Agent-based modelling for the adoption of beneficial water management practices in eastern Canada - A case of the cost-share program in agri-environmental policy design

by Ran Sun, James Nolan, and Suren Kulshreshtha

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Ran Sun* James Nolan† Suren.Kulshreshtha‡

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Abstract

Beneficial water management practices (BWMPs) are farm management practices with environmental benefits of mitigating adverse impacts generated from conventional tile drainage. However, the adoption of BWMPs typically reflects the dilemma of agri-environmental technologies: although there are high social benefits, low private incentives mainly prevent technology adoption by farmers. Due to micro-level studies' limitations of using the econometric models from the ex-post perspective and absence from policy interventions, this study employed agent-based modelling (ABM) to bring new insights into technology adoption. The dynamic adoption/diffusion process of BWMPs was calibrated through the ABM model. Furthermore, a case on cost-effectiveness evaluation of the cost-share program was exemplified in this study to explain how ABM can support the agri-environmental policy design. Conclusively, this model can be used as a powerful and flexible tool in policy ex-ante evaluation and design regarding social-ecological systems based on various perspectives of policy goals, such as participants, land, total social benefits and cost-effectiveness. Moreover, the application of ABM or complex adaptive systems, incorporated with interdisciplinary research and potentially interfaced with big data, machine learning and reinforcement learning techniques in the future, can shed light on the economy's complexity, which may be ignored by established economic theory.

Keywords: Agri-environmental technology adoption, Agent-based modelling, Beneficial water management practices, agri-environmental policy, ABM simulation

*Department of Agricultural and Resource Economics, University of Saskatchewan, Saskatoon, Canada, SK S7N 5A8, email: ran.sun@usask.ca.

†Department of Agricultural and Resource Economics, University of Saskatchewan, Saskatoon, Canada, SK S7N 5A8, email: james.nolan@usask.ca.

‡Department of Agricultural and Resource Economics, University of Saskatchewan, Saskatoon, Canada, SK S7N 5A8, email: suren.kulshreshtha@usask.ca

1 Introduction

As a focal driving force for agricultural development, the diffusion and application of innovative agricultural technology eventually depend on farmers' adoption of new technologies. In particular, given the severe challenges of increasing agri-environmental concerns, including natural resource destruction, soil, water and air pollution, and issues regarding climate change, agri-environmental beneficial technologies or practices are expected to be voluntarily implemented by farmers to sustain agriculture (FAO, 1991, 2007, 2016). Based on that, studying the mechanism of the adoption and diffusion of these agricultural technologies by farmers are essential for understanding the factors and barriers of technology adoption and enhancing extensive technology implementation, thus abating the deterioration of the agri-environment and improving the efficiency of agricultural production and development.

During the past decades, considerable research has been done to identify factors affecting the adoption of various agricultural technology (see literature review of Knowler and Bradshaw (2007), Baumgart-Getz et al. (2011), Oorschot et al. (2018), Ugochukwu and Phillips (2018) and Pathak et al. (2019)). These factors are from wide-range aspects, such as the economic return of the technology, risks, farmers' socio-demographics, and farmers' perceptions and attitudes on the technology. Likewise, learning and social networks have been studied for their effects on the diffusion of technology based on socio-psychological theory (Abrahamson and Rosenkopf, 1993; Munshi, 2004; Conley and Christopher, 2001; Conley and Udry, 2010). However, only a few studies involved the dynamic adoption process due to the unavailability of panel data, while the dynamics imply the spatial-tempo essence of the adoption/diffusion process of technology (Jaffe and Stavins, 1995). Also, micro-level studies using the econometric models always reveal an explicit limitation that most of them are from an ex-post perspective and absent from the effects of policy interventions, which can not be compatible with the objective of potential policy instruments' design and evaluation (Doss, 2006). In particular, the path dependence of complex technological innovations is commonly important can play an important role in technology adoption (Rycroft and Kash, 2002). However, the analysis of materiality and feasibility of agricultural technology, including land and climatic conditions and precedent technology, has not been explained adequately in the literature.

The above insufficiency of existing studies suggests the potential embrace of new complex models in technology adoption, such as agent-based computational models, especially when it involves agricultural social-ecological systems. Agent-based modelling (ABM) in social simulation, also known as artificial society, is an emerging research field that integrates computer science with sociology, economics, and system science (Epstein and Axtell, 1996). The theoretical basis of using ABM in addressing problems in economics lies in the theory of Complexity economics, proposed by W. Brain Arthur in a series of complexity economics research (e.g. Arthur (1999), Arthur (2014) and Arthur (2021)). Based on the core ideas and concepts of complexity economics, ABM representing a typical computational economics modelling tool serves as an essential economic adaptation of the complex adaptive systems paradigm (Tesfatsion, 2003).

Followed by the development of complexity science and computational economics, many studies using ABM have made significant progress in the research regarding the social-ecological system, including land planning, pollution regulation and comprehensive environmental management. Nolan et al. (2009) explained the advantages of using ABM to explore research questions in agricultural and resource economics. Regarding agricultural policy evaluation, ABM often involves the transition of land use and farm structure. For example, Berger (2001) studied the impacts of various policies (such as credit support, irrigation technology investment) on land use of an agricultural region in Chile using a spatial multi-agent programming model to simulate how market-driven sustainable technological changes led to increased employment in agricultural production and hindered the protection of land resources. Similarly, Happe et al. (2006) applied the ABM of AgriPoliS to investigate the agricultural structural change resulted from a payment policy switch from production attached to land use only. Environmental policy evaluation using ABM is another prevailing research emphasis. The policies include conservation regulations, nature resource evaluation, transportation and land use planning. For example, emissions cap and trade have been studied using ABM to simulate the transmission and feedback process of policy and identify the dynamic impact of such factors on market efficiency, like transaction costs, corporate feedback, and consumer demand (Zhang et al., 2010, 2011; Huang and Ma, 2016). Bakam et al. (2012) assessed the relative cost-effectiveness of market-based GHG mitigation policy instruments in the agricultural sector by incorporating transaction costs. Berger and Troost (2014) and Troost et al. (2015) argued ABM as a complementary tool for assessing farmer responses to alternative climate change policies. Morgan and Daigneault (2015) modelled the impact of a greenhouse gas price on farm-level land use, net revenue, and environmental indicators such as nutrient losses and soil erosion. Recent research in ABM of agricultural agents has integrated spatial analysis, including geographic and climatic information. Wise and Crooks (2012) took traditional farming areas in northern New Mexico as a case study, which applied empirical GIS data to construct a visional social-ecological system and then analyzed the accumulative influences of regional water system, water system structure on sustainable development of land. Shahpari and Allison (2017) proposed a spatial ABM Crop GIS-ABM developed in Agent Analyst toolbox (developed by ESRIArcGIS) to simulate the interactions between the geographic agent (represented in vector polygon) and generic farmer agent.

In general, ABM has the flexibility in calibrating and simulating interactions between agents and also adaptation between agents and their environment surrounded as a complex system (Nolan et al., 2009). ABM is conducive to reflect the collective decision-making of technology adoption by farmers and thus dynamic diffusion process in the real world. Based on that, the objective of this study is to develop an agent-based computational model for the adoption of beneficial water management practices (BWMPs) in eastern Canada. RePast ABM tool-kit in the Eclipse development platform based on the JAVA language was used to develop and implement the model [1]. Therefore, an Adoption-BWMPs class package has been developed in this study with the RePast class library to implement the following functions:

- import and generation of the spatial environment and the agents' attributes;

[1]RePast (Recursive Porous Agent Simulation Toolkit) was originally developed by researchers from the Social Science Computing Research Center of the University of Chicago and was subsequently extended by Argonne National Laboratory as a packaged software infrastructure (North et al., 2013).

- identification and recording the technology feasibility through the interactive decision-making of agents to the environment;
- simulation of agents' decision-making based on their attributes and motivation, including farm production, farm drop-out of operation, adoption of base technology and BWMPs, social communication;
- simulation with various scenarios, such as policy instruments and climate change impacts on agricultural production and BWMPs' adoption;
- results output for all agents by year, including individual production and adoption results and collective statistics presenting the dynamic adoption and accumulative adoption curve.

Besides, the verification and validation (V&V) process in the ABM results was performed based on the Monte Carlo simulation experiments in the social system through multiple trials on the model, enabling a robustness check of the model.

To sum up, this ABM model on the adoption of BWMPs can calibrate the dynamic adoption/diffusion process derived from individuals' decision-making institutions and their networks and simulate policy instruments' effects on improving the adoption. Thus, this model can evaluate policy instruments based on their agri-environmental goal from an ex-ante perspective, thereby implying the predictive insights in the agri-environmental policy design by applying ABM in supporting public decision-making.

2 Conceptual framework

The ABM model is developed under GIS data to represent the research site of Essex County in Ontario, where agents representing farms are plotted randomly and connected in networking topology. From this spatial representation of the problem, critical questions concerning the adoption of BMWPs in this region arise: (1) What would be the adoption rate of BWMPs among the farms at the regional scale over time? (2) How would climate change affect the production and adoption decision, and if adopted, what would be the overall social (e.g., environmental and human health) and economic benefits? (3) Given an agri-environmental policy and its associated costs, what would be the change in the technology adoption, and what are the overall benefits of the policy inducing producers to adopt BWMPs in this region?

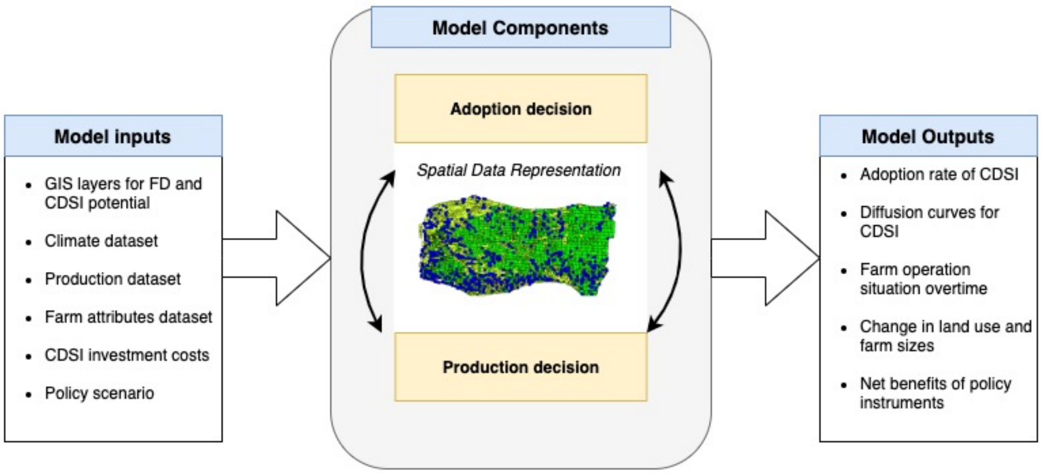


Figure 1: Framework of ABM for adoption of BWMPs (adapted from Berger (2001))

Figure 1 depicts the model's conceptual framework of ABM using gray-box format for addressing the above questions concerning the adoption of BWMPs. The left-side box indicated the inputs, whereas the right-side box indicated the outputs from the model. The main body of the model is composed of: (1) an environment to represent GIS data; (2) a large number of agents operating farms specified at the region; (3) decision-making heuristics, including farm production decision and technology adoption decision; (4) agents' interactions and adaptive processes. Agents and environment are integrated to construct a tempo-spatial dynamic system to observe and compare the results over time.

3 GIS-based Implementation of ABM

Figure 2 shows the diagram of the process and scheduling of the ABM model. For each run of the simulation model, agents are obliged to make various farm management decisions based on randomly assigned conditions from input data, including sale prices of crops, operation costs and neighbourhood. During the course, agents renew their production decisions and adoption decisions under extended agri-environmental policy scenarios. The implementation of ABM are explained in detail in the following sub-sections: Description of input data (Section 3.1), Initialization (Section 3.2), Production decision-making algorithm (Section 3.3), Adoption decision-making algorithm (Section 3.4) and Policy scenarios and evaluation method (Section 3.5).

3.1 Description of input data

3.1.1 Data for constructing GIS environment

Two GIS layers were used to construct the spatial map for this model's environment and also to decide the feasibility of implementing the BWMPs based on technology and land conditions as following:

- Tile Drainage Records (TDR's) are rough sketches of where tile drainage has been installed and were collected from Land Information Ontario (LIO)[2];
- Controlled Drainage/Subirrigation (CDSI) Report includes polygonal data layer delineates areas according to their suitability for implementing the BWMPs.This data set was created based on guidance from a Technical Steering Committee composed of representatives from Land Improvement Contractors of Ontario (LICO), Agriculture and Agri-Food Canada, Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA) and the Ontario agricultural community [3].

In addition, to connect tempo-spatial climatic conditions into the environment of ABM, data of weather stations, historical precipitation and temperature in Essex County were obtained from Environment Canada [4].

[2]Tile Drainage Area (Ontario GeoHub): `https://geohub.lio.gov.on.ca/datasets/tile-drainage-area`

[3]Controlled Drainage (Ontario GeoHub): `https://geohub.lio.gov.on.ca/datasets/4b2e0e3cdd0f48f0a832e568629daf56`

[4]Historical climate (Environment Canada): `https://climate.weather.gc.ca/prods_servs/cdn_`

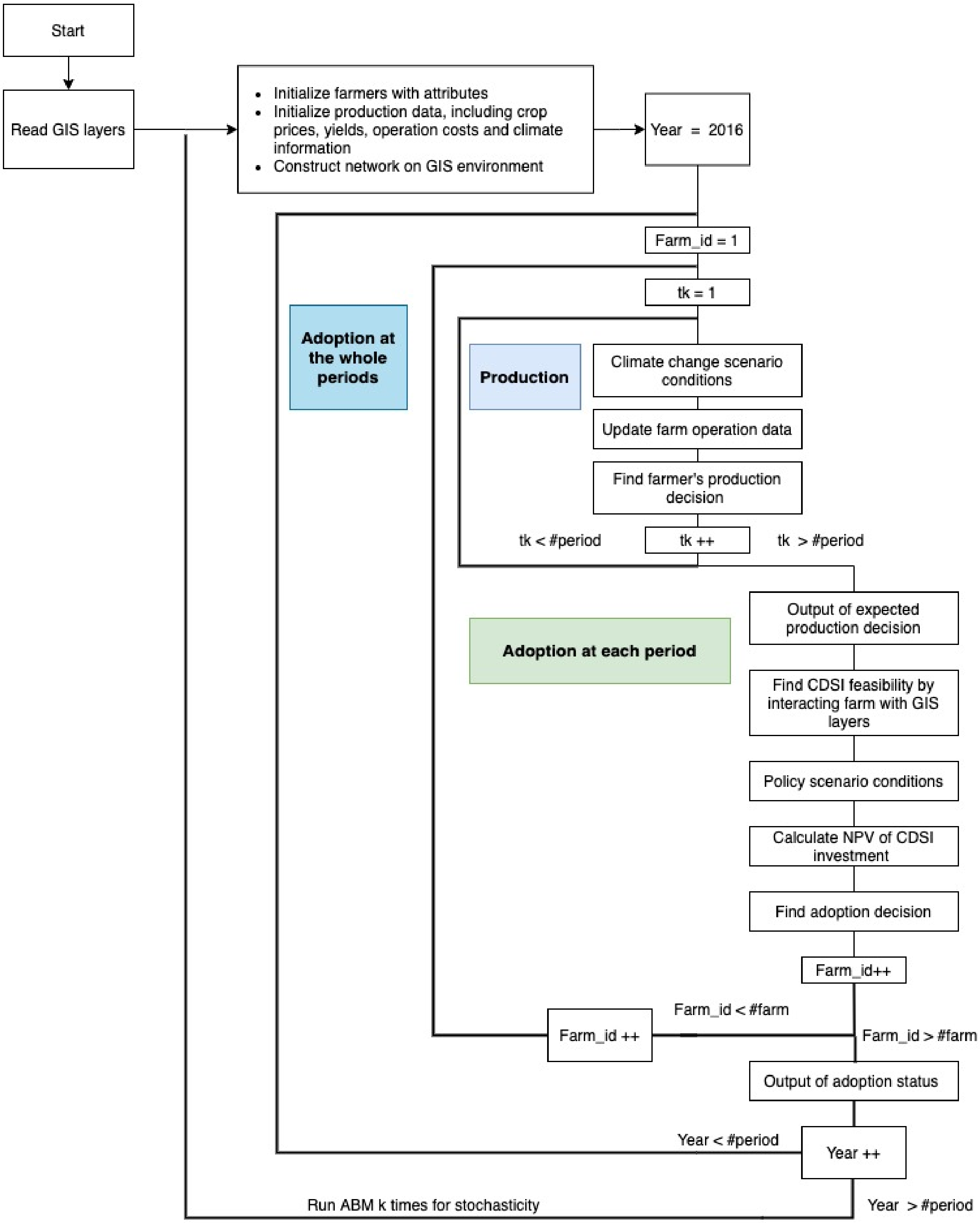


Figure 2: Process overview and scheduling for a model run

3.1.2 Agents data

The agents were built based on the Individuals File, 2016 Census, Public Use Microdata Files (PUMF)[5]. Specific variables indicating characteristics of the Canadian population were used to filter agents in this ABM to represent the farm operators in the research area. Finally, 933 samples with their operators' and farm characteristics were imported to create agents in the ABM model. Algorithm 1 in Appendix presents a filter to clean data for building agents based on group and variables of Census. The data contained the following characteristics to describe farm operators: Sex, Education, Household type and Income. The farm size, tenure were randomly assigned to each sample according to the value of Income.

Table 1: Statistical tests of key indicators' comparison between agents and Essex farm operators

Indicators	Agents	Essex	Statistics	P-value
Mean of operators' age	57.56	58	-1.1365	0.2560
Age: Under 35 years	5%	5%	-0.0976	0.9222
Age: 35 to 54 years	31%	29%	1.6183	0.1056
Age: 55 years and over	63%	56%	4.2553	0.0000
Gender: Female	25.8%	24%	1.2768	0.2020
Mean of Farm size(acres)	328.101	328.317	-0.0127	0.9898
Area rented or leased from others	22.4%	24%	-1.1709	0.2419

To verify the reliability of agents in this model to imitate the farm operators in the research area in presence, Figure 1 shows statistical tests of fundamental indicators' comparison between agents and regional farm operators. For most indicators, including operators' age, gender, farm size and tenure ratio, there is no significant difference between agents and Essex statistics. The proportion of operators' age group of 55 years and over indicated the only statistically significant difference, which agents showed a 6% higher proportion in this group than regional-level.

climate_summary_e.html

[5] Individuals File, Census of Population (Public Use Microdata Files): https://www150.statcan.gc.ca/n1/en/catalogue/98M0001X

3.1.3 Costs and benefits of BWMPs

The input data regarding the benefits and costs of BWMPs were derived from prior research about the socio-economic assessment of BWMPs. Marmanillo Mendoza (2020) conducted an economic analysis of BWMPs in Quebec and Ontario with detailed investment costs and benefits of BWMPs. The Net present value (NPV) was estimated in Marmanillo Mendoza (2020)'s on-farm economic analysis model to interpret the economic return of implementing BMWPs by farmers. Environmental evaluation of BWMPs based on primary field biophysical experimental data and life cycle assessment (LCA) were from the authors' unpublished report for the same project regarding the integrated socio-economic assessment of BWMPs.

3.1.4 Farm operation data

Historical data in respect to the farm operation in Essex, Ontario, including climate(Average temperature and precipitation), crop prices and operation costs data, were entirely collected from the public source (see Table 2). As the objective of ABM involves the prediction of technology adoption, the forecast of farm operation data, especially future climatic conditions and crop commodity prices, can be highly vital for the model to provide practical and validated insights for decision-making.

This study employed a supervised machine learning model (Prophet) based on historical time-series data to forecast future climate and prices. Taylor and Letham (2018) described this algorithm "Forecasting at scale," and Prophet toolkit based on R and python was released by Facebook's Core Data Science team [6]. Prophet can work best with time series that have substantial seasonal effects and several seasons of historical data. Considering the relationship between corn, soybean, wheat prices in the long-term cycle of commodities price fluctuation, the soybean and wheat price ratio based on corn price are used as the train data to predict the soybean and wheat prices.

Historical data regarding operation costs were collected from annual Field corp budgets, provided by OMAFRA to support farm management of estimating costs and evaluating cropping

[6]Prophet: `https://facebook.github.io/prophet/`

alternatives [7]. Similarly, field crop statistics between 2004 and 2019 are reported by OMAFRA, including acre seeded, acre harvest and yields [8]. The future yields for the running period (2016-2050) are generated randomly from a Gaussian distribution with average yields as the mean and standard error of historical yields between 2004 and 2019 as standard deviation.

Table 2: Historical dataset of farm operation and projection method

Historical dataset	Frequency	Range	Data source	Projection method
Climate data (Average temperature and precipitation)	Daily	1969-2019	ECCC	Time Series Forecasting With Prophet based on Machine Learning (ML)
Corn price	Weekly	1992-2019	OMAFRA	
Soybean price	Weekly	1998-2019	OMAFRA	
Wheat price	Weekly	2004-2019	OMAFRA	
Operation costs (Field crop budgets)	Yearly	2016 2018-2020	OMAFRA	Projecting with annual growth
Yields - Corn, soybean,wheat (bushels per acre)	Yearly	2005 - 2019	OMAFRA	Randomly generated from N($Yields_{avg}$, $Yields_{sd}$)

3.2 Initiation

This ABM established a GIS environment for the research area to represent the abstract agricultural landscape. Total 933 agents were initialized in the GIS environment, and the model was implemented for annual steps of 34 years (2016-2050). The properties of agents include:

- making their own decisions according to individual utility functions with bounded rationality;
- composing of network based on their location (coordinates in GIS map);
- responding to the feasibility of environment in the decision-making and responsive to the environment;

[7]OMAFRA Publication 60 - Field Crop Budgetshttp: //www.omafra.gov.on.ca/english/busdev/facts/pub60.htm

[8]OMAFRA Field Crops Statistics: http://www.omafra.gov.on.ca/english/stats/crops/index.html

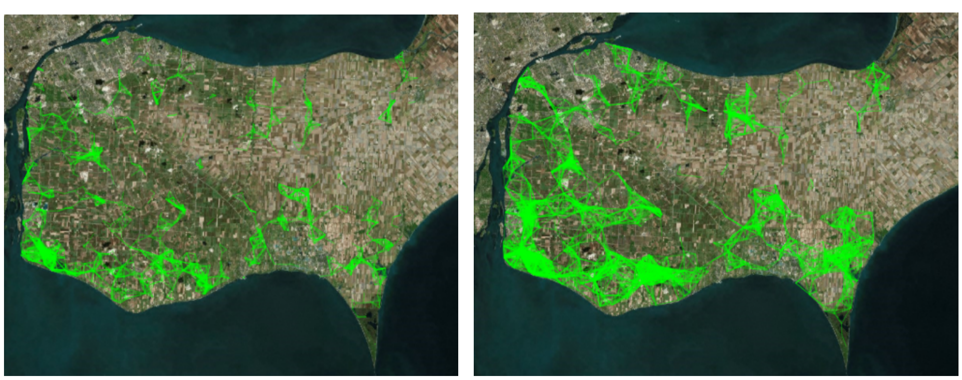
- interacting with neighbour agents within a spatial distance.
- continuing or merging with other agents according to operation and age.

The basic global parameters configured in the initialization stage can be found in Table 3.

Table 3: Global parameters configured to initialize the model

Parameter	Description	Value	Change rule
numAgents	Total numbers of agents	933	Farm drop-out algorithm
startYear	Starting year of simulation	2016	Configurable
period	Total running steps of model	34	Configurable
dist	Distance for agents to build network	1000	Configurable
climateChange	Climate change scenario	(False, True)	Configurable
policyScenario	Policy scenario	(False, True)	Configurable

In terms of network construction, this study simulates farmers' social cycles by indicating the agent's social network radius, within which agents have close interactions with neighbour agents around it (see Figure 3). The social network's visual interface from the model illustrates the location of agents and their networking in the social circle that use the farmer as the center and a certain distance as the radius. The smaller the social network radius with the smaller the social circle of farmers means fewer interactions between this agent and its networks. The agents outside the networks of a particular agent do not directly affect his decision, but there are also possible indirect interactions between local social networks.



(a) Distance = 1000 m (b) Distance = 2000 m

Figure 3: Network construction in the model

3.3 Production decision-making algorithm

Agents' production decision-making contains three aspects, including individual-level decision-making, collective-level decision-making and possible farm drop-out. The production decision-making rules and interpretations are in the following subsections. In addition, pseudo-codes illustrate the concrete algorithm for the production decision-making rules in Algorithm 2 in Appendix.

3.3.1 Individual decision-making

Production decision-making constitutes an essential basis for farmers to adopt other agricultural technology due to the classic assumption of farm management to maximize profits. Above all, two assumptions need to be clarified to simplify the problem based on local agricultural production features. One is farmers are price-takers which means that the market faced by each farmer is completely competitive and market prices (including input prices and output prices) are all given exogenously; the other one is no employment of labour in farming, which coincides with the situation that in Southern Ontario, family-operated farm still account for a large proportion, especially in field crop production.

Linear programming (LP) is used to describe the production optimization algorithm for an agent by allocating farmland to three field crops: corn, soybean, wheat, to achieve profit maximization. The LP problem of farm production decision-making can be explained in the following form with objective function and constraints (see Equation 1). The profit is defined as production profit as the total market value of crops minus operational costs (excluding land cost/rent and utilities). Despite various agricultural production restrictions, such as land, water, labour force, and capital investment, the LP algorithm here only considers the restrictions bounded by the most crucial land input. The land acres for corn, soybean and wheat may not be larger than the total acre of farm size. Notably, because farmers may have habitual farming behaviour in allocating farmland and lagging in adjusting their production decisions based on market prices promptly, acres are set in a range between a minimum of historical planting proportion for three field crops, respectively.

$$
\begin{aligned}
& Max \;\; Profit = \sum_{i=corn,soybean,wheat} (Yields_i * Price_i - Costs_i)\; Acre_i \\
& S.t. \;\; Acre_{corn} + Acre_{soybean} + Acre_{wheat} \leq farmSize \\
& \qquad Acre_{corn},\; Acre_{soybean},\; Acre_{wheat} \geq 0 \\
& \qquad Acre_i \leq max_i Ratio \\
& \qquad Acre_i \geq min_i Ratio
\end{aligned}
\tag{1}
$$

The LP in this model is solved by lp_solve [9], which is a Mixed Integer Linear Programming (MILP) solver [10]. This Java native interface (JNI) supports the full functionality of lp_solve in a Java programming environment.

3.3.2 Collective feedback

However, individual decision-making mechanisms based on the design from "rational choice" cannot adequately reflect the equilibrium of supply and price in the market. When the profit margin of one crop is explicitly higher than that of other crops, all rational agents in the system will adopt a convergent decision to switch farmland from low-priced crops to high-priced crops without considering the descending price adjustment due to increased supply. Therefore, a feedback mechanism from collective production decisions has been designed to adjust crop prices' expected value in this ABM. The parameter is given by

$$\Delta\; Price_i = \alpha\; + \beta\; \Delta\; Acres_i \quad i = corn,\; soybean,\; wheat. \tag{2}$$

The function implies that if too much farmland were allocated to a specific crop, this crop's price would change correspondingly. Here, a generally negative parameter β means the price of

[9] lp_solve reference guide: `http://lpsolve.sourceforge.net/5.5/`

[10] lp_solve was initially developed by Michel Berkelaar at the Eindhoven University of Technology and extended to a Java interface made by Juergen Ebert (University of Koblenz-Landau, Germany).

drop i would fall when seeded acre for that crop increased. The parameters were estimated by a regression model of crop prices on seeded acres.

3.3.3 Farm drop-out from farming

Based on the farm and farmers' situation, agents decide whether to continue farm operation next year. So the number of agents changes according to the rules of the farm drop-out farming decision. The two main reasons for an agent closing farm are profitability and farmers' age. Accordingly, the concrete rules of closing a farm are placed as follows:

- When a farm has suffered a profit loss for two consecutive years, the operator chooses to end the farm and sell farmland to a buyer. The buyer will be selected as the other farm with the highest profit from this farm's network. This agent's farmland will be merged into the buyer's farm.
- When the farmer's age exceeds the retirement age, the farmer will arrange the farm operator after retirement based on household type. Specifically, the farm operation will be transferred to the next generation if the heir/heiress is available, while else this farmer will consider ending farm operation and selling farmland to potential buyers. If the farm cannot be sold due to no proper buyer, the farmer will continue to operate until finally finding the buyer.

3.4 Adoption decision-making algorithm

The algorithm 3 for adoption decision-making rules is given by pseudo-codes in Appendix.

3.4.1 Land feasibility

The precondition of technology adoption is to assess whether a farm with a random plotted location can implement the BWMPs according to land suitability. The rules are composed of two conditions. One is whether the farm has been installed tile drainage as the base technology, and the other is whether the farmland can upgrade to new technology based on soil type and land slope.

3.4.2 Economic rule for adoption

The economic concern for making the adoption decision-making rule is the investment return of the new technology and farm operating net margin. In specific, an agent makes the adoption decision each year according to the rules below:

- The net present value (NPV) of implementing BWMPs should be positive, meaning that the farm can obtain economic benefits from the investment. NPV is calculated each year for each farm to present the net return of CDSI investment starting from the current year till the whole life expectancy of the technology (see Equation 3). Initial costs as fixed costs will happen in the current year, and maintenance costs will be paid yearly in future.

$$NPV_t = \sum_{i=t}^{t_{i+l}} \frac{P_{adopted} - P_{unadopted}}{(1+r)^{i-t_{base}}} - C_{fixed} - C_{maintenance} * farmSize \tag{3}$$

- The operating profit margin of farms considering the adoption of BWMPs should be higher than the average profit margin of farms, meaning that relatively good business capability constitutes a basis for farms to invest in technology.

- The profit of the farm can cover initial investment costs. Although funds and loans can be applied to support the BWMPs, the farm should contain enough cash for adoption regarding down-payments and installation fees.

3.4.3 Diffusion of technology adoption through network

The ABM enables calibrating the diffusion of technology adoption through the interactions between agents' networks. This function can investigate potential "herd behaviour" or "bandwagon effect" in the adoption of BWMPs from a simple point that an agent's decision-making probably can be affected by other agents from its network. Through the network, farmers observe their neighbours' adoption decisions as percentage values of neighbours who have adopted the technology for base technology and BWMPs. The values of $P_{spatial}(FD, i)$ and $P_{spatial}(CDSI, i)$

measure the popularity of base technology and BWMPs within the network that are connected to the specific agent.

$$
\begin{aligned}
P_{spatial}(FD,i) &= Network(FD,i) \ / \sum Network(FD,i) \\
P_{spatial}(CDSI,i) &= Network(CDSI,i) \ / \sum Network(CDSI,i)
\end{aligned} \tag{4}
$$

where Network(FD, i) and Network(CDSI, i) represent the number of farmers that have adopted the water management technology FD or improved CDSI within the farmer i's network. A threshold ratio indicates the condition triggering the effect of collective decision-making on the farmer. When $P_{spatial}(FD,i)$ and $P_{spatial}(CDSI,i)$ exceeds the threshold, the farmer may relax the rules of economic constraints on adoption and decide to adopt the technology.

3.5 Policy scenarios and evaluation method

Considering the high initial costs of implementing BWMPs, the government prefers using economic incentives like the cost-share program to encourage the voluntary adoption of BMWPs by farmers. Thus a cost-share program scenario was exemplified in this study to simulate how policy intervention would affect farmers' decision-making on the production and adoption of BWMPs. By assigning the attributes of policy variables, the effects of policy variables on the agents' behaviour compared to the status quo can be observed through a functional established "stimulus-response model."

Three indicators are used as following to comprehensively compare the effects between policy instruments on the adoption of BWMPs:

- adoption rate comparison: policy scenario vs. base scenario
- adoption farmland comparison: policy scenario vs. base scenario

- policy cost-effectiveness comparison:

$$ratio_{policy} = \frac{\sum_i^n (AdopedYear_{policy} - AdoptedYear_{base}) * (N_p + N_s)}{Costs_{policy}} \quad (5)$$

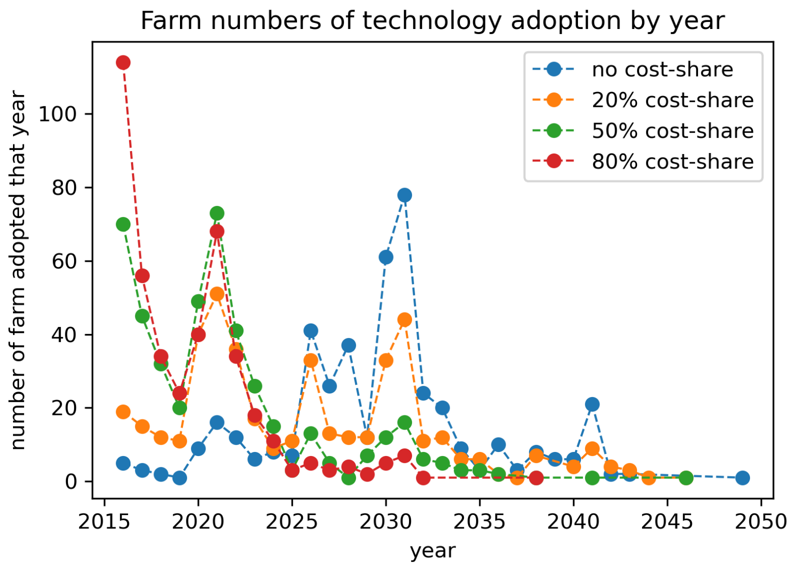
where n is the affected number of farmers under policy scenarios. N_p and N_s are private net benefits and social net benefits of the implementation of BWMPs by farmers.

4 Results

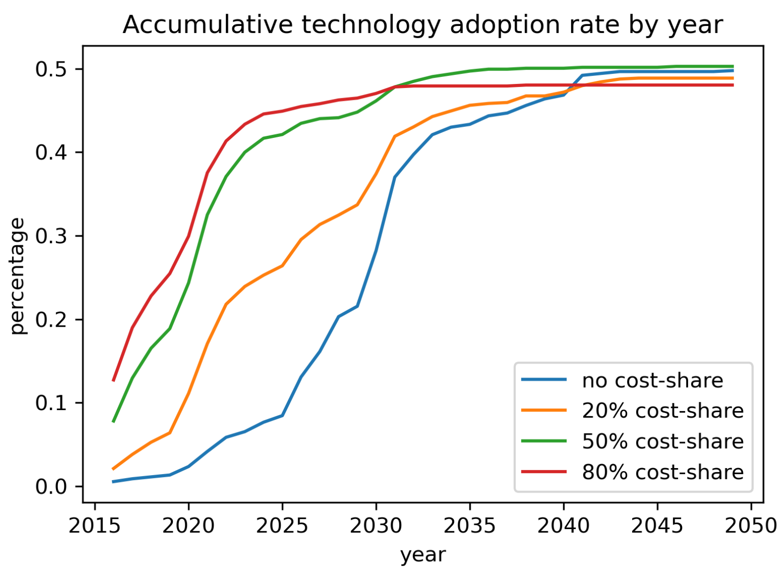
4.1 Cost-share program induced BWMPs adoption

Given a policy scenario with cost-share subsidies on the initial investment costs of BWMPs, Figure 4 shows the results of simulated adoption of BWMPs based on 15 trials per cost-share ratio. The base scenario indicated by ”no cost-share” shows in the figure. Considering the base scenario, the adopted farm numbers by year indicate that before 2025, the adoption of BWMPs will first sporadically appear, and then rising volatility, and then increase dramatically around the 2030s, followed by a rapid decline to the few adoptions in the 2040s. The adoption fluctuation is accompanied by three ”ascending-peak-descending” waves, happening from 2020 to 2023, from 2025 to 2028, and the last one from 2029 to 2033, respectively. The accumulative technology adoption rate gives the diffusion curve of the adoption rate by the year. The curve is generally compatible with the conventional S-shape curve but much steeper, starting to ascend slowly and speeding up to get the high peak of adoption in the 2030s. After the peak, the accumulative adoption will remain about 47% for farm numbers under no cost-share scenario.

The comparable results of both numbers of adopted farms each year and the accumulative adoption rate under various ratios in cost-share programs illustrate that cost-share programs can accelerate farmers' adoption by shortening their adoption year, but no significant effect on enhancing the ultimate adoption rate. For example, if 80% cost-share program was conducted, a 40% adoption rate goal can be achieved around 2020, ten years ahead compared with no program in-



(a) Numbers of adopted farm by year



(b) Accumulative adoption rate by year

Figure 4: Simulated adoption of BWMPs with cost-share program scenario (based on 15 trials on each cost-share ratio))

volved. However, the final adoption rate will not be improved by the implementation of cost-share programs. Unlike the conventional convex curve explaining technology adoption with decreasing marginal adoption rate, simulated marginal adoption rate from this model continues to increase until reaching the highest point as the critical point, then turning to decreased marginal adoption rate, even close to zero in the late period. Given that the highest operating profit margin happens around 2030 from the production decision-making simulation, the recovery of farming profitability causes a possible explanation for when the peak in adoption occurs. Nevertheless, the next highest operating profit margin happens around 2042, it cannot incentivize large amounts of adoption, and the final adoption rate fails to exceed 50%.

4.1.1 Cost-share program evaluation

Aside from the overall impacts on the adoption rate, the effectiveness of policy can be evaluated by comparing social benefits associated with implementing BWMPs and the program's direct payment to affected adopters. Table 4 and Table 5 show the simulation results of each trials and a summarized cost-effectiveness evaluation of various cost-share program at 20%, 50% and 80%, respectively. The number of farms affected by the cost-share program and years of shortened to adopt technology increase significantly as the subsidized ratio of technology costs. Average farm size of the affected farm by program increase by around 20 acres from 20% cost-share to 50% and 80%. Social benefits of implementing BWMPs are from prior research on socio-economic evaluation (\$ 40.46 ha^{-1} and \$ 508 $ha^{-1}yr^{-1}$, respectively). Also, total payments can be estimated by the initial structure and installation costs of the technology, multiplying various cost-share ratios.

Subsequently, the cost-effectiveness ratio, indicating the ratio of social benefits to direct program payments, can be calculated to evaluate policy effectiveness under various ratio scenarios. In this case, the cost-effectiveness ratio is 43, 20 and 12, resulted from the cost-share ratio increasing from 20% to 80%. The cost-effectiveness ratio means the value of social-benefits gained from each dollar expenditure on the program. The highest value of cost-effectiveness among the cost-share scenarios is 20%. Hence a higher ratio of green payments may not necessarily lead to an

Table 4: Results of 15 trials on simulation under cost-share program

No.	Number of farm affected by policy			Years of shorten			Avg. acres of farm		
	20%	50%	80%	20%	50%	80%	20%	50%	80%
1	202	237	265	-11	-13	-15	278	282	303
2	205	236	251	-11	-13	-15	272	292	274
3	198	240	240	-12	-13	-14	256	284	286
4	206	257	236	-11	-14	-14	317	286	287
5	195	238	262	-12	-13	-15	314	296	270
6	198	235	240	-11	-13	-14	272	282	286
7	191	235	257	-11	-14	-15	305	300	250
8	185	230	249	-11	-13	-14	243	270	286
9	206	225	235	-11	-13	-14	317	270	274
10	217	231	249	-12	-13	-14	281	297	287
11	220	231	241	-12	-13	-14	259	275	301
12	229	227	230	-11	-12	-14	261	284	299
13	202	240	231	-11	-13	-14	274	285	293
14	205	257	241	-11	-14	-14	268	298	291
15	254	230	261	-11	-13	-15	101	288	263
Mean	208	237	246	-11	-13	-14	268	286	283
S.d.	17	9	11	0.39	0.37	0.44	52	10	15

increase in program effectiveness. The selection of policy like cost-share ratio should combine the effects of policy on adoption (number of farms or farmland) and program cost-effectiveness based on policy's specific purpose.

Table 5: Results of cost-effectiveness for various cost-share ratio (based on 15 trials per scenario)

Ratio	No. of farms	Years of shorten	Avg.acres of farm	Social benefits ($/per farm)	Payments ($/per farm)	Cost-effectiveness
20%	208	11	267.83	566,424	13,236	43
50%	237	13	285.93	713,901	35,328	20
80%	246	14	283.45	692,108	56,033	12

5 Conclusions

The dynamic process of agricultural technology adoption is exceptionally complex by its nature, with various factors involved in the agricultural system that can substantially affect farmers' decision-making. The factors are composed of different aspects, such as technology, farm, farmer, and the network between stakeholders. In light of agri-environmental beneficial technology, like BWMPs, an important question is whether and/or how to design policy instruments to support the adoption of the technology based on its social benefits since there are insufficient economic incentives for the individual farm. This study develops an agent-based simulation model to calibrate the dynamic adoption process of beneficial water management systems by farms in eastern Canada and then conduct an ex-ante analysis on policy instruments' effects on improving agri-environmental technology adoption. Subsequently, a comprehensive decision-making tool can be developed by the basic ABM model with flexible connections between multiple agri-environmental policy goals and the projected direct public funds associated with the agri-environmental program for the future design of agri-environmental policy instruments. This model integrates the theoretical and empirical knowledge of interdisciplinary decision-making systems, including complex science, agricultural and resource economics, geography and ecologic planning, systems simulation. Notably, ABM is potentially interfaced with big data and machine learning techniques, bringing novel sights on established economic theory in the future.

Nowadays, the application of ABM in economics research is still rare and in great need of further studies, especially in developing representative cases modelling equilibrium or dynamic non-equilibrium in economics. Some pivotal questions are proposed for the improvement of ABM. Firstly, the standardization of modules and algorithms in the model design should be adopted. Although some guiding protocols like ODD have been proposed, these protocols have not been strictly accepted and observed in ABM (Grimm et al., 2020). Secondly, in terms of validation, to what extent the outputs of ABM can be considered as ”consistent” with the real world needs to be solved for the results are only verified subjectively by tuning parameters to meet the consistency of data from real-world (Heckbert et al., 2010). The model can be primarily affected by the subjective consciousness of researchers and developers. Moreover, the ABM results may not be robust and can be significantly affected by the initial conditions (Ligtenberg et al., 2004). Due to these conditions are derived based on the research objective, there exists selection bias. Although ABM has many imperfections, it can still be used as a flexible tool to provide insights into predictive dynamic behaviour by calibrating the complex socio-ecological systems and conducting ex-ante analysis on incentives.

For further research, agents' decision-making institutional mechanism algorithms can be further optimized by closely combining the latest AI research, such as reinforcement learning and autonomous behaviour of the agent interacting with the environment. For example, the drastic increase numbers of adopted farm around 2030, which reveal the convergence of farmers' optimal decision-making, can be resulted from lack of lagged effects. However, the current model can not catch such effects unless introducing reinforcement learning. Also, restricted by the computing capacity of personal computers, the ABM in this study only contains Essex county as a representative area of eastern Canada for adoption process simulation and policy evaluation. Expanding to a larger area needs an improvement in the computing environment, especially for storing and reading GIS data. Thus, large-scale ABM simulation should combine with new big data techniques like Distributed computing framework to enrich and optimize the project, especially in exploring statistical tests for a cause-and-effect relationship (Pu et al., 2019). In addition, a dynamic monitoring and self-correction mechanism can be modified with the model for improving the interpretation capacity of information from the simulated results. For example, the simulated adoption results from the model can be modified automatically based on the investigation of actural adoption to provide instructions to adjust policy. Hence, improving the capability and validation of ABM in understanding and addressing problems in the real world is a critical extension for further research.

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Appendix: Algorithm pseudo-code

The pseudo-code of the different algorithms and procedures developed for the implementation of ABM has been listed in this appendix.

Algorithm 1 Agent data pre-processing algorithm

```
Read data
if Province = "Ontario"
and Industry sectors = "Agriculture, forestry, fishing and hunting"
and Class of worker (derived)= "Self-employed"
and Age ="20 to 74 years" then
    keep sample
else
    drop sample
end if
if Income = null and Education = null then
    drop sample
else
    keep sample
end if
Keep Sex, Education, Household type, Income
Save data
```

Algorithm 2 Production decision-making algorithm

INITIALIZE production data-set

for $year_t$ in periods, separately **do**

//Construct production decision-making rule for each running step

for $agent$ in $Agent$ **do**

for $crop$ = corn, soybean, wheat **do**

$price,\ yields,\ costs \leftarrow$ randomly draw price, yields, costs from annual production input data.

end for

$acres_{Corn},\ acres_{Soybean},\ acres_{Wheat} \leftarrow$ call lp_solve to solve the individual LP production problem.

$profit, revenue, profitMargin \leftarrow$ calculate profit = $\sum(Yields_i{*}Price_i{-}Costs_i)\ Acre_i\ , i = corn, soybean, wheat$, revenue = $\sum(Yields_i{*}Price_i)\ Acre_i\ , i = corn, soybean, wheat$, profitMargin = profit / revenue.

// Farm drop-out from farming due to low profit

if $(profit_t\ +\ profit_{t-1})$ ¡ 0 **then**

call search function for buyer with highest profit from network

if buyer != null **then**

agent.active = false and buyer.farmSize += agent.farmSize.

else

farm cannot be sold and continue to operate

end if

end if

// Farm drop-out from farming due to retirement

$retireAge \leftarrow$ randomly draw from $N(Mean_{retireAge}, Sd_{retireAge})$

if $age \leq retireAge$ and hhtype = with children **then**

$agent.age -= 20 \leftarrow$ farmer retired and handle farm to next generation.

else if $age \leq retireAge$ and hhtype = without children **then**
call search function for buyer with highest profit from network
if buyer != null **then**
agent.active = false and buyer.farmSize += agent.farmSize.
else
$agent.age = avgAge \leftarrow$ farmer retired and change operator:
end if
else
farmer no need to consider retirement
end if
agent.age ++.
end for
// Collective feedback for the adjustments of crop prices based on seeded acres
for $crop$ = corn, soybean, wheat **do**
$price_{t+1}$ $\leftarrow$ calculate adjusted crop price for next year $price_{t+1}$ = $price_t$ [1+ ($Acres_t$- $Acres_{t-1}$) β] based on collective farming decisions.
end for
end for

Algorithm 3 Adoption decision-making algorithm

INITIALIZE parameters $l = lifeExpect$, $c_1 = totalInvCost$, $c_2 = annualCdsiCost$, $d = diffYields$, $highProfitMargin = m$

for $year_t$ in periods, separately **do**

  // Construct adoption decision-making rule for each running step

  for $agent$ in $Agent$ **do**

    for remainYear = tk **do**

      $npv \leftarrow$ calculate npv for $remainYear = startYear + period - 1 - t$

      if remainYear $\leq$ lifeExpect **then**

        if profit ≤ 0 **then**

          $npv = \sum(d * profit)/(1+r)^{(l-tk)} - c_1 - c_2 * l$

        else

          $npv = \sum(d * revenue)/(1+r)^{(l-tk)} - c_1 - c_2 * l$

        end if

      else

        if profit ≤ 0 **then**

          $npv = \sum(d * profit)/(1+r)^{(l-tk)} * (1 + tk/(l-tk)) - c_1 - c_2 * l$

        else

          $npv = \sum(d * revenue)/(1+r)^{(l-tk)} * (1 + tk/(l-tk)) - c_1 - c_2 * l$

        end if

      end if

    end for

    //Adoption condition based on economic rule

    if agent.FD = True and agent.CDSIpotential = True and $npv > 0$ and $profitMargin > m$ and $profit > c_1$ **then**

      if adoptedYear = null **then**

        adoptedCDSI = True and adoptedYear = t

```
        end if
    end if
    //Adoption condition combining technology diffusion
    call search function for agents with FD and CDSI from network
    rateFDwithinNet, rateCDSIwithinNet ← calculate P_spatial(FD, i) and P_spatial(CDSI, i)
    for FD, CDSI do
        if nonAdopted and profitMargin > m and ratewithinNet > rateThreshold then
            adopted = true and adoptedYear = t
        end if
    end for
  end for
end for
```