availability of financial incentives as the major economic concerns of adopting BMPs, providing subsidies would be a qualified method to motivate the implementation of certain BMPs.

In general, a minimum subsidy rate of 40% is required to positively affect the implementation of reduced tillage. When subsidies are offered, the economic score of implementing the reduced tillage is increased, which strongly encourages farmer agents who are highly motivated by the economic factors to adopt the reduced tillage solely. However, for those who have distributed their preferences toward the economic, environmental, and social factors evenly, S_{RB} and S_{RBW} are more preferred than S_{RT} as the relatively low environmental effectiveness of S_{RT} results in a lower utility score. Although the implementation costs of the reduced tillage system are subsidized, the subsidy rate of 20% is too low to have a strong impact on implementing BMP scenarios that contain the reduced tillage. It has demonstrated that the differences in economic scores between 0% subsidy and 20% subsidy are smaller than 0.1 in most cases. Furthermore, the IRs of S_{RB} and S_{RBW} show small fluctuations when the subsidy rates are lower than 40% due to the relatively high level of variances in the outputs of S_{RB} and S_{RBW}. By examining the p-values and the variable importance of the BMP scenarios that adopt the reduced tillage, it suggests that a subsidy rate that is higher than 80% could facilitate the implementation of the reduced tillage more effectively.

For the no-till system, the results have demonstrated that at least 40% of the implementation costs should be subsidized to encourage the adoption of it. Among the three BMP scenarios that implement a no-till system, S_{NT} usually has the highest economic benefits following S_{NBW}. Although the environmental score of S_{NT} is the least among the three BMP scenarios, the value of neighbours' behaviour for S_{NT} is the greatest in most of cases due to the larger number of fields that are potentially suitable for S_{NT} adoption. Accordingly, the implementation rate of S_{NT} is higher than S_{NB}. Though the cost of S_{NBW}, which is the sum of expenses of three BMPs, is the highest, crop yields that are increased by implementing windbreaks make the BMP scenario that has the second greatest economic score. Moreover, S_{NBW} has an environmental effectiveness that is higher than S_{NB}. Consequently, S_{NBW} is more preferred than S_{NB} by farmers. As can be seen from Table 4-8, the critical value 0.05 resides between the p-values of the 80% subsidy level and 100% subsidy level for S_{NB}. Hence, instead of subsidizing 100% of the implementation costs, there should exist a percentage of subsidy rate between 80% and 100%, which is enough for effectively facilitate the adoption of S_{NB}.

Simulation results show that the no-till system is preferred by farmer agents, which is equivalent to the results obtained from the field survey. The no-till system has the advantage of obtaining higher economic and environmental benefits. Therefore, even though 100% of the implementation costs are subsidized, the IR of the reduced tillage is still lower than the no-till system. However, the reduced tillage would be preferred when a farmer is very familiar with this BMP, requiring an extremely high knowledge level, and has assigned a greater preference weight to social factors.

Unfortunately, the results demonstrated that providing subsidies cannot significantly affect the implementation of grassed waterways. Though an overall increasing trend can be identified for the growth of subsidies, the p-value of the developed LR indicates that the increase in percentage of subsidies is not statistically significant. The number of fields adopted with the grassed waterway, on average, is 0.87, which means that nearly no farmer would like to adopt the grassed waterway. One of the reason is that, the implementation of the grassed waterway is highly constrained by the existing drainage pattern. Thus, the value of neighbours' behaviour for the grassed waterway is smaller than the values of other BMPs. According to the values of the three evaluated factors (economic, environmental, and social factor), the environmental score of the grassed waterway is at a medium level while the economic benefits of the grassed waterway are at a medium-high level comparing to other BMPs, the IR of the grassed waterway still remains at an extremely low level. Therefore, it suggests that the impacts of social factors have greater influence to the implementation of the grassed waterway in the Upper Medway Creek subwatershed. When the subsidy rates for the grassed waterway have reached 100%, the economic benefits of the grassed waterway become the largest among all of the BMP. However, its environmental efficiencies are lower than the windbreak, and its social scores are significantly lower than other BMP scenarios. Accordingly, a small utility score would be acquired for the grassed waterway, which makes it become uncompetitive among the eleven BMP scenarios.

To effectively motivate farmer agents to adopt the riparian buffer strip, the subsidies should cover at least 60% of the implementation expenses. As shown in Figure 4-5-D, the IRs of S_{RB} and S_{RBW} are significantly lower than the IRs of S_{NB} and S_{NBW}. This is because, except for the BMP expenses of the tillage system, all other parameter values of S_{RB} and S_{RBW} are equal to those of S_{NB} and S_{NBW}, respectively. As a result, the economic and environmental benefits of BMP scenarios that adopt no-till system (S_{NB} and S_{NBW}) are greater than those that implement the reduced tillage (S_{RB} and S_{RBW}). S_{RB} and S_{RBW} will be selected by farmers only when farmer's knowledge level regarding the reduced tillage is evidently higher than the no-till system; also, the preference weight of a farmer towards the social factor is relatively high. By checking the economic scores, S_{BS} always has the greatest economic returns; while the economic score of S_{NB} is the lowest. Nevertheless, the economic scores of S_{BS}, S_{NB}, and S_{NBW} are very close to each other when the subsidy rate is equal to or lower than 20%. However, when the subsidy rate is 20% or lower, S_{NBW}, which has an environmental score that is more than twice of S_{BS}, and thus became the best selection among all the BMP scenarios that implement riparian buffer strips. With the increase of the subsidy rate for the riparian buffer strip, the economic benefits of S_{BS}, S_{NB}, and S_{NBW} become greater. However, as the original implementation expenses of the riparian buffer strip are relatively low and the differences between the upper bound and the lower bound (refer to Appendix Table D-1) are small, the subsidies that covers a certain proportion of the implementation expenses of the riparian buffer strip are very low. As a result, the impacts of adding subsidies to the riparian buffer strip on the implementation of S_{NB} and S_{NBW} would not be evident. This has also been proved by the p-values derived from the LR (refer to Table 8). As a result, subtle increases (about 1%) have been found for the IRs of S_{NB} and S_{NBW}. For S_{BS} which adopts the riparian buffer strip individually, its economic benefits are mainly depending on the BMP costs when all of the other economic parameters (e.g. off-farm income, farm income, crop costs) are the same as those of other BMP scenarios that implement riparian buffer strips. Hence, the growth of subsidies has greater impacts on the IR of S_{BS}. Comparing to the impacts of increasing subsidies to the reduced tillage or the no-till system, adding subsidies to riparian buffer strips has smaller influences to the implementation of S_{RB} to S_{NBW} since the original implementation expenses of the reduced tillage or the no-till system are greater than the expenses of the riparian buffer strip.

According to the p-value and the variable importance (refer to Table 4-7), a minimum subsidy rate of 60% is needed to effectively facilitate the adoption of the WASCoB. The results have showed that among the five examined BMPs, the economic and environmental scores for the WASCoB are not outstanding; while the social score, specifically the larger value of neighbours' behaviour, for the WASCoB presents a relatively higher level. Comparing to the reduced tillage that has the similar environmental effectiveness with the WASCoB, the greater economic benefits and social influences of the WASCoB have resulted in a higher IR than that of the reduced tillage. However, although economic returns and social scores for the no-till system are similar with the WASCoB in the majority of cases, the lower environmental effectiveness of the WASCoB makes it less preferred than the no-till by farmers. When 60% of the implementation expenses were subsidized, the economic score of the WASCoB becomes larger than that of the no-till, and at this point, the IR of the WASCoB has exceeded the no-till at the first time. The economic benefits of the WASCoB are relatively low comparing to those of the grassed waterway and the riparian buffer strip. Whereas the IR of the WASCoB is still greater than the grassed waterway since it contributes to greater values of environmental and social scores.

According to the results of the sensitivity analysis, increasing farmers' knowledge level regarding a particular BMP is able to facilitate the implementation of this BMP. However, the adoption of a BMP could only be improved to a certain extent through increasing knowledge level as it is also influenced by other factors such as costs or environmental effectiveness. Generally, the effects of the growing subsidies are greater than the increases in the farmers' knowledge because economic factors are given larger preference weights than social factors. Nevertheless, for the grassed waterway, social factors have made a greater contribution to the IR. Accordingly, increasing farmers' knowledge level has a greater influence on encouraging the adoption of the grassed waterway. According to the model results, the no-till system and WASCoB present the greatest opportunity for increased adoption by adding subsidies; while the windbreak and WASCoB show the highest potential of increased adoption after implementing education programs. Under these circumstances, it is recommended that both educational activities and financial incentives could be provided simultaneously for BMPs to encourage the implementation of BMPs, specifically the adoption of the grassed waterway. To effectively increase the adopting of BMPs, subsidy rates of 80%, 40%, 60% and 60% are recommended for the reduced-tillage, no-till, riparian buffer strip and WASCoB, respectively. The subsidy programs are highly recommended for the no-till system and WASCoB, and the educational activities are especially recommended for the windbreak, WASCoB, as well as the grassed waterway.

5.4 Limitations and Improvements

Three major limitations and constrains could be identified in this study. The first limitation is limited number of field survey responses. Only five responses were obtained from the field survey, which may not fully generalize the agriculture-related dynamics that are occurring in the Upper Medway Creek subwatershed. First, instead of simulating all of the potential BMP combinations, only those mentioned in the five survey responses have been included in this study. Therefore, BMP scenario alternatives examined in this study, which are highly related to agent decision-making processes, may not include all of the BMP scenarios that are implemented in the Upper Medway Creek region. Similarly, the crop rotations assigned to each field in the model may not correspond to those that are actually followed by farmers in reality due to the lack of field survey data. Only three major land-cover change patterns identified in Section 4.2 have been included in this study. Classes such as Barley and Beans have been excluded, which reduces the diversity of the crop rotations implemented in the Upper Medway Creek region. Consequently, the performance of the developed model in representing the BMP implementation and crop rotations in the real world can be degraded. Additionally, the preference weights for the economic, environmental, and social factors have been randomly generated from a normal distribution because of the inadequate data on how farmers distribute their preferences to the three factors. As Brown and Robinson (2006) has noted, randomly drawing agents' preferences on each factor from a uniform distribution would lead to results with higher variation though it has been proven to be useful to represent the simplified reality.

One of the primary limitations of the developed ABM is the stochastic elements included in the model. To simulate the dynamics in farmer decision-making processes which involve complex interactions between agents and their environment, quantitative and qualitative data of massive size is required. However, gathering all of the required data, which are further used to parameterize the model, with high level of details would be impractical (Valbuena et al., 2010; Filatova et al., 2013). In the developed ABM, data of the costs, the farm/off-farm income, as well as the environmental effectiveness of BMPs are very limited. The majority of the data used to parameterize the model are not particular to the Upper Medway Creek region. To make sure that data used in the model are capable to cover all possible situations that could happen in the region, the values of economic and environmental parameters have been randomly generated from the possible ranges based on previous literatures or government archives. Furthermore, due to the lack of cadastral data for the Upper Medway Creek subeatershed, the land manager of each agricultural field has been determined by randomly selecting from the forty farmers in the study area. This could be unrealistic since farmers tend to manage contiguous fields rather than fields separated from each other, which could result from random determination. Accordingly, uncertainties could be brought into the model, which results in a sensitive model performance (Filatova et al., 2013).

Finally, the model faces a challenge of validation. In the view of previous literature (e.g. Filatova et al., 2013, Valbuena et al., 2010, and Parker et al., 2003), proving that the model is robust and it has the capacity to replicate the real-world is a major challenge identified for the ABM. For this study, several steps have been conducted to assess the model performance. First, many replication runs were performed to the developed ABM to determine the model's internal validity. The value of CV was calculated to indicate the consistency and variability in the model in regard to the randomness. To test the credibility of the model, the results from running the model 100 times were compared to those obtained from a random generator. A sensitivity analysis was also performed, which instead of testing the robustness of the model, it aims to investigate how changing a parameter may affect the model outputs. However, none of these methods can evaluate whether the developed ABM can provide an accurate representation of reality or whether it is acceptable for its intended purpose. This could be difficult for this study because of three reasons. First, empirical data or historical data about the BMP adoption rate in the upper Medway Creek subwatershed is unavailable. Therefore, we don't have reference data to compare with the model outputs. Second, no similar research or other method has been conducted to the upper Medway Creek subwatershed, which add challenges to use the comparison to other model validation method. Third, the conceptual validation cannot be performed to this study either as there is a lack of experts.

To overcome these limitations and challenges, several improvements could be achieved in the future work. First, a detailed field survey has to be conducted to collect more accurate data and provide a more comprehensive understanding of how famers make agricultural decisions in the real world. To get more responses, reward (e.g. gift card) may be offered to survey participants. Responses from the field survey can be used as information and data for constructing the model. (Brown and Robinson, 2006). Moreover, more factors (e.g. precipitation, carbon allowances, direct farmer communication) and more BMPs (e.g. manure applications) could be assessed in the model. During the simulation, some estimations could be made to economic factors based on the available data (e.g. input costs of a crop may increase along with the rising fuel price for machinery). The adaptive process can also be considered in the future modelling effort. In this way, a more precise representation of agricultural decision-making processes can be provided.

To reduce the uncertainties generated by stochastic elements in the model, opinions from a group of experts and stakeholders about how to parameterize the model should be incorporated into the model (Valbuena et al., 2010). Additionally, the developed ABM may be combined with hydrological model such as the SWAT (e.g. Kent, 2014). On the one hand, the hydrological model is able to provide a more accurate estimate of the environmental effectiveness for different BMPs implemented in the study area. According to Ng et al. (2011), the hydrological model with sufficient input data can produce an accuracy estimation of nutrient and pollutant loads and crop yields for varied BMPs. These estimates can be used as inputs in the developed ABM to improve the model performance. On the other hand, it allows a simulation of the impact of famers' decision-making dynamics on the water quality and therefore, better understanding the relationship between the BMP implementation and water quality and identifying appropriate conservation strategies. Model validation can be improved using two methods. First, if experts can be involved in this research, the face validity technique, which evaluates whether the model behaves reasonably by asking experts, can be applied to increases the diversity of the model validation. Second, another ABM can be developed using a heuristic decision tree method of which results could be compared with those obtained from this study.

5.5 Chapter Summary

In summary, according to the coefficient of variance, the developed ABM is robust in simulating farmers' decision-making on BMP application within the Upper Medway Creek subwatershed. The sensitivity analysis indicates that the increasing subsidies and farmers' knowledge level to a BMP can positively affect the implementation of that BMP in general. For each BMP, different proportion of implementation costs needs to be subsidized to effectively encourage the BMP adoption. Comparing to the knowledge level, subsidies make greater contribution to motivating farmers to adopt the BMP. Three major limitations and challenges have been identified for this study: 1) lack of survey data; 2) randomness in the developed ABM; 3) model validation. Future work such as combining the optimizing decision-making structure with the heuristic structure or incorporate expert opinions can be conducted to improve the model performance.

Chapter 6 Conclusion

In Canada, water quality plays a critical role in the agriculture system. However, water quality can be negatively impacted by inappropriate agricultural activities. The application of pesticides, manure and fertilizers has led to an increasing amount of chemicals, nutrients and other pollutants in the surface runoff that is transported to surface water bodies causing problems such as eutrophication. The Medway Creek subwatershed, which has been suffering from a severe surface water quality problem for several years, has been identified as a region that requires environmental improvements (UTRCA, n.d. c). In order to maintain good water quality and develop a sustainable agricultural system, strategies and policies have been suggested by the local government and conservation authorities to encourage the implementations of different agricultural BMPs. In the agri-environment system, farmers who are heterogeneous with regard to their demographic characteristics, property size, preferences, and perception of public policies play an essential role in making BMP decisions. Hence, understanding how BMP decisions are made under different internal and external factors is significant for simulating human-natural systems and establishing sustainable development strategies and policies.

To simulate and understand the dynamics of farmer's decision-making on the BMP adoption under different socio-economic and environmental situations in the Upper Medway Creek subwatershed, an ABM has been developed using the optimizing decision-making structure. A weighted sum function was used to evaluate the influences of economic, environmental and social factors on farmers' decision-making. Results from the model pre-test was compared to those obtained from a random generator to examine how does the developed ABM perform against the random generator. The sensitivity analysis has been performed to the developed ABM using the OFAT method to examine the impacts of different potential interventions, including government subsidies or educational activities, on farmers' decision-making in certain BMP adoption.

After twenty per-test runs, relative low variations have been found in the results, which indicates that the developed ABM is robust in simulating farmers' decision-making on BMP applications within the Upper Medway Creek subwatershed. Results of the sensitivity analysis demonstrate that both providing subsidies and improving knowledge level of BMPs could encourage the implementation of certain BMP in general. While a threshold has to be met to effectively facilitate the implementation of BMPs. Compared to educational activities, subsidies make a greater contribution to motivating farmers to adopt the BMP. However, an exception has occurred to the grassed waterway, where results indicate that increasing farmers' knowledge levels have greater impacts than offering subsidies. Therefore, strategies that combine educational activities with financial incentives are more recommended for encouraging the implementation of BMPs, especially the grassed waterway. According to the sensitivity analysis, a subsidy rate, which indicates the proportion of implementation costs to be subsidized to effectively encourage the BMP adoption, has been suggested for every BMP except for the windbreak. For reduced-tillage, no-till, riparian buffer strip and WASCoB, the subsidy rates are 80%, 40%, 60% and 60%, respectively. While increasing the subsidies cannot significantly facilitate the adoption of the grassed waterway. Results of the sensitivity analysis for the windbreak suggest a subsidy rate of 75% which is identical to the amount of subsidies provided by the existing windbreak cost-share program. Thus, subsidy rates for BMPs suggested by this study can be considered as supportive information for further explorations.

Several limitations and challenges have been identified for this study. First, the lack of survey data limits the performance of the model in simulating the farmers' decision-making and therefore, reduces the accuracy and reliability of the model results. The second limitation is caused by the random elements included in the developed ABM. The stochastic elements increase the uncertainties in the outputs, which results in a model with high sensitivities. Finally, the model faces a challenge of validation. Because the data about the BMP adoption rate in the real world is scarce, it is difficult to evaluate the capacity of the developed ABM in representing and replicating the reality. Under these circumstances, future research should be implemented focusing on designing field surveys that investigate more details related to the model parameters. Strategies such as rewarding participants may be applied to encourage farmers to participate in the survey. Responses from the field survey can be used as information and data for constructing the model (Brown and Robinson, 2006). Future developments could also be carried out by exploring more factors (e.g. precipitation, carbon allowances, direct farmer communication) and more BMPs (e.g. manure applications) in the model to simulate farmers' decision-making more precisely. To reduce the uncertainties generated by stochastic elements, researchers may also consult with stakeholders expertized in agriculture and socio-economic field when parameterizing the model. Additionally, the ABM may be combined with hydrological models in the future to estimate the environmental effectiveness (e.g. soil erosion rate, sediment reduction) of each BMP. In such a way, more accurate environmental feedbacks of implementing BMPs can be used as inputs, which improves the performance of the developed ABM.

In conclusion, the developed ABM is able to provide a robust simulation of local farmers' decision-making processes on the BMP adoption based on economic, environmental and social factors. It is able to produce encouraging outcomes of different potential interventions in a timely manner accounting for the heterogeneities and dynamic interactions among farmers and their environment. Although ABMs have been developed by previous studies to model and analyse the farmer decision-making on BMP adoptions under different social-environmental factors (e.g. Kent, 2014; Ng et al., 2011), the number of examined BMPs in these studies is very limited, in most of the cases, does not exceed three BMPs. Moreover, BMPs simulated in previous research are different from those evaluated in this study. Considering all facts mentioned previously, the developed ABM is capable of serving as a guide for future modelling efforts of the WP3 of the AWF project in simulating modelling human-environmental dynamics in agricultural land use and BMP adoption. It provides a proof of concept for assessing the impacts of different socio-economic and environmental factors on farmers decision-making process of the adoption of BMP. As a framework, the ABM built in this study could be tuned to provide a more accurate simulation of farmer decision-making. Results presented in this study could be fit into a hydrological model, specifically the SWAT, to explore changes in the water quality. They can also help better understand the dynamics of farmer's decision-making on BMP applications, offer supportive data for policymakers to encourage BMP implementation effectively, as well as insights to develop appropriate strategies for water quality preservation.

References

2017 Watershed Report Card - Medway Creek. (2017). Retrieved from http://thamesriver.on.ca/wp-content/uploads/WatershedReportCards/

Agriculture and Agri-Food Canada. (2012). Factors Affecting the Adoption of Agricultural Beneficial Management Practices. Retrieved from http://www.agr.gc.ca/resources/prod/doc/prog/WEBs_EPBH_BMP_PGB2012_eng.pdf

Agriculture and Agri-Food Canada. (2013, July). Tillage Trade-offs in a Prairie Watershed Retrieved from http://www.agr.gc.ca/eng/?id=1338581452818

Agriculture and Agri-Food Canada. (2014). Agriculture and Water Quality. Retrieved from http://www.agr.gc.ca/eng/science-and-innovation/agricultural-practices/water/watershed-protection/agriculture-and-water-quality/?id=1371491033072

Agriculture and Agri-food Canada. (2016 a). ISO 19131 AAFC Annual Crop Inventory – Data Product Specifications. Retrived from http://open.canada.ca/data/en/dataset/ba2645d5-4458-414d-b196-6303ac06c1c9

Agriculture and Agri-Food Canada. (2016 b). Water. Retrieved from http://www.agr.gc.ca/eng/science-and-innovation/agricultural-practices/water /?id=1187702145201

Agriculture and Agri-Food Canada. (2016 c). Risk to soil and water quality from agriculture. Retrieved from https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/risk-soil-water-quality-agriculture.html

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In Action control (pp. 11-39). Springer, Berlin, Heidelberg.

Alberta Agriculture and Forestry. (2007). Grassed Waterway Improvement and Gully Restoration. Retrieved from https://www1.agric.gov.ab.ca/$department/deptdocs.nsf/all/agdex1344

Alberti, M., Asbjornsen, H., Baker, L. A., Brozovic, N., Drinkwater, L. E., Drzyzga, S. A., Jantz, C. A., Gragoso, J., Holland, D. S., Kohler, T. A., Liu, J., McConnell, W. J., Maschner, H. D. G., Millington, J. D. A., Monticino, M., Podesta, G., Pontius Jr, R. G., Redman, C. L., Reo, N. J., Sailor, D., & Urquhart, G. (2011). Research on coupled human and natural systems (CHANS): approach, challenges, and strategies. The Bulletin of the Ecological Society of America, 92(2), 218-228.

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecological Modelling, 229, 25-36.

An, L., Linderman, M., Qi, J., Shortridge, A., & Liu, J. (2005). Exploring complexity in a human–environment system: an agent-based spatial model for multidisciplinary and multiscale integration. Annals of the association of American geographers, 95(1), 54-79.

Arbor Day Foundation. (n.d.). How to Plant Field Windbreaks. Retrieved from https://www.arborday.org/programs/graphics/conservation-trees/field-windbreaks.pdf

Arbuckle, J. G., & Roesch-McNally, G. (2015). Cover crop adoption in Iowa: The role of perceived practice characteristics. Journal of Soil and Water Conservation, 70(6), 418-429.

Aubry, C., Papy, F., & Capillon, A. (1998). Modelling decision-making processes for annual crop management. Agricultural systems, 56(1), 45-65.

Balana, B. B., Lago, M., Baggaley, N., Castellazzi, M., Sample, J., Stutter, M., Slee, B., & Vinten, A. (2012). Integrating economic and biophysical data in assessing cost-effectiveness of buffer strip placement. Journal of environmental quality, 41(2), 380-388.

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. Journal of environmental management, 96(1), 17-25.

Bazghandi, A. (2012). Techniques, advantages and problems of agent based modeling for traffic simulation. International Journal of Computer Science Issues (IJCSI), 9(1), 115.

Becu, N., Perez, P., Walker, A., Barreteau, O., & Le Page, C. (2003). Agent based simulation of a small catchment water management in northern Thailand: description of the CATCHSCAPE model. Ecological Modelling, 170(2-3), 319-331.

Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. Econometrica, 22(1), 23-36.

Bert, F. E., Rovere, S. L., Macal, C. M., North, M. J., & Podestá, G. P. (2014). Lessons from a comprehensive validation of an agent based-model: The experience of the Pampas Model of Argentinean agricultural systems. Ecological Modelling, 273, 284–298.

Bharathy, G. K., & Silverman, B. (2013). Holistically evaluating agent-based social systems models: a case study. Simulation, 89(1), 102-135.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences, 99(suppl 3), 7280-7287.

Borin, M., Vianello, M., Morari, F., & Zanin, G. (2005). Effectiveness of buffer strips in removing pollutants in runoff from a cultivated field in North-East Italy. Agriculture, ecosystems & environment, 105(1-2), 101-114.

Brandle, R. J. (n.d.). How Windbreaks Work. Retrieved from https://www.fs.usda.gov/nac/documents/morepublications/ec1763.pdf

Brown, C. E. (2012). Applied multivariate statistics in geohydrology and related sciences. Springer Science & Business Media. PP. 155-157

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. Ecology and society, 11(1).

Castella, J. C., Trung, N. H., & Boissau, S. (2005). Participatory simulation of land-use changes in the northern mountains of Vietnam: the combined use of an agent-based model, a role-playing game, and a geographic information system. Ecology and Society, 10(1), 1-32.

Castle, C. J., & Crooks, A. T. (2006). Principles and concepts of agent-based modelling for developing geospatial simulations.

Chardon, W. J., & Schoumans, O. F. (2007). Soil texture effects on the transport of phosphorus from agricultural land in river deltas of Northern Belgium, the Netherlands and North-West Germany. Soil Use and Management, 23(SUPPL. 1), 16–24.

Chiang, L. C., Chaubey, I., Maringanti, C., & Huang, T. (2014). Comparing the selection and placement of best management practices in improving water quality using a multiobjective optimization and targeting method. International journal of environmental research and public health, 11(3), 2992-3014.

Credit Valley Conservation. (n.d.). Erosion Control Structures. Retrieved from https://cvc.ca/your-land-water/the-farm-gate-2/agri-environmental-projects/erosion-control-structures/

D'Emden, F. H., Llewellyn, R. S., & Burton, M. P. (2006). Adoption of conservation tillage in Australian cropping regions: an application of duration analysis. Technological Forecasting and Social Change, 73(6), 630-647.

Dafa-Alla, M. D., & Al-Amin, N. K. (2011). Design, efficiency and influence of a multiple-row, mix-species shelterbelt on wind speed and erosion control in arid climate of North Sudan. Research Journal of Environmental and Earth Sciences, 3(6), 655-661.

Davies, J. M., & Mazumder, A. (2003). Health and environmental policy issues in Canada: the role of watershed management in sustaining clean drinking water quality at surface sources. Journal of environmental management, 68(3), 273-286.

De Leeuw, E. D. (2008). Choosing the method of data collection.

Deadman, P. J. (1999). Modelling individual behaviour and group performance in an intelligent agent-based simulation of the tragedy of the commons. Journal of Environmental Management, 56(3), 159-172.

Deadman, P., Robinson, D., Moran, E., & Brondizio, E. (2004). Colonist household decisionmaking and land-use change in the Amazon Rainforest: an agent-based simulation. Environment and Planning B: Planning and Design, 31(5), 693-709.

Devlin, D. L., McVay, K., Pierzynski, G. M., & Janssen, K. (2002). Best Management Practices for Phosphorus. Kansas State University. Retrieved fromhttps://www.bookstore.ksre.ksu.edu/pubs/MF2321.pdf

Esri. (2018). World Imagery Map Contributors. Retrieved from https://www.arcgis.com/home/item.html?id=10df2279f9684e4a9f6a7f08febac2a9

Evans, T. P., & Kelley, H. (2004). Multi-scale analysis of a household level agent-based model of landcover change. Journal of Environmental Management, 72(1), 57-72.

Feather, P. M., & Amacher, G. S. (1994). Role of information in the adoption of best management practices for water quality improvement. Agricultural Economics, 11(2-3), 159-170.

Filatova, T., Verburg, P. H., Parker, D. C., & Stannard, C. A. (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental modelling & software, 45, 1-7.

Flitter, H., Laube, P., Lüscher, P., Rogers, S., & Hägi, S. (2013). Suitability analysis. Retrieved from http://www.gitta.info/Suitability/en/html/Normalisatio_learningObject1.html

Garbey, M., Casarin, S., & Berceli, S. A. (2017). Vascular adaptation: pattern formation and cross validation between an agent based model and a dynamical system. Journal of theoretical biology, 429, 149-163.

Gasser, P. (1993). Best management practices: Field Crop Production. Ottawa: Agriculture Canada.

Gedikoglu, H., & McCann, L. M. (2012). Adoption of win-win, environment-oriented, and profit-oriented practices among livestock farmers. Journal of Soil and Water Conservation, 67(3), 218-227.

Government of Canada. (n.d.). Hourly Minimum Wages in CANADA for Adult Workers. Retrieved from http://srv116.services.gc.ca/dimt-wid/sm-mw/rpt2.aspx

Government of Ontario. (2006). Clean Water Plan. Retrieved from https://www.ontariocanada.com/registry/view.do?postingId=3782&language=en

Government of Ontario. (2018, June). Eastern White Cedar. Retrieved from https://www.ontario.ca/page/eastern-white-cedar

Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., & Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models–A review. Environmental modelling & software, 87, 39-48.

Hansson, S. O. (2005). Decision Theory -A Brief Introduction. Retrieved from https://people.kth.se/~soh/decisiontheory.pdf

Happe, K., Kellermann, K., & Balmann, A. (2006). Agent-based analysis of agricultural policies: an illustration of the agricultural policy simulator AgriPoliS, its adaptation and behavior. Ecology and Society, 11(1).

Hawes, E., & Smith, M. (2005). Riparian buffer zones: Functions and recommended widths. Eightmile River Wild and Scenic Study Committee, 15, 2005.

Heckert, A., & Filliben, J. J. (2003). Dataplot reference manual. NIST Handbook, 148.

Hey, J. D., & Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. Econometrica: Journal of the Econometric Society, 1291-1326.

Hodges, L., & Brandle, J. (n.d.). Field Windbreaks. Retrieved from https://www.fs.usda.gov/nac/documents/morepublications/ec1778.pdf

Hofmann, N. (2015, November). Conventional tillage: How conventional is it? Retrieved from http://www.statcan.gc.ca/pub/16-002-x/2008003/article/10688-eng.htm

Howmuch. (n.d.). Tree Planting Costs. Retrieved from https://howmuch.net/costs/tree-install

Huigen, M. G. (2004). First principles of the MameLuke multi-actor modelling framework for land use change, illustrated with a Philippine case study. Journal of Environmental Management, 72(1-2), 5-21.

Ikerd, J. (2001). Economics of Sustainable Farming. Retrieved from http://web.missouri.edu/ikerdj/papers/EconomicsofSustainableFarming.htm

Ingram, J. (2008). Agronomist–farmer knowledge encounters: an analysis of knowledge exchange in the context of best management practices in England. Agriculture and Human Values, 25(3), 405-418.

Johnston, A.E., & Steén, I. (2000). Understanding Phosphorus and Its Use in Agriculture, 1-40.

Kansas, M. (1989). An Evaluation of the Cost Effectiveness of Agricultural Best Management Practices and Publicly Owned Treatment Works in Controlling Phosphorus Pollution in the Great Lakes Basin. U.S. Environmental Protection Agency. Retrieved from https://webcache.googleusercontent.com/search?q=cache:cafplvMuXaQJ:https://yosemite.epa.gov/ee/epa/eerm.nsf/vwRepNumLookup/EE-0317!OpenDocument%26Click%3D+&cd=1&hl=en&ct=clnk&gl=ca

Kent, G. (2014). Modeling and analysis of management for an agro-ecosystem using an agent-based model interface for the soil and water assessment tool (SWAT).

King, K. W., Williams, M. R., Macrae, M. L., Fausey, N. R., Frankenberger, J., Smith, D. R., Kleinman, P. J. A., & Brown, L. C. (2015). Phosphorus transport in agricultural subsurface drainage: A review. Journal of environmental quality, 44(2), 467-485.

Kirby, R. M., Bartram, J., & Carr, R. (2003). Water in food production and processing: quantity and quality concerns. Food control, 14(5), 283-299.

Klock, R., Simard, G., Mullock, J. (2002). The Weather of Ontario and Quebec Ontario and Quebec. Ottawa, ON. PP. 73-75

Land Information Ontario. (2010). DISCOVERING ONTARIO DATA. Retrieved from https://www.javacoeapp.lrc.gov.on.ca/geonetwork/srv/en/main.home?uuid=7a99025f-b894-4b8c-97c4-60f830fa1acc

Läpple, D., & Hennessy, T. (2014, April). Assessing the Impact of Financial Incentives for Participation in Extension Programmes: Evidence from Ireland. In Proceedings of the 88th Annual Conference, Paris, France (pp. 9-11).

Le, Q. B., Park, S. J., Vlek, P. L., & Cremers, A. B. (2008). Land-Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled human–landscape system. I. Structure and theoretical specification. Ecological Informatics, 3(2), 135-153.

Ligmann-Zielinska, A. (2009). The impact of risk-taking attitudes on a land use pattern: an agent-based model of residential development. Journal of Land Use Science, 4(4), 215-232.

Ligmann-Zielinska, A., Kramer, D. B., Cheruvelil, K. S., & Soranno, P. A. (2014). Using uncertainty and sensitivity analyses in socioecological agent-based models to improve their analytical performance and policy relevance. PloS one, 9(10), e109779.

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

Liu, R., Zhang, P., Wang, X., Wang, J., Yu, W., & Shen, Z. (2014). Cost-effectiveness and cost-benefit analysis of BMPs in controlling agricultural nonpoint source pollution in China based on the SWAT model. Environmental monitoring and assessment, 186(12), 9011-9022.

Liu, T., Bruins, R. J., & Heberling, M. T. (2018). Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis. Sustainability, 10(2), 432.

Liu, X., Li, X., & Anthony, G. O. Y. (2006). Multi-agent systems for simulating spatial decision behaviors and land-use dynamics. Science in China Series D: Earth Sciences, 49(11), 1184-1194.

Liu, X., Zhang, X., & Zhang, M. (2008). Major factors influencing the efficacy of vegetated buffers on sediment trapping: A review and analysis. Journal of Environmental Quality, 37(5), 1667-1674.

López, A., Valera, D. L., Molina-Aiz, F. D., Lozano, F. J., & Asensio, C. (2017). Sonic anemometry and sediment traps to evaluate the effectiveness of windbreaks in preventing wind erosion. Scientia Agricola, 74(6), 425-435.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. Journal of simulation, 4(3), 151-162.

Macrae, M., Deadman, P., Robinson, D., Wandel, J., Pomeroy, J., Petrone, R. de Loe, R., Li, Y., Helgason, W., Gordon, R., Fonstad, T., Elliot, J., Brouwer, R., & Baulch, H. (n.d.). Agricultural Water Futures in Canada: Stressors and Solutions (AWF).

Maitland Conservation. (2017). Erosion Control Structures. Retrieved from http://www.healthylakehuron.ca/docs/GG_WASCoB_Factsheet_March_2017.pdf

Malawska, A., & Topping, C. J. (2016). Evaluating the role of behavioral factors and practical constraints in the performance of an agent-based model of farmer decision making. Agricultural Systems, 143, 136-146.

Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: a review of applications. Landscape Ecology, 22(10), 1447-1459.

Medway Creek. (n.d.). Retrieved from http://thamesriver.on.ca/education-community/watershed-friends-of-projects/medway/

Mialhe, F., Becu, N., & Gunnell, Y. (2012). An agent-based model for analyzing land use dynamics in response to farmer behaviour and environmental change in the Pampanga delta (Philippines). Agriculture, ecosystems & environment, 161, 55-69.

Millington, J., Romero-Calcerrada, R., Wainwright, J., & Perry, G. (2008). An agent-based model of Mediterranean agricultural land-use/cover change for examining wildfire risk. Journal of Artificial Societies and Social Simulation, 11(4), 4.

Mtibaa, S., Hotta, N., & Irie, M. (2018). Analysis of the efficacy and cost-effectiveness of best management practices for controlling sediment yield: A case study of the Joumine watershed, Tunisia. Science of the Total Environment, 616, 1-16.

Murray-Rust, D., Robinson, D. T., Guillem, E., Karali, E., & Rounsevell, M. (2014). An open framework for agent based modelling of agricultural land use change. Environmental modelling & software, 61, 19-38.

Natural Resources Conservation Service. (2010 a). RIPARIAN FOREST BUFFER. Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_026098.pdf

Natural Resources Conservation Service. (2010 b). WATER AND SEDIMENT CONTROL BASIN. Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_026238.pdf

Ng, T. L., Eheart, J. W., Cai, X., & Braden, J. B. (2011). An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. Water Resources Research, 47(9).

Ontario Ministry of Agricultural, Food and rural Affairs. (2015, October). Soil Erosion – Causes and Effects. Retrieved from http://www.omafra.gov.on.ca/english/engineer/facts/12-053.htm

Ontario Ministry of Agricultural, Food and rural Affairs. (2016). 2017 FIELD CROP BUDGETS. Retrieved from http://www.omafra.gov.on.ca/english/busdev/facts/pub60.htm

Ontario Ministry of Agricultural, Food and rural Affairs. (2018 a). Provincial Field Crop Production and Prices. Retrieved from http://www.omafra.gov.on.ca/english/stats/crops/index.html

Ontario Ministry of Agricultural, Food and rural Affairs. (2018 b). Area, Yield, Production and Farm Value of Specified Field Crops, Ontario, 2012 - 2017 (Imperial and Metric Units). Retrieved from http://www.omafra.gov.on.ca/english/stats/crops/estimate_new.htm#Imperial

Ontario Ministry of Agricultural, Food and rural Affairs. (n.d.). No-till: making it work. Ottawa. PP. 1

Ontario Soil and Crop Improvement Association. (2015). GLASI Priority Subwatershed Project. Retrieved from http://www.ontariosoilcrop.org/wp-content/uploads/2015/08/UTRCA-GLASI-PSP-BROCHURE-INSERT-WEB.pdf

Ontario Soil and Crop Improvement Association. (2016). Farmland Health Incentive Program. http://www.ontariosoilcrop.org/wp-content/uploads/2015/12/FHIP-2016-Brochure-WEB-compressed.pdf

Ontario Woodlot Association. (n.d.). DESIGNING AND CARING FOR WINDBREAKS. Retrieved from https://www.ontariowoodlot.com/publications/owa-publications/extension-notes/designing-and-caring-for-windbreaks

Oreskes, N., Shrader-Frechette, K., & Belitz, K. (1994). Verification, validation, and confirmation of numerical models in the earth sciences. Science, 263(5147), 641-646.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., & Deadman, P. (2003). Multi-agent systems for the simulation of land-use and land-cover change: A review. Annals of the association of American Geographers, 93(2), 314-337.

Parker, J. S., Moore, R., & Weaver, M. (2007). Land tenure as a variable in community based watershed projects: some lessons from the Sugar Creek Watershed, Wayne and Holmes Counties, Ohio. Society and Natural Resources, 20(9), 815-833.

Parry, H. R., Topping, C. J., Kennedy, M. C., Boatman, N. D., & Murray, A. W. (2013). A Bayesian sensitivity analysis applied to an Agent-based model of bird population response to landscape change. Environmental Modelling & Software, 45, 104-115.

PENNINGTON. (n.d.). The Best Time to Plant Grass Seed. Retrieved from https://www.pennington.com/all-products/grass-seed/resources/the-best-time-to-plant-grass-seed

Quam, V. C., Gardner, J., Brandle, J. R., & Boes, T. (n.d.). Windbreaks in Sustainable Agricultural Systems. Retrieved from https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1128&context=natrespapers

Qudrat-Ullah, H., & Seong, B. S. (2010). How to do structural validity of a system dynamics type simulation model: The case of an energy policy model. Energy policy, 38(5), 2216-2224.

Rahelizatovo, N. C., & Gillespie, J. M. (2004). Factors influencing the implementation of best management practices in the dairy industry. Journal of soil and water conservation, 59(4), 166-175.

Reimer, A. P., Gramig, B. M., & Prokopy, L. S. (2013). Farmers and conservation programs: explaining differences in Environmental Quality Incentives Program applications between states. Journal of Soil and Water Conservation, 68(2), 110-119.

Rezvanfar, A., Samiee, A., & Faham, E. (2009). Analysis of factors affecting adoption of sustainable soil conservation practices among wheat growers. World Applied Sciences Journal, 6(5), 644-651.

Roberts, A. P., (2017). Windbreaks and Shelterbelts: Benefits [PowerPoint slides]. Retrieved from https://www.harvesthastings.ca/sites/www.harvesthastings.ca/files/Peter%20Roberts.pdf

Robinson, D. T., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. A., Huigen, M., Wittmer, H., Gotts, N., Promburom, P., Irwin, E., Gatzweiler, F., Barnaud, C., & Berger, T. (2007). Comparison of empirical methods for building agent-based models in land use science. Journal of Land Use Science, 2(1), 31-55.

Rounsevell, M. D. A., Robinson, D. T., & Murray-Rust, D. (2012). From actors to agents in socio-ecological systems models. Phil. Trans. R. Soc. B, 367(1586), 259-269.

Rudolph, D. L., Devlin, J. F., & Bekeris, L. (2015). Challenges and a strategy for agricultural BMP monitoring and remediation of nitrate contamination in unconsolidated aquifers. Groundwater Monitoring & Remediation, 35(1), 97-109.

Rykiel Jr, E. J. (1996). Testing ecological models: the meaning of validation. Ecological modelling, 90(3), 229-244.

Sargent, R. G., & Smith, L. C. (2011). Verification and validation of simulation models. In Simulation Conference (WSC), Proceedings of the 2009 Winter (pp. 183-198). IEEE.

Schindler, D. W., Hecky, R. E., Findlay, D. L., Stainton, M. P., Parker, B. R., Paterson, M. J., Beaty, K. G., Lyng, M., & Kasian, S. E. M. (2008). Eutrophication of lakes cannot be controlled by reducing nitrogen input: Results of a 37-year whole-ecosystem experiment. Proceedings of the National Academy of Sciences, 105(32), 11254–11258.

Schlueter, M., McAllister, R. R. J., Arlinghaus, R., Bunnefeld, N., Eisenack, K., Hoelker, F., Milner-Gulland, E. J., Muller, B., Nicholson, E., Quaas, M., & Stöven, M. (2012). New horizons for managing the environment: A review of coupled social-ecological systems modeling. Natural Resource Modeling, 25(1), 219-272.

Schreinemachers, P. (2005). The (Ir) relevance of the crop yield gap concept to food security in developing countries. With an application of Multi Agent Modeling to Farming Systems in Uganda, University of Bonn (forthcoming), 2.

Schreinemachers, P., & Berger, T. (2006). Land use decisions in developing countries and their representation in multi-agent systems. Journal of land use science, 1(1), 29-44.

Schroter, J. B., & Kansas, H. (n.d.). Grassed Waterways versus Underground Outlet Tile. Retrieved from https://www.nrcs.usda.gov/wps/portal/nrcs/detail/ks/newsroom/features/?cid=stelprdb1242792

Sengupta, R., Lant, C., Kraft, S., Beaulieu, J., Peterson, W., & Loftus, T. (2005). Modeling enrollment in the Conservation Reserve Program by using agents within spatial decision support systems: an example from southern Illinois. Environment and Planning B: Planning and Design, 32(6), 821-834.

Shubham Industries. (n.d.). Mould Board Plough. Retrieved from http://www.siipl.com/mould-board-plough

Simon, H. A. (1956). Rational choice and the structure of the environment. Psychological review, 63(2), 129.

St. Clair Conservation. (n.d.). WASCoB - Erosion Control Structure. Retrieved from https://www.scrca.on.ca/wp-content/uploads/2018/04/Erosion-Control-Structure-WASCoB-Case-Study.pdf

Stange, C., & Brandle, J.R. (n.d.). Windbreak Management. Retrieved from https://www.fs.usda.gov/nac/documents/morepublications/ec1768.pdf

Statistics Canada. (2012). Snapshot of Canadian agriculture. Retrieved from http://www.statcan.gc.ca/pub/95-640-x/2011001/p1/p1-01-eng.htm

Steele, K., & Stefánsson, H. O. (2015). Decision Theory. Retrieved from https://plato.stanford.edu/entries/decision-theory/

Stone, R. & McKague, K. (2009, May). Grassed Waterways. Retrieved from http://www.omafra.gov.on.ca/english/engineer/facts/09-021.htm

Swetnam, R. D. (2007). Rural land use in England and Wales between 1930 and 1998: Mapping trajectories of change with a high resolution spatio-temporal dataset. Landscape and Urban Planning, 81(1–2), 91–103. https://doi.org/10.1016/j.landurbplan.2006.10.013

Tamini, L. D. (2011). A nonparametric analysis of the impact of agri-environmental advisory activities on best management practice adoption: A case study of Quebec. Ecological economics, 70(7), 1363-1374.

Ten Broeke, G., Van Voorn, G., & Ligtenberg, A. (2016). Which sensitivity analysis method should I use for my agent-based model?. Journal of Artificial Societies and Social Simulation, 19(1), 5.

Tiwari, K. R., Sitaula, B. K., Nyborg, I. L., & Paudel, G. S. (2008). Determinants of farmers' adoption of improved soil conservation technology in a middle mountain watershed of central Nepal. Environmental management, 42(2), 210-222.

Tosakana, N. S. P., Van Tassell, L. W., Wulfhorst, J. D., Boll, J., Mahler, R., Brooks, E. S., & Kane, S. (2010). Determinants of the adoption of conservation practices by farmers in the Northwest Wheat and Range Region. Journal of Soil and Water Conservation, 65(6), 404-412.

Tourte, L., Buchanan, M., Klonsky, K., & Mountjoy, D. (2003). Estimated Costs & Potential Benefits for Non-Engineered Grassed Waterways. U.C. COOPERATIVE EXTENSION.

Tsai, Y., Zia, A., Koliba, C., Bucini, G., Guilbert, J., & Beckage, B. (2015). An interactive land use transition agent-based model (ILUTABM): Endogenizing human-environment interactions in the Western Missisquoi Watershed. Land use policy, 49, 161-176.

Tuite, A. R., Gallant, V., Randell, E., Bourgeois, A. C., & Greer, A. L. (2017). Stochastic agent-based modeling of tuberculosis in Canadian Indigenous communities. BMC public health, 17(1), 73.

Turinawe, A., Mugisha, J., & Drake, L. (2015). Soil and water conservation agriculture in subsistence systems: Determinants of adoption in southwestern Uganda. Journal of Soil and Water Conservation, 70(2), 133-142.

United States Department of Agriculture. (2002, March). Windbreaks: An Agroforestry Practice. Retrieved from https://www.fs.usda.gov/nac/documents/agroforestrynotes/an25w01.pdf

United States Department of Agriculture. (2007, December). Engineering Field Handbook - Chapter 7.

United States Department of Agriculture. (2012, May). What is a windbreak? Retrieved from https://nac.unl.edu/documents/workingtrees/infosheets/wb_info_050712v8.pdf

United States Department of Agriculture. (n.d.). Guide to Texture by Feel. Retrieved from https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/edu/?cid=nrcs142p2_054311

Univerisity of Waterloo. (n.d.). Welcome to Agricultural Water Futures (AWF). Retrieved from https://uwaterloo.ca/agricultural-water-futures/

University of Saskatchewan. (n.d.). Global Water Futures. Retrieved from https://gwf.usask.ca/

Upper Thames River Conservation Authority. (n.d. a). Buffer Strips. Retrieved from http://thamesriver.on.ca/landowner-grants-stewardship/farmland-bmps/farmland-bmp-buffer-strips/

Upper Thames River Conservation Authority. (n.d. b). Erosion Control Structures. Retrieved from http://thamesriver.on.ca/landowner-grants-stewardship/farmland-bmps/farmland-bmp-erosion-control-structures/

Upper Thames River Conservation Authority. (n.d. c). MEDWAY CREEK COMMUNITY-BASED ENHANCEMENT STRATEGY. Retrieved from http://thamesriver.on.ca/wp-content/uploads/MedwayCreek/MedwayCBES-report.pdf

Upper Thames River Conservation Authority. (n.d. d). Windbreaks. Retrieved from http://thamesriver.on.ca/landowner-grants-stewardship/farmland-bmps/farmland-bmp-windbreaks/

Urbina, A., Paez, T. L., Urbina, A., Hasselman, T., Wathugala, W., & Yap, K. (2003). Assessment of model accuracy relative to stochastic system behavior. In 44 th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference.

Uusi-Kämppä, J., & Kilpinen, M. (2000). Suojakaistat ravinnekuormituksen vähentäjänä. Maatalouden tutkimuskeskus.

Valbuena, D., Verburg, P. H., & Bregt, A. K. (2008). A method to define a typology for agent-based analysis in regional land-use research. Agriculture, Ecosystems & Environment, 128(1-2), 27-36.

Valbuena, D., Verburg, P. H., Bregt, A. K., & Ligtenberg, A. (2010). An agent-based approach to model land-use change at a regional scale. Landscape ecology, 25(2), 185-199.

Varble, S., Secchi, S., & Druschke, C. G. (2016). An examination of growing trends in land tenure and conservation practice adoption: results from a farmer survey in Iowa. Environmental management, 57(2), 318-330.

Vignola, R., McDaniels, T. L., & Scholz, R. W. (2013). Governance structures for ecosystem-based adaptation: Using policy-network analysis to identify key organizations for bridging information across scales and policy areas. Environmental science & policy, 31, 71-84.

Walker, F. (2000). Best management practices for phosphorus in the environment. Agricultural Extension Service, University of Tennessee, PB, 1645.

Wang, D., Gong, J., Chen, L., Zhang, L., Song, Y., & Yue, Y. (2012). Spatio-temporal pattern analysis of land use/cover change trajectories in Xihe watershed. International Journal of Applied Earth Observation and Geoinformation, 14(1), 12-21.

Ward, P. S., Bell, A. R., Parkhurst, G. M., Droppelmann, K., & Mapemba, L. (2016). Heterogeneous preferences and the effects of incentives in promoting conservation agriculture in Malawi. Agriculture, Ecosystems & Environment, 222, 67-79.

Willock, J., Deary, I. J., McGregor, M. M., Sutherland, A., Edwards-Jones, G., Morgan, O., Dent, B., Grieve, R., Gibson, G., & Austin, E. (1999). Farmers' attitudes, objectives, behaviors, and personality traits: The Edinburgh study of decision making on farms. Journal of Vocational Behavior, 54(1), 5-36.

Wollni, M., & Andersson, C. (2014). Spatial patterns of organic agriculture adoption: Evidence from Honduras. Ecological Economics, 97, 120-128.

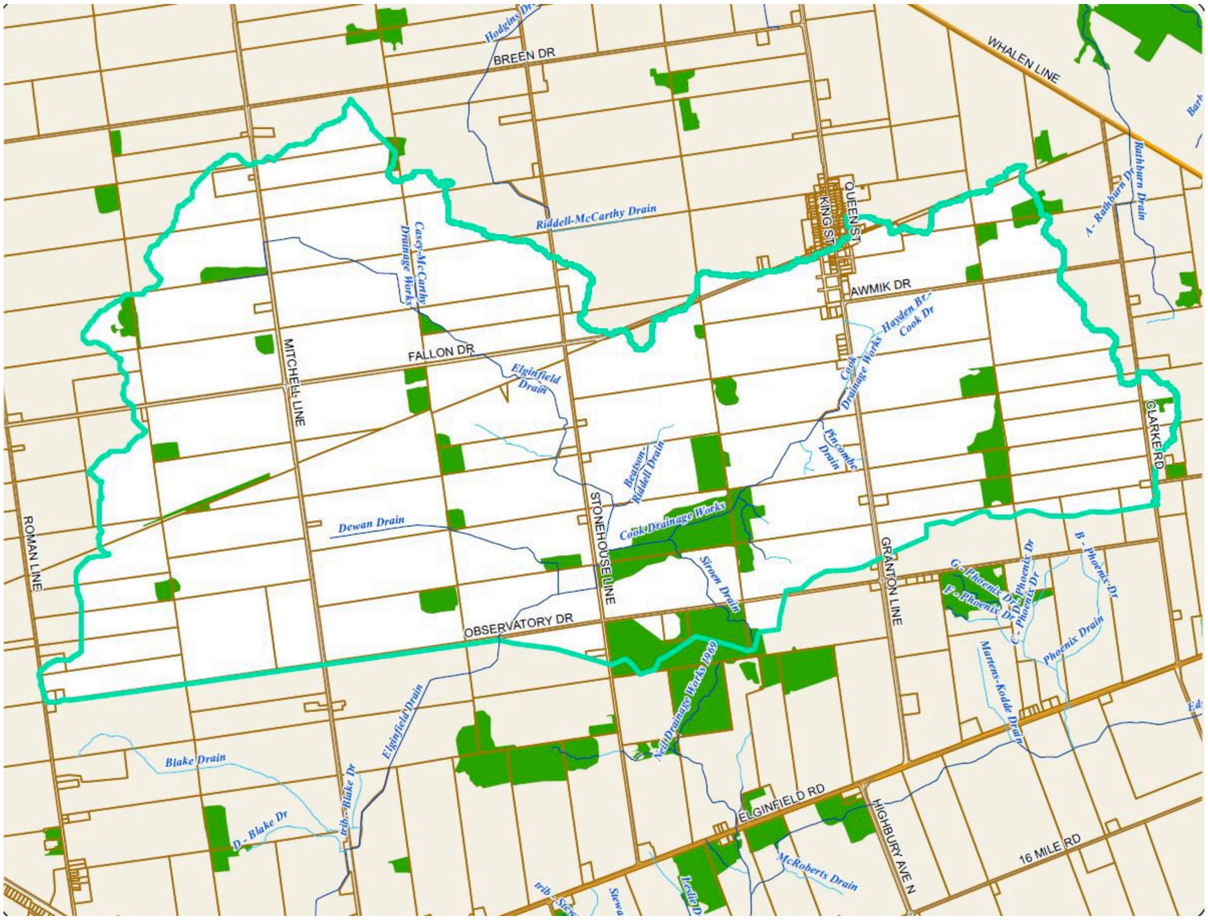
Woods, B. R., Luloff, A. E., Osmond, D., & Hoag, D. (2014). Toward a synthesis: Lessons from thirteen cropland watershed-scale studies. Society & Natural Resources, 27(4), 341-357.

Yang, W., Liu, Y., Simmons, J., Oginskyy, A., & McKague, K. (2013). SWAT Modelling of Agricultural BMPs and Analysis of BMP Cost Effectiveness in the Gully Creek Watershed. University of Guelph, Guelph, Ontario. Xi.

Zhang, R., & Mahadevan, S. (2003). Bayesian methodology for reliability model acceptance. Reliability Engineering & System Safety, 80(1), 95-103.

Zhang, X. Y., Trame, M. N., Lesko, L. J., & Schmidt, S. (2015). Sobol sensitivity analysis: a tool to guide the development and evaluation of systems pharmacology models. CPT: pharmacometrics & systems pharmacology, 4(2), 69-79.

Appendix A Base Map of the Upper Medway Creek Subwatershed



Data Source: UTRCA

Figure A-1 Image of the Upper Medway Creek subwatershed

Appendix B Average Working Hours and Wages of Off-farm Job

Table B-1 Proportion of operators' average weekly hours of off-farm work

Avg. Weekly Off-farm Work Hours	Percent of Operators
More than 40 hours	18
30 to 40 hours	13.7
20 to 29 hours	6.5
Less than 20 hours	8.6
Data Source: Statistics Canada (2012)	

Table B-2 Ontario minimum general wage (in $/hour)

	2015	2016	2017	2018	2019
Minimum Wage (CAD)	11.25	11.40	11.60	14.00	15.00
Data Source: Government of Canada (n.d.)					

Appendix C Costs, Market Price, and Yields of Field Crops

Table C-1 Annual costs of each field crop in 2017 (in $/acre)

	Total Inputs	Total Machinery	Other Costs	Total Costs
Corn	241.25	124.65	137.3	503.2
Soybean	139.95	111.75	38.2	289.9
Winter Wheat	198.70	118.6	18.1	335.4
Hay	144.65	102.57	15.8	263.02
Data Source: OMAFRA (2016)				

Table C-2 Annual average yields of each field crop from 2012 to 2017

	2012	2013	2014	2015	2016	2017
Winter Wheat	2.13	2.18	2.10	2.13	2.47	2.38
Corn	3.89	4.09	4.09	4.33	4.03	4.24
Soybean	1.31	1.25	1.24	1.27	1.25	1.24
Hay	2	2.5	2.6	2.7	2.4	2.8
Data Source: OMAFRA (2018 a.)						

Table C-3 Annual average market price of each field crop from 2008 to 2015

Crop	2008	2009	2010	2011	2012	2013	2014	2015
Corn	188.40	165.60	210.00	246.40	264.40	236.00	186.80	182.00
Soybean	418.52	392.22	411.11	452.22	521.11	507.78	515.56	441.11
Winter Wheat	173.70	159.63	194.44	232.96	275.56	238.15	235.93	293.70
Hay	117.30	118.10	126.90	136.60	221.48	192.89	150.61	138.89
Data Source: OMAFRA (2018 b.)								

Appendix D Costs and Environmental Effectiveness of BMPs

Table D-1 Range of annual costs of each BMP

BMP Name	Annual Costs ($/Acre of Field)	Source
Conventional Tillage	$50/acre - $83/acre	OMAFRA (2016)
Reduced Tillage	97% of conventional tillage costs	Kansas (1989)
No-till	93% of conventional tillage costs	Kansas (1989)
Grassed Waterway	$1.57/acre - $44.46/acre	Kansas (1989) Tourte et al. (2003)
Buffer Strip	$6.32/acre - $18.98/acre	Mtibaa et al. (2018)
WASCoB	$26.3/acre - $78.8/acre	Kansas (1989) UTRCA (n.d. a)
Windbreak (Planting)	$961 - $2819.25/km	Roberts (2017) Kansas (1989)

Table D-2 Environmental Efficiencies of each BMP

BMP Name	P Loss (%)	Sediment Control (%)	Soil/Wind Erosion (%)	Source
Conventional Tillage	NA	NA	NA	NA
Reduced Tillage	25 - 50	NA	30 - 60	Kansas (1989)
No-till	50 - 80	NA	60 - 80	Kansas (1989)
Grassed Waterway	40 - 50	60 - 80	NA	Kansas (1989)
Buffer Strip	24 - 85	53 – 97	NA	Hawes and Smith (2005)
WASCoB	25 - 50	60 - 95	NA	Kansas (1989)
Windbreak	NA	17 - 34	62 - 95	López et al. (2017) Dafa-Alla and Al-Amin (2011)