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Factors Affecting Adoption of Water Management Practices by Vegetable Producers in Eastern Canada

Ana-Maria Bogdan[a] and Suren Kulshreshtha[b,*]

[a] Quantitative Research Manager and Specialist, Canadian Hub for Applied and Social Research, University of Saskatchewan, Saskatoon, SK.

[b] Professor, Department of Agricultural Economics, University of Saskatchewan, Saskatoon, SK

*Corresponding author; Telephone 306-966-4014; Fax: 306-966-8413; E-Mail: suren.kulshreshtha@usask.ca

Abstract

Irrigation and drainage practices are necessary to produce high value horticultural crops. With an increasing population, and a decrease in water resources brought forward by climate change and competing uses from other sectors, there is a concern that water for irrigation purposes might be less readily available in the future. This situation can pose serious economic risks to agricultural producers and environmental risks to habitats and ecosystems. Producers' adoption of improved water management practices or technologies has a potential to solve this issue. This study evaluated best (beneficial) management practices (BMP) in Ontario and Quebec for three crops – tomatoes, cranberries, and onions. To identify key determinants of adoption and perception of the BMP, a binary logistic (logit) model was estimated. Factors considered included a mixture of farm, producer and BMP characteristics. Producers’ perception that a BMP is better than the one they are currently using (degree to which a BMP is being perceived as a better alternative), explained most of the adoption outcomes. A grower with specialized farm, with higher education, a positive perception of the BMP, and mainly financial goals from farming was indicated to adopt the BMP more likely.

Keywords: Adoption, Best Management Practices, Ontario, Quebec, Water Table Management

1. Introduction

In Eastern Canada, irrigation and drainage practices are necessary to produce high value horticultural crops, such as fruits and vegetables. With an increasing population, decrease in water resources brought forward by climate change and competing uses from other sectors, the concern is that water for irrigation purposes might be less readily available in the future (Chiotti and Lavender, 2008; Government of Ontario, 2011; Council of Canadian Academies, 2013; Lemmen et al., 2008; Yagouti et al., 2006). This situation can pose serious economic risks to agricultural producers and environmental risks to habitats and ecosystems. To sustain both livelihoods and ecosystems, changes in the current agricultural practices, particularly in on-farm water management, are needed. In the last decades, producers, researchers and policymakers have explored different technologies and practices aimed at minimizing the impact of intensive agricultural production systems on water, land and air resources. Across Canada, efforts have been also focused on developing policies to address these environmental threats posed by agricultural systems.

Agricultural producers across Canada, also acknowledge their responsibility to care for natural resources (Environics, 2006). This is a favourable factor for adoption of such BMPs but results in uncompensated on-farm costs and off-farm benefits, which could become inhibitors of BMP adoption. A survey of producers in eastern Canada suggested a host of variables that producers consider in deciding for adoption of a new technology (Bogdan and Kulshreshtha, 2021). Past experiences and historical data on adoption of these BMPs, in the context of Canadian agriculture, confirm that while some agri-environmental practices (especially those showing positive economic outcomes) were adopted more rapidly and more widely, while others tended to be modestly adopted and with insufficient effects in reducing the degradation of the environment (MacKay et al., 2010; Eilers et al., 2010; Council of Canadian Academies, 2013).

Knowledge of the factors influencing agricultural producers' decisions regarding adoption of improved management practices can be important for policy purposes. Alternative policy instruments can be compared as to their efficacy in incentivizing adoption of a BMP. This is typically based on prediction of the likelihood that adoption of particular innovations will take place under the selected policy instrument.

The major objective of this study is to identify factors that affect adoption of water management BMPs in crop production. The sub-objectives of the study include: (i) Identify reasons for adoption and non-adoption of beneficial management practices/technologies of agricultural producers; and (ii) Identify constraints and conditions under which agricultural producers adopt these beneficial management practices/technologies.

2. Material and Methods

2.1 Factors affecting adoption of a BMP

Studies in the area of adoption decisions of agricultural innovations use predominately the Diffusion of Innovation Theory (Rogers, 2003), as their main conceptual underpinning. However, in recent years, there has been growing interest in connecting adoption decision-making to another theoretical model – Theory of Planned Behavior, used to explain human behaviour (Lynne, 1995; Reimer et al., 2012). This theory was proposed initially by Ajzen (1991), and later developed into the Reasoned Action Approach (Fishbein and Ajzen, 2011). According to this Theory, the decision-making process is framed as "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation" (Rogers, 2003), and includes multiple stages: (1) knowledge, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation (Rogers, 2003). In the first stage, the individual becomes aware that the innovation exists. In the second stage, the individual pursues the new knowledge gained, and information regarding the innovation of interest, and an attitude is formed. Following these two stages, individuals make a decision regarding the adoption or rejection of the innovation, after an evaluation of alternative options. This is the stage during which a choice to adopt is made.

Factors affecting adoption of irrigation technology vary from case to case, but in general inclusion of a combination of economic, social and environmental factors predominate (Albrecht and Ludwig, 2019). Perception of a new technology has also been shown to be an important factor (Kulshreshtha and Brown, 1993: Reimer et al., 2012). Studies suggest that factors that affect adoption could be divided into 4 categories: (1) Producer characteristics and attitudes, (2) Farm characteristics, (3) BMP characteristics, and (4) Context characteristics (Traore et al., 1998; Filson et al., 2009; Baumgart et al., 2012; Bjornlund et al., 2009; Graveline and Gremont, 2021; Lynne et al. 1988; Rouzaneh et al., 2021; Wang et al. 2021). Characteristics of the producer are related to age, experience in farming, and education level. Farm characteristics that may affect adoption could include size, importance of the enterprise where the BMP would be employed. Some BMPs are simple to understand and could be easily adopted. Complexity of a BMP may play a role its adoption. The context characteristics are embedded in larger ecological, social, economic and political systems, which affect producers' adoption decisions.

2.2 Study Regions

This study is based on a cross-sectional survey of fruit and vegetable growers in southern Ontario and Quebec. Location of these study areas are shown in Figure 1. It was designed to understand growers' attitudes and perceptions regarding specific BMPs as well as the factor that affect their decision to adopt. Data were collected using a web-based survey, distributed to local growers.

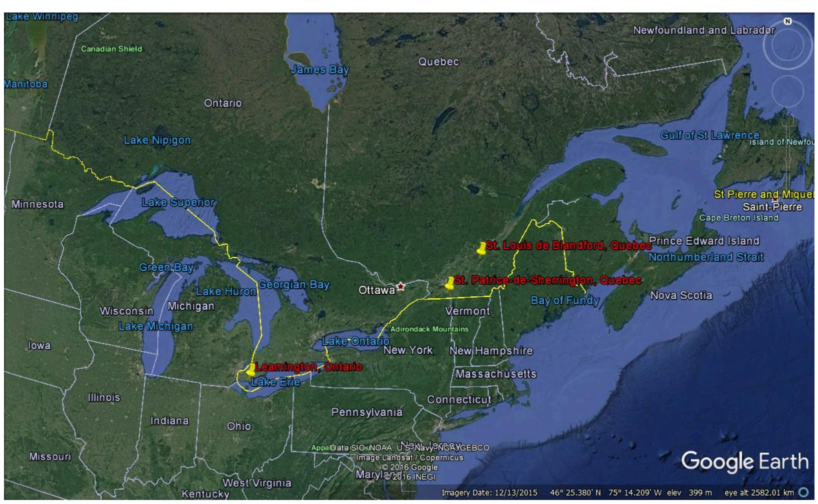

Figure 1. Map of Eastern Canada showing Research Sites

On the tomato farm, baseline scenario surface drip irrigation was evaluated against BMP -- subsurface drip irrigation, whereas on the cranberry farm, baseline scenario reflected the effects of growing cranberries under a relatively wet water management strategy, without water table control, and the BMP scenario represented a drier water table management strategy, where tensiometers were used to assess water needs (Table 1). For the onion farm, comparison of no irrigation and no water table management, and the BMP scenario of sprinkler irrigation system together with the use of a tensiometer to help determine crop water needs.

Table 1. Summary of Salient Features of Research Sites

Name of the Research Site	**Province of Location**	**Commodity Produced**	**Selected BMP for water management**	**Baseline BMP**
Leamington	Ontario	Tomato	Subsurface drip irrigation	Surface drip irrigation
Saint-Louis-de-Blandford	Québec	Cranberries	Sprinkler irrigation and water table control	Sprinkler irrigation and no water table control
Saint-Patrice-de-Sherrington	Québec	Onions	Sprinkler irrigation	No irrigation / Dryland production

2.3 Farm-level Data Collection: Structured Questionnaires for Regional Agricultural Producers

Data collection for identification of factors influencing the adoption of BMP and for modeling agricultural producers' decision-making process was based on the use of structured questionnaires using web-based technology. A questionnaire was developed for each case study, which was translated into French, and pilot tested. All surveys were created using Fluid Surveys, a web-based survey programming tool. Each survey instrument included six sections: (1) Description of the improved water management system; (2a) Adoption: motivations, barriers and perceptions; (2b) Non-adoption: motivations, barriers and perceptions; (3) Opinions: prodcer-environment interactions; (4) Policy changes for adoption (only for non-adopters); (5) Prodcer personal information; and (6) Farm background information. The questionnaire was associated with description of the improved (BMP) technology relevant to a given grower, which distinct for each one of the grower groups. These descriptions are shown in Appendix (Tables A.1 to A.3).

The information provided to regional growers regarding the characteristics of the BMP was derived from secondary literature and findings coming from the case study farm. The data collected from the individual case studies was supplemented by that obtained from governmental factsheets and research reports.

2.4 Sampling Design, Respondent Recruitment and Collection Procedures

Data were collected for a sample of producers, following different procedures for their selection in the three regions. Sample size for various regions is sow in Table 2. For tomato producers, the sample was drawn only from the two Ontario counties, whereas for cranberry and onion producers, samples were drawn from the entire province of Québec. In 2011 there were a total of 228 tomato producers[1] in the Essex and Chatham Kent counties, and 1,422 across the province of Ontario (Statistics Canada, 2011). Across Quebec, in 2011, there were 72 farms that reported growing cranberries, while 358 farms reported growing dry onions (Statistics Canada, 2011). Given the small number of each of the growers, it was not possible to use a random sampling method. The sample selection technique used in this study was nonprobability sampling.

Table 2. Number of Farms in the Population and in the Sample

Farm type	Population	Sample	% Sample from Population
Tomato Farms	228	39	17.11%
Cranberry Farms	72	19	26.39%
Onion Farms	358	12	3.35%
Total Farms	**658**	**70**	**10.63%**

Agricultural producers in Ontario and Québec, involved in tomato, cranberry and onion production were surveyed in June 2016, November 2016 and March 2017, respectively. The scope of the survey was to assess growers' opinions regarding their adoption decision related to specific BMPs and their perceptions of these proposed practices and technologies. All respondents were contacted by e-mail. A reminder was sent to them after two weeks from the

[1] This number does not reflect the recent changes brought by the closure of HJ Heinz Company in mid-2014. It has been estimated that approximately 40% of the producers in the Leamington area are no longer growing tomatoes for processing.

date of the original message. Based on available data, an estimated 210 growers were contacted[2]. The overall response rate was 35% (with 51% for tomato growers, 46% for cranberry producers and only 11.5% for on5

2.5 Modelling Decision Adoption

Throughout the social sciences, research related to binary choices is abundant in the fields of economics, sociology, policy, and many others. That is, because many of the choices humans are faced with are "either/or" in nature (Hill et al., 2008). Typical examples include whether to purchase a commodity, whether to irrigate or not to irrigate, or to vote or not to vote, etc. The agricultural producer faces a similar choice, when deciding whether to adopt an improved practice or technology for his or her farm. As presented earlier, the decision process is influenced by the attributes of the decision-maker, the decision object, socio-economic context, among others.

Binary choice models are statistical models used to estimate the value of a response variable with a change in some stimulus variables. In these models, the assumption is that the choice of the decision-maker is bounded by two choices, mutually exclusive, which are coded with 1 or 0 -- adoption of a new practice or non-adoption, respectively. Binary choice models are used to estimate the probabilities associated with these options and the relationship of the dependent variable and a set of predictors or independent variables.

The models were developed based on the results of the study survey reported by Bogdan and Kulshreshtha (2021). In this survey, after a description of the BMP, respondents were asked to answer the following question:

- For cranberry producers -- “Would you adopt subirrigation for your cranberry production?”
- For tomato producers -- “Would you adopt subsurface drip irrigation for your tomato production?”
- For onion producers -- “Would you adopt sprinkler irrigation for your onion production?”

Responses were coded as 1=Yes and 0=No, and were named under the ordered categorical variable named ADOPT. Three models were developed. The first one included only those

[2] This was based on the assumption of an overlap of 50% on UPA’s growers’ list with MAPAQ’s.

variables that reflect producers' perceptions of the BMPs and their characteristics. The second model included factors that encompass farm and producer characteristics. The third model combines all the variables found in the previous two models. The models' specifications are shown below. Description of these variables is shown in Table 3.

Table 3. Description of Variables Considered for the Binary Logistic Model

Acronym	**Description**	**Type of measure**	**Expected Sign**
Dependent variable			
ADOPT	Distinguishes between adopters and non-adopters	Categorical 1 = yes 0 = no	
Explanatory variables			
AGE	Farmer's age group	1 = under 35 years 2 = between 35-55 3 = over 55 years	-
EDUC	Farmer's level of education	1 = High school 2 = College/Technical Degree 3 = University or Professional Degree	+
EXP	Years of farming experience	Continuous, numeric	-
OWN	Percentage of land owned	Continuous, numeric	+
ORG	Membership in agricultural organizations	Continuous, numeric	+

BMP	Previous adoption of BMPs	1 = yes 0 = no	+
GOALS	Farming related goals	0 = exclusively economic 1 = economic and non-economic	+
CROP	Type of crop related to the BMP adoption	1=Tomatoes 2=Cranberries 3=Onions	?
INOME	Percentage of the grower's income coming from farming	Continuous, Numeric	+
FSIZE	Farm size in acres	Continuous, Numeric	+
CROSIZE	The acres allocated to the crop related to the BMP adoption	Continuous, Numeric	-
SALES	Farm's sale levels	1= Less than $50,000 2= $50,000-$99,000 3= $100,000-$249,000 4= $250,000-$499,999 5= $500,000-$1,000,000 6= More than $1,000,000	+
CROSALE	Percentage of sales corresponding to the crop of interest	Continuous, Numeric	+

Model 1 (M1):

$$ADOPT = \beta_0 + \beta_1 EXPERIENCE + \beta_2 BETTER_{NEUTRAL} + \beta_2 BETTER_{DISAGREE} + \beta_3 GOALS + \varepsilon_i \quad (1)$$

Model 2 (M2):

$$ADOPT = \beta_0 + \beta_1 CROP\ SIZE + \beta_2 CROP\ SALES\ SHARE + \beta_3 EDUCATION_{MID} + \beta_4 EDUCATION_{LOW} + \varepsilon_i \quad (2)$$

Model 3 (M3):

$$ADOPT = \beta_0 + \beta_1 CROP\ SIZE + \beta_2 CROP\ SALES\ SHARE + \beta_3 EDUCATION_{MID} + \beta_4 EDUCATION_{LOW} + \beta_5 BETTER_{NEUTRAL} + \beta_6 BETTER_{DISAGREE} + \beta_7 GOAL + \varepsilon_i \quad (3)$$

2.6 Selection of the Analytical Technique

There are several statistical techniques used to model discrete outcomes. Among the commonly used ones are linear, probit, tobit, and logit regression models. The tobit model is not commonly used although some examples are found (Adsena and Zinnah, 1993). Within the agricultural adoption literature, the most commonly used model is the logistic regression. The binary discrete choice regression models are described using the two possible outcomes (Equation 4). Variable Y is defined, and it can assume two values:

$$Y = \begin{cases} 1 & \text{decision} - \text{maker chooses to } \textit{adopt} \text{ the BMP} \\ 0 & \text{decision} - \text{maker chooses to } \textit{not adopt} \text{ the BMP} \end{cases} \quad (4)$$

The linear probability model is represented by a simple linear function, as shown in equation (5). Here the value of the dependent variable (0 or 1) is regressed against several selected independent variables.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip} + \varepsilon_i \quad (5)$$

Where, Y_i is the response or independent variable for observations i = 1, ..., n; β is a parameter vector, containing regression coefficients β_0 to β_p, indicating the quantified relation between explanatory variables and Y_i; X is a vector of explanatory variables, X_{i1} to X_{ip}, each measured on the i^{th} observation, and ε_i represents the error term for i = 1, …, n independent and normally distributed terms with mean 0 and variance s^2_{ε}.

The results of a linear regression model are straightforward to interpret and easy to communicate. However, there is a wide agreement that its application for dichotomous response variables raises several issues, including nonsensical predictions (Bilder and Loughin, 2014). Another issue frequently mentioned in the context of the linear probability models is heteroskedasticity. This means that the variance of error terms is not constant, which results in inefficient estimators. Furthermore, the standard errors of estimates are biased (Hill et al., 2008).

The probit model allows for the values of the choice probability to be bounded by 0 and 1, as lower and upper limits, accounting for one of the linear regression model limitations. It is related to the standard normal distribution of the probability and it is modeled as a linear combination of the predictors. The probit (and the logit) model has a nonlinear S-shaped curve that defines the relationship between an explanatory variable and choice probability (Hill et al., 2008). The logit model, also known as the binary logistic regression model, is very similar to the probit model. The logit is used widely in the literature to model producers' adoption decisions. Compared to the linear model it has the advantage of bounding probability of occurrence between 0 and 1. One of the main theoretical differences between the probit and the logit resides in the difference in the probability density functions underlying them. The probit model has a standard normal cumulative distribution function, whereas the logit model is based on a logistic cumulative distribution function. Both functions have similar S-shaped curves, with the logistic distribution being more spread out at the tails (Hill et al., 2008; Bilder and Loughin, 2014).

In selecting one model over the other, Chen and Tsurumi (2010) propose several estimators of model quality, to differentiate between models (i.e., Akaike information criterion). These criteria discriminate between models, and help select the better one, in cases where the dependent variable is unbalanced. In cases, where this equal split exists, either one of the models can be equally used. In this study, the logistic regression model was used to explain adoption, due to its wide use in this area of research.

Logistic regression models are categorized as generalized linear models (GLMs). They consist of a random component, Y which has a Bernoulli distribution, a systematic component, the linear predictor Z_i of p explanatory variables, as defined in Equation (6), and a link function – which specifies the link between the expected value of the random component E(Y) and the linear predictor (Bilder and Loughin, 2014). In the logit model, the probability P_i that Y=1 usually takes the form shown in equation (7):

$$Z_i = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip} \tag{6}$$

$$P_i = \frac{e^{z_i}}{1+e^{z_i}} \tag{8}$$

A regression model can also be written using equation (9):

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip} + \varepsilon_i = \mathrm{logit}(P_i) = \ln odds \tag{9}$$

Here, P_i is the probability that the i^{th} observation has an outcome Y_i is 1, conversely $1\text{-}P_i$ is the probability that Y_i is 0. The *odds* are the ratio of P_i and $1\text{-}P_i$. By taking the natural logarithm of the *odds* ratio (*ln odds*), the linear prediction equation is obtained.

Estimation of the binary logistic regression model is realized using a Maximum Likelihood Estimation (MLE) technique. The MLE method seeks to find those values of parameters for which the log-likelihood function is maximized (Hill et al., 2008). The log-likelihood function, used to estimate parameters $\beta_0, \beta_1, \ldots, \beta_p$, for a response variable Y_i, is expressed in equation (10), where π_i represents probability and Π denotes product.

$$\log\left[L\left(\beta_0, \beta_1, \ldots, \beta_p \middle| y_1, \ldots, y_n\right)\right] = \log\left(\prod_{i=1}^{n} \pi_i^{y_i} (1-\pi_i)^{1-y_i}\right) \tag{10}$$

In this study, the logistic regression model was selected for modelling adoption decisions. While there are no major distinctions between a probit and a logit model, in this study, the logistic regression was used to build the study model, because it has been the standard in the area of producers' decision adoption modelling.

2.7 Models estimation

To estimate both the binary logit models, the Statistical Software Package for Social Scientists (SPSS), version 25 was used. All predictors were introduced in the model at once, in one step. To estimate the ordinal logit regression model, the SPSS PLUM (Polytomous Universal Model) procedure was used, which is an extension of generalized linear models for ordinal dependent variable prediction.

3. Results

3.1 Sample Characteristics

There were 70 growers who completed the survey, of which 39 were tomato growers (56% of total who responded), 19 were cranberry growers (making 27% of the total respondents) and the remaining 12 were onion producers (constituting 17% of the total respondents). The majority of respondents (56%) in the survey were of working age – between 35 and 54 years old (Table 4). In terms of education levels attained, most respondents had either a technical (34%) or a bachelor's degree (23%). Over 54% of the growers in the sample had over 20 years of farming experience and earned most of their income from farming (as 80% of respondents earned 75% or more of their household income from farming).

Table 4. Demographic and Personal Characteristics of Respondents (N = 70)

Respondent Characteristics	**Frequency (N)**	**Percent of total respondents (%)**
Age		
18 to 24	4	5.71%
25 to 34	9	12.86%
35 to 44	13	18.57%
45 to 54	26	37.14%
55 to 64	12	17.14%
65 and over	6	8.57%
Education		
High School	9	12.86%
College	7	10.00%
Technical Degree	24	34.29%
Bachelor's degree	16	22.86%
Graduate or Professional Degree	14	20.00%

Household Income from Farming		
No income from farming	3	4.29%
25% of income from farming	4	5.71%
50% of income from farming	7	10.00%
75% of income from farming	22	31.43%
100% of income from farming	34	48.57%
Farming Experience		
Under 10 years	15	21.43%
Between 10 and 20 years	17	24.29%
Between 21 and 30 years	17	24.29%
Over 30 years	21	30.00%

In summary, respondents willing to adopt the proposed BMP, referred to as adopters, are different from non-adopters in regard to education, farming goals, farm size, share of sales coming from their tomato, cranberry or onion enterprises, share of owned land and farming experience. When compared to non-adopters, adopters had a statistically significant higher level of education attained, less farming experience, and financial farming goals. In addition to this, adopters also had smaller farms, a higher share of sales coming from the study crops, and owned a higher share of the land, relative to non-adopters.

To determine the relationship between ADOPT and all the independent variables, a logistic regression was estimated with ADOPT as the outcome and each of the variables listed on the right-hand side of equations 1 to 3 as independent variables. Subsequently, the model, which only consists of the intercept (i.e., β_0) to the fit of the model, was compared with the intercept and the independent variable (i.e., the model with parameters β_0 and $\beta_{EXPERIENCE}$). This comparison was conducted using the Likelihood Ratio Test in which the test statistic (TS) is shown in equation (11):

$$TS = -2 \log L_{Reduced} - (-2 \log L_{Full}) \quad (11)$$

The TS has a Chi-Square distribution with the degrees of freedom equal to the difference in the number of parameters between the two models. With p-values < 0.05, sufficient evidence was found to conclude that the model, which includes any of the following variables: EXPERIENCE, BETTER, GOALS, CROP SIZE, CROP SALES SHARE and EDUCATION, is a better model than the model containing only the intercept. This led to the conclusion that there is a relationship between the above-mentioned independent variables and the ADOPT variable.

For each model, a Pseudo model fit statistic was calculated using equation (12):

$$1- (-2 \log L_{Full} / -2 \log L_{Reduced}) \qquad (12)$$

This statistic was estimated for each one of the models containing only one of the independent variables. Based on these simple models, the following results were obtained. When modelling ADOPT only using EXPERIENCE as an independent variable, results show that 11.58% of adoption is explained by producers' experience. The next factor used to model adoption was the categorical variable BETTER. This independent variable represents the degree to which growers agree that the proposed BMP is a better alternative than the current water management systems used. This simple model shows that 26.58% of adoption can be explained by the degree to which producers perceive the BMP as a better alternative. Producers' GOALS explained 10.23% of the outcome variable, and the farm area allocated to the production of tomatoes, cranberries or onions (CROP SIZE) variable accounted for 5.2% of variability. In addition, the percentage of sales accruing from these fruits and vegetables, out of total farm sales explained 9.4% of adoption decisions. Lastly, EDUCATION was used to explain adoption, and the results indicated that this independent variable explains 12.16% of adoption.

The robustness of regression models can also be perturbed by influential cases, such as the outliers or those that can influence the results of the regression model significantly. Several indicators are generally used to identify these effects. Amongst the common indicators are standardized Pearson's residuals, deviance, Pregibon's leverage or Pregibon's Delta-Beta similar and Cook's distance (King, 2008). In this study, influential cases were identified by calculating Cook's distance coefficients and for finding observations that had a high leverage, Pregibon's leverage coefficient was calculated. Based on this analysis, some cases were discarded. Test for autocorrelation were made and no evidence was found. Multicollinearity is problem in a regression model. Upon testing it was found that neither one of the three developed models had multicollinearity issues.

3.3 Result of Estimated Models

The estimated coefficients for each one of the three models are summarized in Table 5, which contains parameter log odds estimates for the three logistic regression models containing factors influencing fruit and vegetable growers' adoption decision.

Table 5. Parameter log odds estimates for the logistic regression model for factors influencing fruit and vegetable proeducers' adoption of BMP decision in Ontario and Québec

Model 1	***Coefficient (log odds)***	***S.E.***	***Wald***	***df***	***Sig. (p)***	***Odds Ratio***	***95% CI (lower)***	***95% CI (upper)***
EXPERIENCE	-0.08	0.03	6.08	1	0.01	0.93	0.87	0.98
BETTER			6.67	2	0.40			
BETTER(Neutral)	-22.06	12791	0.00	1	0.99	0.00	0.00	0.00
BETTER (Disagree)	-2.12	0.82	6.67	1	0.01	0.12	0.02	0.60
GOALS	2.20	0.82	7.13	1	0.01	8.99	1.79	45.06
CONSTANT	2.05	0.88	5.46	1	0.02	7.80		
Model 2	***Coefficient (log odds)***	***S.E.***	***Wald***	***df***	***Sig. (p)***	***Odds Ratio***	***95% CI (lower)***	***95% CI (upper)***
CROP SIZE	0.03	0.01	12.63	1	0.00	1.03	1.01	1.05
CROP SALES SHARE	0.06	0.02	9.25	1	0.00	1.06	1.02	1.11
EDUCATION			7.51	2	0.02			
EDUCATION (MID)	-5.30	2.03	6.83	1	0.01	0.01	0.00	0.27
EDUCATION (LOW)	-2.06	1.04	3.94	1	0.05	0.13	0.02	0.97
CONSTANT	-6.28	2.08	9.11	1	0.00	0.00		
Model 3	***Coefficient (log odds)***	***S.E.***	***Wald***	***df***	***Sig. (p)***	***Odds Ratio***	***95% CI (lower)***	***95% CI (upper)***

CROP SIZE	0.04	0.02	6.96	1	0.01	1.04	1.01	1.08
CROP SALE SHARE	0.03	0.03	1.31	1	0.25	1.03	0.98	1.08
EDUCATION			7.47	2	0.02			
EDUCATION (MID)	-11.79	4.32	7.46	1	0.01	0.00	0.00	0.04
EDUCATION (LOW)	-5.55	2.49	4.98	1	0.03	0.00	0.00	0.51
BETTER			6.67	2	0.04			
BETTER(Neutral)	-8.64	3.37	6.95	1	0.01	0.00	0.00	0.13
BETTER (Disagree)	-5.76	2.50	5.32	1	0.02	0.00	0.00	0.42
GOALS	1.69	1.31	1.68	1	0.20	5.44	0.42	70.45
CONSTANT	-0.86	2.53	0.12	1	0.73	0.42		

***Log Odds** – also referred to as logit is the natural log of the odds ratio of an outcome;*

***S.E** – coefficients standard errors, used for testing whether the parameter is significantly different from 0; by dividing the parameter estimate by the standard error the t-value is obtained;*

***Wald** – Test used to determine whether the parameter is different than 0, test with a chi-square distribution;*

***Df** – degrees of freedom for each one of the parameters;*

***Sig. (p)** – p-value of the 2 tailed test*

***Odds Ratio** – exponentiation of the log odds*

***95% CI lowe**r –lower bound for the 95% confidence interval expressed as odds ratio*

***95% CI upper** – upper bound for the 95% confidence interval expressed as odds ratio*

For the first model (M2), estimated coefficients suggest that growers with more farming experience were less likely to adopt the proposed BMPs. In contrast, producers, whose goals were predominantly financial, were more likely to adopt the BMPs, whereas growers with non-financial goals (or mixed goals) were less likely to adopt a given BMP. Producers’ perceptions of the BMPs contributed to the adoption decision in a positive way. Estimates indicate that growers who perceived the BMP as a better alternative than their current practice or technology were more likely to adopt the BMP. Using M1, one can calculate the chance of adopting a BMP for a producer with no farming experience, farming goals, which are not exclusively financial, and with the perception that the proposed BMP is a better alternative than the current water management system that they are using now. Those results will be contrasted with the changes of adopting this BMP if the producer has the same characteristics as above, no experience and mixed farming goals, and with a perception that the proposed BMP is not a better alternative. It was found that the chances of adopting a BMP in the first situation, where producers see the BMP as a better alternative, were 89%, which was reduced to 48% if the producer did not perceive the BMP as a better alternative.

For the second model (M2), estimated coefficients suggest that more specialized growers (those with a higher share of land cultivated with the study crop -- tomatoes, cranberries or onions) and with a higher share of sales coming from these crops, were more likely to adopt the proposed BMPs. Furthermore, growers with higher educational attainment were also more likely to adopt. Based on M2 results the chances of adopting a BMP were calculated, for a producer with average crop size and crop sales share and high level of education attained. Those results were contrasted with the changes of adopting this BMP if the producer has the same characteristics as above, average crop size and sales share and low level of education attained. The chances of adopting a BMP in the first situation, where producers have high levels of education, were estimated to be 70%, but if producers had low education levels, chances of adoption decrease to 65%.

The third model outperformed the other two on several fit statistics. Estimated coefficients for the third model (M3) show that multiple factors contribute significantly to explaining adoption behavior. Similar to previous models, a specialized grower, with higher education, who also perceives the BMP to be a better alternative, and whose farming goals are mainly financial ones, is more likely to adopt the proposed BMPs. All coefficients associated with this model are presented in Table 5.

Compared to M1, the independent variable BETTER has a smaller effect on decision in M3. Also noticeable is the weight EDUCATION plays in adoption decisions in the third model. Furthermore, based on the three models developed, one can observe that different socio-demographical factors can explain adoption reasonably well. However, it is the third model that seems to have an improved performance of the adoption decision by producers. The distinction between the first two models and the third one consists in the fact that the latter model contained farm, producer, and BMP related characteristics. In addition, a notable finding was the fact that with a simple model (such as the one containing only the factor BETTER), over 25% of the variance in the ADOPT variable can be explained.

3.3 Model Evaluation

Based on the model fitting information, M3 is the one performing better on multiple indicators, when compared to M1 and M2. For each of the models, the fit of the null model (one with only containing the intercept) was compared with the fit of the full model. This comparison was realized using the LR (likelihood ratio) Test[3]. With P-values < 0.01, for each one of the models, there was evidence to conclude that the full models are better models than the null ones. The likelihood ratio (LR) under Chi-Square quantifies the variability attributable to the model, and implicitly evaluates the extent to which a set of predictors improve the model. The highest LR indicator 65.71 was obtained for M3, in comparison to those for M1 and M2 of 47.65 and 45.46, respectively, indicating that M3 explains better the outcome variable.

The log likelihood (LL) for the full models, or more specifically the -2LL[4] is another indicator of model fit, with lower values representative of better fit. The -2LL value for Model 3 was 25.72, as against 43.78 for Model 1 and 41.78 for Model 2 (Table 6).

Table 6. Measures of fit for logit models

Measure	Model 1	Model 2	Model 3
LR	47.65	45.46	65.71
$-2 \log L_{Model}$	43.78	41.78	25.72
$-2 \log L_{Full}$	91.43	87.24	91.43
Pseudo Model Fit R^2	0.52	0.52	0.72
Cox and Snell R^2	0.51	0.51	0.63
Nagelkerke / Cragg & Uhler's R^2	0.69	0.69	0.84
AUC	0.94	0.92	0.97
AIC	53.78	51.78	81.71
BIC	64.73	63.03	99.23

[3] In SPSS the LR Test results are provided in the "Omnibus Tests of Model Coefficients"

[4] The multiplication with 2 is used to transform the log-likelihood into a Chi-Square distribution, important for testing statistical significance

% Correctly Predicted	83.3%	88.9%	87.9%
Specificity	78.1%	91.2%	88.2%
Sensitivity	88.2%	86.2%	87.5%

In addition to the above three criteria for evaluation, several other measures were also estimated and compared among the three models. One of these measures was pseudo R^2 value, as they are indicative of the percentage of variation in the outcome variable that is explained by the model. Cox and Snell and Nagelkerke / Cragg & Uhler's pseudo R^2 values were calculated and used to assess the models. In addition to these two values, a pseudo model fit statistic was also calculated, using the following formula 1- (-2 log L_{Full} / -2 log $L_{Reduced}$), where $L_{reduced}$ is the model containing only the intercept and L_{Full} the model with intercept and predictors. Based on these values, the first two models explained somewhere between 51% and 69% of variability in ADOPT, whereas the third model explained somewhere between 63% and 84% (Table 6). These results suggest that the third model (M3) is the best model among the three estimated models based on explanatory power.

Another insight into the robustness of models is given by classification-based approaches, like Area Under the Curve (AUC) and percentage of correctly classified cases. In terms of performance related to predicting the proper outcome, M3 scored better than M1 and M2. For the first model, the AUC was 0.94, and it correctly classified 83.3% of the cases. For M2 the AUC value was 0.92 and the model correctly classified 88.9% of cases. The highest values of AUC were obtained for M3, for which the AUC was 0.97 and the model correctly classified of 87.9% of cases.

4. Discussion

Three regression models were estimated to understand the role played by factors in influencing adoption behavior. Study results show that a specialized grower, with higher education, who also perceives the BMP as a better alternative, and whose farming goals are mainly financial ones, is more likely to adopt the proposed BMPs. The likelihood of adopting the proposed BMPs can be explained relatively well by the three different combinations of factors. However, the models that best explain variations in likelihood of adoption contains a mixture of farm, producer and BMP related variables. When evaluated individually for factors, the one related to BETTER (meaning the degree to which a BMP is being perceived as a better alternative), explained most of the outcome for the variable ADOPT.

Producers' perceptions of BMPs characteristics are key factors in adoption decisions. Given that one of the most important characteristics of a BMP in the adoption process is whether producers perceive the BMP as a better alternative than the current practice, this variable was used as an outcome variable in understanding what influences perceptions. While certain variables remained the same as in the adoption model, some of them were different. Based on the estimated model, several variables had a negative influence on producers' perception of the BMP as being a better alternative. With higher order goals, producers were less likely to find the alternative as a better one. Like this finding, producers with a higher level of education were less likely to see the proposed BMP as a better alternative. Respondents with more experience were also less likely to perceive the BMP as a better alternative. Producers, who perceived the BMP as expensive were estimated to assign a lower likelihood of the BMP being a better alternative. There were also three factors that influenced perception of the BMP in a positive way. (i) Producers perceiving the BMP as providing benefits to society were more likely to perceive the practice as a better alternative. (ii) The respondents obtaining a larger percentage of their revenue from the crop of interest were more likely to see the proposed water management system as a better alternative. (iii) The growers who think making best use of scarce resources is important and believe the proposed BMP reduces water use on their farm, were more likely to perceive the BMP as a better alternative.

Findings of this study are in line with previous research, which show differences in education, farming experience, farming goals and degree of farm specialization between adopters and non-adopters can influence adoption decisions. An interesting finding, contrary to existing knowledge, was that there was no association between producers past adoption behavior and future intentions of adopting a BMP. In terms of motivations for adopting or reasons for non-adopting improved water management systems, a large majority of factors are related to the financial effect of the BMP on the farm (Baumgart-Getz et al., 2012; Feder and Umali, 1993; Knowler and Bradshaw, 2007; Lamba et al., 2009; Pannell et al., 2006; Prokopy et al., 2008). Furthermore, this study showed that perceiving a BMP as a better alternative is positively associated primarily with adoption and the innovation's capacity to benefit the producer financially. Positive environmental and societal effects of the BMP (i.e., GHG emissions reduction) were also relevant factors that contributed to producers perceiving the innovation as a better alternative. However, these non-financial factors did not influence producers' decisions to adopt a BMP. Perceiving the BMP as a better alternative was statistically significant across two of the three groups of surveyed producers – tomato and cranberry growers. Our assumption is that this is due to two important factors in adoption decisions -- commodity grown and BMPs characteristics.

5. Conclusions

A comparison of non-adopters to adopters suggests that producers who had attained higher education levels, had a higher share of income coming from agricultural activities, and had less faming experience and primarily financial goals from farming are good candidates for adoption of the study BMPs. Adopters also had a higher share of sales coming from the selected crop (tomato, cranberry or onion) and owned a higher share of their farmed land than non-adopters own.

If a BMP was perceived by producers as a better alternative if it provides an added economic benefit, as well as reduced a cost or added benefits the local and global community. Producers perceived the proposed BMPs as being profitable, but expensive, capable of improving crop yields and having the potential to reduce water use on their farms. Relative to non-adopters, adopters perceived the BMPs as a better alternative than their current water management systems.

Economic factors predominantly influenced decisions of producers for adoption of the BMPs. Among these, influencing factors included BMP's capacity to increase yields, the profitability of investment, and ability to perform a trial of the technology. In addition to these factors, adopters also found non-financial factors like demonstrating environmental stewardship, important. Main factors identified as reasons to not adopt the BMPs, in the order of their importance were: market stability, profitability of investment, initial cost of the system, and the risk of investment.

Producers not willing to adopt the new water management systems thought that an increase in the share supported by the government for these systems, together with increased governmental technical assistance and tax credits were important in changing their opinion towards adoption. Approximately half of non-adopters also indicated that an increase in water use costs might change their views on adoption.

Producers see themselves as having to bear certain environmental responsibilities including making best use of resources, reducing water use, and GHG emissions coming from agriculture, and thereby responsible for minimizing environmental damages caused by their farm. Most producers agreed that society should share the costs of minimizing agriculture's impact on the environment. Furthermore, producers believe that cost-share programs, supporting the adoption of improved agricultural practices and technologies, represent good usage of public funds.

Given that one of the most important characteristics of a BMP in the adoption process is whether producers perceive the BMP as a better alternative than the current practice, producers with higher order farming goals (financial and lifestyle or social goals) and with higher education levels were less likely to find the alternative better than their current practice. Whereas, more specialized producers perceiving the BMP as providing benefits to society, and who thought that making best use of scarce resources is important, along with the belief that the proposed BMP would reduce water use on their farm, were more likely to perceive the practice as a better alternative. In terms of the environmental effects of the three proposed BMPs, there is not sufficient evidence to understand if the BMPs bring additional benefits or not. In terms of GHG emission levels, even though the proposed BMPs had on average lower emissions over two growing seasons, compared to the status quo practices and technologies, these differences were not statistically significant (Edwards, 2014; Grant, 2014; and Lloyd, 2016. However, in all cases under the proposed BMPs the GHG emission balance was positive, varying from 0.57 CO_2-eq t/acre in cranberries, to 0.74 CO_2-eq t/acre in onions, and 2.32 CO_2-eq t/acre in tomatoes. Given that an average cranberry farm cultivates 400 acres, and a carbon cost of $20/t, an average cranberry farm produces an annual negative externality of $4,560. An average onion farm has 15 acres under cultivation, their annual average negative externality adds up to $222, whereas for the average tomato farm the average externality is somewhere between $1,000 and $1,500 on an annual basis. These costs are likely to increase five times by 2022, as the Canadian government plans to increase the carbon tax to $50/t.

Given the potential role of these technologies and practices to reduce GHG emission levels, and subsequently to reduce these costs for the global society, it is important to study them in more depth, over a longer period of time and over a broader geographic area and farm types, the effect of improved water management systems on GHG emission levels. It is important to communicate to producers about linkages between water use efficiency and GHG emissions and about BMPs that have already been shown to reduce these emissions efficiently. Extension programs and officers need to focus on the added benefits brought forward by the proposed BMPs; they need to highlight its relative advantage compared to the status quo technology and practice. Furthermore, the need for technical assistance was also identified by surveyed producers as an important factor contributing to their decision to adopt a BMP, as was the ability to trial the technology.

Besides advisory and communication policy responses, some economic instruments can also be considered. One mechanism of eliminating these negative externalities is to reflect these costs in the price of the crop. This transfers the cost of these externalities to consumers. However, this would not represent an ideal situation, because producers would not be incentivized to find solutions for GHG reduction, also unrealistic, since producers are more often in the position of a price taker in the market, as opposed to them dictating prices.

Appendix

Table A.1. Information provided to tomato producers prior to the survey

As you might already know, subsurface drip irrigation is a low-pressure, low-volume system, with drip tubes placed below the soil surface at a depth of approximately 15-20 cm (depending on soil type, crop and tillage practices). Previous studies found that subsurface drip irrigation in tomato production has the following characteristics:

Characteristic	Costs and Benefits Details[1]
Capital investment cost	• 1,500-2,000 $/acre[2]
Life expectancy	• 10-15 years[3]
Tomato yields	• Increased by 8% using subsurface drip as compared to surface drip • Increased by 25% using subsurface drip as compared to sprinkler • Increased by 60% using subsurface drip as compared to non-irrigation
Annual operating costs	• Decreased annual costs by 40-45% under subsurface drip irrigation as compared to surface drip irrigation[4]
Uniform ripening	• Green tomatoes percentage reduced by 16% under subsurface drip, as compared to non-irrigation
Nutrients use	• Increased efficiency of both N and P use under drip irrigation, as compared to non-irrigation
Water use	• Increased efficiency by 32% under subsurface drip as compared to non-irrigation
Greenhouse gas emissions	• Tomatoes grown using subsurface drip irrigation have 14-18%[5] lower GHG emissions than tomatoes grown with surface drip irrigation
Other	• Less labor needed with subsurface drip when compared to surface drip • More specialized machinery implements for subsurface drip in comparison to surface drip • Increased managerial decision making • Increases field accessibility • Increased need for accuracy when installing the subsurface drip as opposed to surface drip, sometimes additional resources are needed (i.e. GPS)

[1] Details are only for reference; they vary depending on the characteristics of your own farm, the subsurface drip irrigation system selected, etc.
[2] The assumption is that there was no previous irrigation system in place;
[3] Based on the most expensive part to replace from the irrigation system;
[4] Based on the assumption that the subsurface drip tape is left under the ground for 3-4 years, whereas the surface drip tape removed each year.
[5] Based on a case study farm located in Leamington, Ontario

Table A.2. Information provided to cranberry growers prior to the survey

Subirrigation is a dual-purpose water management system that provides both irrigation and drainage. Additional water can be supplied through the same pipes that are used for drainage. Optimal use of subirrigation is achieved when the water table is accurately managed. Modifying an already existing drainage system, in cranberry production, so that it allows for subsurface irrigation could be a feasible option. Control structures and pumps required to move the water in and out of each cranberry basin, are required for subirrigation. In some cases the modification of the current drainage system might involve only the installation of additional pipelines. Sprinkler irrigation is still expected to be used in spring and late autumn to protect cranberries against frost and in summer for heat protection. For an optimal use of subirrigation for water management in cranberry production, several requirements should be met:

i. Water table depth maintained between 0.6 and 0.7 m
ii. Irrigation should be started when soil water tension reaches between 7.0 and 8.0 kPa
iii. Water table management informed by accurate measuring devices (i.e. tensiometer);
iv. Unobstructed drainage system, equipped with control structures and a sufficient distance between the drains;

Previous studies found that subirrigation with water table control - in cranberry production, has the following characteristics:

Characteristic	Costs and Benefits[1]
Capital investment cost	• Range could be on average between 250 - 1450 $/acre[2], depending on your farm o Tensiometers: 128 – 362 $/acre o Additional pipelines: 526 – 769 $/acre o Drain control structure and ditch rehabilitation: 404 – 485 $/acre o Drain cleaning: 97 – 122 $/acre
Life expectancy	• 20 years[3]
Cranberry yields	• Increase in cranberry yields could be of 51% under subirrigation with water table control as compared to sprinkler irrigation and no water table management[4]. This increase in yields was due to improved drainage, which was needed for using sub irrigation in an optimal way. In situations where the drainage system is well functioning, it is possible that subirrigation might have no effect at all on yields[6].
Energy costs	• A reduction of 84.4% in annual energy costs related to irrigation under subirrigation with water table control as compared to sprinkler irrigation and no water table management[4].
Water use	• Water use was reduced by 84.4% as well when subirrigation and water table control was used as compared to sprinkler irrigation and no water table control[4].
Greenhouse gas emissions	• There are no significant differences between greenhouse gas emissions from cranberry fields under different soil water scenarios throughout most of the growing season. • For the most part of the growing season the cranberry fields were a sink of methane, however when the fields were flooded, due to over irrigation, during harvest and the spring snowmelt, they became a source[5].
Other	• Less labor needed for subirrigation when compared to sprinkler irrigation • Increased managerial decision making related to irrigation

1. Details are only for reference; they vary greatly depending on the characteristics of your own farm
2. Based on Jabet (2014), research of economic profitability of different water management practice in cranberry production, St. Louis de Blandford, Quebec
3. Based on the most expensive part to replace from the system;
4. Based on Pelletier (2014), case study on 30 acres, including 2012 and 2013 growing seasons, in St. Louis de Blandford, Quebec
5. Based on Grant (2014), case study including 2011 and 2012 growing seasons, in St. Louis de Blandford, Quebec
6. Based on Vanderleest (2014), case study including 2013 and 2014 growing seasons, Winsconsin

Table A.3. Information provided to onion producers prior to the survey

Previous studies found that sprinkler irrigation and the use of tensiometers for triggering irrigation - in onion production, has the following characteristics:

Characteristic	Costs and Benefits[1]
Capital investment cost	• Depending on your farm the investment could involve[2]: o Tensiometers: 128 – 362 $/acre o Sprinkler irrigation system: 1,400 $/acre o Water reservoir 150-300 $/acre
Life expectancy	• 15 years[3]
Onion yields	• A significant increase was obtained under optimal irrigation conditions for the jumbo size compared to unirrigated plots – irrigation triggered based on tensiometer readings. Under sprinkler irrigation an yield average of nearly 17 mg/acre compared with the unirrigated plots an average of 5 mg/acre[4].
Energy costs	• An increase of 67.5% in annual energy costs related to irrigation under sprinkler irrigation as compared to no irrigationt[4]. Tensiometers were used for triggering irrigation.
Water use	• Water use was increased by 67.5% as well when onons were irrigated as compared to no irrigationl[4]. Tensiometers were used for triggering irrigation.
Greenhouse gas emissions	• There are no significant differences between greenhouse gas emissions from onion fields whether irrigated or not
Other	• More labor needed for irrigation when compared to no irrigation • Increased managerial decision making related to irrigation • Frost protection • Increased onion quality with irrigation • Prevent soil erosion

[1] Details are only for reference; they vary greatly depending on the characteristics of your own farm
[2] Based on CRAAQ 2008 and Jabet (2014), research of economic profitability of different water management practice in cranberry production, St Louis de Blandford, Quebec
[3] Based on the most expensive part to replace from the system;
[4] Based on Rekika (2014), case study including 2008 and 2009 growing seasons, in Sherrington, Quebec
[5] Based on Grant (2014), case study including 2011 and 2012 growing seasons, in Sherrington, Quebec

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