What determine the adoption of conservation agriculture? A hot evidence from Québec

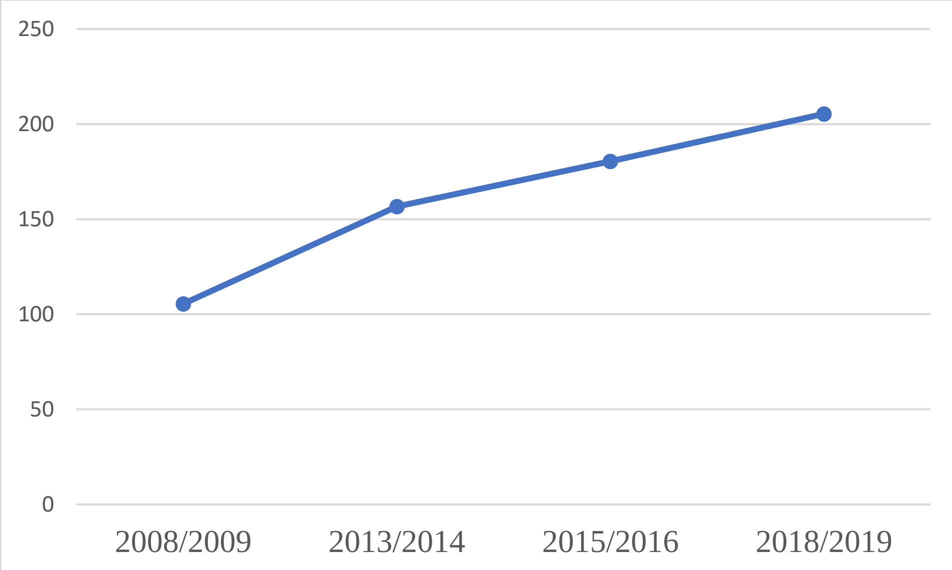
Abstract

Conservation agriculture (CA) is promoted by various organisations and scholars as alternative to conventional agriculture to meet growing food demand with minimal damage on environment; but its factors of adoption have not been well identified. The study uses the recent composite index of adoption of CA developed by Takam Fongang *et al.* (2023) to analyse the factors of adoption of conservation agriculture among maize and soybean farmers in Québec. Using data from 63 maize and soybean producers and a Tobit model, the study shows that adoption of CA increases with favourable farmer's perception regarding the yield and the easiness of implementing CA, off-farm job and education. The study therefore appeals for more technical assistance to farmers and more education for farmers which can be achieved through farmer field schools.

1. Introduction

Over the past decades, conservation agriculture (CA) has been promoted by various organisations like Food and Agriculture Organisation of the United Nations (FAO) and scholars as alternative to conventional agriculture to meet growing food demand with minimal damage on environment (Hobbs *et al.*, 2008; Lal, 2018). CA is sustainable agricultural practice characterized by three pillars including the absence or minimum mechanical soil disturbance, the permanent soil cover by mulch and/or cover crop, and crop rotation involving ideally at least three crops (Kassam, A. *et al.*, 2018). Although initially developed for fighting soil erosion (Kassam, A. *et al.*, 2018), CA has been shown to provide different benefits to farmers and society including among others, the reduction of labour demand, production cost, greenhouse gas emission, the increase of water infiltration, organic matter, etc. (AFD, 2006; Kassam, A *et al.*, 2011; Knowler et Bradshaw, 2007). For example, several studies have reported the positive effect of CA on soil quality and crop yield (Khonje, M. G. *et al.*, 2018; Manda *et al.*, 2016; Sharma *et al.*, 2011; Thierfelder *et al.*, 2013), on mitigating the production risks (Kassie *et al.*, 2015), and on household income (Tambo et Mockshell, 2018). These good performances of CA are normally obtained through better water infiltration, better soil moisture and better soil organic matter (Sharma *et al.*, 2011; Thierfelder *et al.*, 2013), and through reduction of soil erosion, labour requirement, production cost and chemical fertilizer, etc. (Kassam, A. *et al.*, 2018). Despite the benefits associated with CA adoption, the rate of CA adoption remains low. Although the statistics show an increasing adoption of CA over years (See figure 1), the proportion of cropland under CA remains low and was estimated to 14.7% of the global cropland area in 2018/2019 (Kassam, A *et al.*, 2022).

Figure 1: CA cropland area (in million hectares) at the global level



Source: Adapted from Kassam, A *et al.* (2022)

In Québec for example, even if the cropland area under CA has been increasing, about 8781 farms (50.8% of total farm) and 468 889 hectares (36% of farmland) were still under conventional tillage in 2021 (Takam Fongang *et al.*, 2023). More recently, a survey of maize and soybean farmers has also shown that only 21.53% of farmers were full adopters of CA in Québec (Takam Fongang et al., 2023). We therefore ask ourselves the following question: Why do some farmers adopt CA and others do not? Understanding the factors of CA adoption is fundamental for sustainable agricultural development given the various benefits of CA, at least in terms of mitigating soil erosion.

Several studies have attempted to explain farmers' decision to adopt CA in the literature, but the results remain controversial and vary from a study to another. Previous studies have classified factors of CA adoption into four main categories including farmer and farm household characteristics, exogenous factors, farm biophysical characteristics, and farm management/financial characteristics (Kagoya *et al.*, 2018; Knowler et Bradshaw, 2007).

- ❖ Farm biophysical characteristics, farmer and farm household characteristics

Several studies have identified farmer and farm household characteristics such as age, education, risk bearing, gender, namely, as well as farm biophysical characteristics such as soil erodibility, well drained soil, temperature, rainfall variability, etc. as factors of CA adoption (Ghazalian *et al.*, 2009; Khonje, M. G. *et al.*, 2018; Tambo et Mockshell, 2018; Wade et Claassen, 2017; Ward *et* *al.*, 2018). Specifically, Ward *et al.* (2018), using a Probit model showed in southern Malawi that CA adoption increased with farm size, level of education of farmer. When studying the factors of adoption of best management practices for enhancing water quality in Quebec, (Ghazalian *et al.*, 2009) found that education, age and farm size have a positive and significant effect on crop rotation adoption. Conversely to Ghazalian *et al.* (2009), Ramsey *et al.* (2019) found that age, education and farm size had no significant effect on adoption of conservative practices (continuous no till and conservation crop rotation) in Kansas. Moreover, Ramsey *et al.* (2019) have instead found that farmers who viewed conservative practices (continuous no till and conservation crop rotation) either as yield-risk reducing practice or as beneficial for soil improvement were more likely to adopt the conservative practices. Other factors such as perception of environmental benefits (Kolady *et al.*, 2020), gender, climate condition and soil characteristics (Davey et Furtan, 2008) have also been found to influence the CA adoption. Indeed, Davey et Furtan (2008) showed using a Probit model that adoption of conservation tillage in the prairies region of Canada were positively correlated with proportion of black and dark gray soil, average maximum temperature for April and the average maximum temperature of June of the previous year and negatively correlated with the proportion of brown soil and the gender. Kolady *et al.* (2020) however, have shown in eastern South Dakota of USA that favorable perception of environment benefits of CA has a positive effect on CA adoption.

- Exogenous factors and farm management/financial characteristics

Concerning the exogenous factors and farm management/financial characteristics, several authors have reported the significant effect of off-farm employment, membership in farmer organisation, family labour, land tenure, peer effect, participation in agri-environmental advisory activities (Bavorová *et al.*, 2020; Fisher *et al.*, 2018; Kagoya *et al.*, 2018; Kolady *et al.*, 2020; Tambo et Mockshell, 2018; Tamini, 2011; Ward *et al.*, 2018; Zhong *et al.*, 2015) For example, (Tamini, 2011), using nonparametric approach to study the impact of agri-environmental advisory activities on the adoption of 6 best management practices, found that the participation to agri-environmental advisory activities has a positive impact on the adoption of conservation tillage in Québec. Kolady *et al.* (2020), on the other hand, found in eastern South Dokota that adoption of conservation tillage and crop rotation increases with the proportion of adopters of conservation tillage and crop rotation in 30-miles radius and hence demonstrating the importance of spatial peer effect on the adoption of conservation agriculture. Other authors have instead focused on the effect of information sources on the adoption of conservation agriculture in the literature. This is the case of Fisher *et al.* (2018) who found in Malawi that while crop rotation adoption was positively correlated with government agent extension contacts, farmer field day visits, non governmental organisation contacts, village extension meeting, and negatively correlated with electronic media contacts, minimum tillage adoption was found to be negatively correlated with private agent extension contacts. The same authors also found that mulching adoption was positively associated with private agent extension contacts but negatively correlated with other farmer advice contacts and village extension meetings.

Despite the abundance of studies investigating the factors of adoption of conservation agriculture in the literature, it is important to note that almost all studies rely on the use of the traditional black and white indicator which supposes that farmers are adopters or not of conservation agriculture whereas the data show that farmers often have a partial adoption of the principle of conservation agriculture (Grabowski et Kerr, 2013; Mango, Siziba, *et al.*, 2017; Takam Fongang *et al.*, 2023). The main drawback of binary approach is that it cannot account for the whole complexity of CA and hence is unable to discriminate among farmers who are full adopters, partial adopters or non-adopters of CA (Takam Fongang *et al.*, 2023).

This study therefore contributes to the current debate by analysing the determinants of CA adoption in Québec. Our contribution differs from previous ones as it uses the recent composite index of adoption of conservation agriculture (CIACA) developed by Takam Fongang *et al.* (2023) for measuring level of adoption of CA among farmers. The advantage of CIACA over binary approach lies on the fact that it permits to classify farmers according to the level of conservation agriculture's principles adoption. Another advantage of the CIACA is related to the use of a three-years time scale which permits to account for the minimum of three crops which often required for rotation in an ideal CA practice (Takam Fongang *et al.*, 2023).

The study was guided by the hypothesis that there is a negative relationship between risk preference and CA adoption. Indeed, although previous studies have reported the effect of risk preference on adoption agricultural innovations (Abadi Ghadim, 2005; Jin *et al.*, 2020; Liu, 2013; Mao *et al.*, 2019; Mohan, 2020), the effect of risk preference on CA adoption remain unclear. For example, while some studies have reported a positive effect of risk aversion and loss aversion on crop rotation adoption (Jin *et al.*, 2020), other studies have reported no significant effect of loss aversion and risk aversion on zero tillage adoption, residue mulching adoption and intercropping adoption (Ward *et al.*, 2018). Following Liu, (2013), we modeled the risk preference of farmers under the cumulative prospect theory (Tversky et Kahneman, 1992) and the risk elicitation experiment was inspired from (Tanaka *et al.*, 2010).

The remainder of the paper is organised as follows. Sections 2 and 3 present respectively the methodology of the study, and results and discussion. Section 4 provides the conclusion of the study.

2. Methodology of the study

2.1. Econometric model

Logit, Probit, Tobit and multinomial Logit models have been regularly used to analyse the determinants of agricultural innovations adoption in the literature (D'Emden *et al.*, 2008; Davey et Furtan, 2008; Kassie *et al.*, 2015; Khonje, M. *et al.*, 2015; MangoMakate, *et al.*, 2017; Shiferaw *et al.*, 2014; Takam-Fongang *et al.*, 2019; Teklewold *et al.*, 2013; Zeng *et al.*, 2018). The choice of one or another model generally depends on the nature of the dependent variable (binary variable, continuous between 0 and 1, categorical variable). Thus, the Tobit model was used in this study to analyse the factors of CA adoption. This method was preferred over other methods because the dependant variable is a continuous variable which can take only the values from the interval 0 to 1. The adoption of conservation agriculture is modelled under the Tobit model as follows:

$$\mathrm{CIACA_i} = \begin{cases} CIACA_i^* & if\ CIACA_i^* > 0 \\ 0 & otherwise \end{cases} \text{ with } CIACA_i^* = \mathrm{X_i}\lambda + \mathrm{Y_i}\alpha + \varepsilon_\mathrm{i} \quad (1)$$

where $\mathrm{CIACA_i}$ and $CIACA_i^*$ are respectively the adoption of conservation agriculture and its corresponding latent variable. $\mathrm{X_i}$ and $\mathrm{Y_i}$ are respectively the vector of risk preference parameters including risk aversion, loss aversion and probability weighting, and the vector of control variables. λ and α are the vectors of parameters to be estimated and and ε_i is the error term. The control variables were selected based on the literature and are presented in table 1. The model was estimated by the maximum likelihood method.

The adoption of conservation agriculture was measured by the composite index of adoption of conservation agriculture ($\mathrm{CIACA_i}$) recently developed by Takam Fongang *et al.* (2023) as follows:

$$\mathrm{CIACA_i} = \left[\frac{\sum_{t=1}^{3}(\mathrm{w_1PL_t+w_2PC_t+w_3PR_t})}{3}\right]_i \quad (2)$$

Where $CIACA_i$ can take any value from 0 to 1 with 0 and 1 standing respectively for non adoption of conservation agriculture and full adoption of conservation agriculture. Any value between 0 and 1 will represents a partial adoption of conservation agriculture. PL_t, PC_t and PR_t stand for respectively the proportions of farm under no or minimum mechanical soil disturbance principle, permanent mulch soil cover/cover crop principle and crop rotation principle in year t; and w_1, w_2 and w_3 are their respective weights. These weights which measure the contribution of each principle to the sustainability of the conservation agriculture were obtained from Takam Fongang *et al.* (2023).

Table 1: Definition of variables used in the model.

Variables	Measurement
Key independent variables	
Risk aversion (σ)	number
Loss aversion (λ)	number
Probability weighting parameter (δ)	number
control variables	
Farmer's perception regarding the yield of CA (prendac)	Mean of expected yield of CA over 20 years*
Farmer's perception regarding the risk of CA (priskac)	Variance of expected yield of CA over 20 years*
Membership to agri-environmental organization (agroenv)	1 if the farmer belongs to an agri-environmental organisation and 0 otherwise
Education of farmer (edu)	1=primary, 2= secondary, 3= college and 4= university
Agricultural training (formagri)	1 if farmer has received an agricultural training and 0 otherwise
Age of the farmer (age)	Years
Off-farm job (travail)	1if the farmer has an off-farm job and 0 otherwise
Logarithm of farm size (logsup)	Hectares
Rented farm (flocation)	Hectares
Farmer's perception regarding the easiness of implementing CA (facilac)	1= CA is very difficult to implement 2= CA is difficult to implement 3= CA is easy to implement 4= CA is very easy to implement

*Explanation of the computerization of farmer's perception regarding the yield and risk of CA is annex 1

Measuring the risk preference

An online experiment based on cumulative prospect theory was used to elicit the risk preferences of farmers in Quebec. Following Tanaka (2010), we assumed that the utility function of farmers is of the following form:

$$U(x,p;y,q) = \begin{cases} V(y) + w(p)[V(x) - V(y)] & if\ x > y > 0\ or\ 0 < x < y \\ w(p)V(x) + w(q)V(y) & if\ x < 0 < y \end{cases} \tag{3}$$

With $V(x) = \begin{cases} x^{\sigma} & for\ gains\ (x > 0) \\ -\lambda(-x)^{\sigma} & for\ losses\ (x < 0) \end{cases}$ (4)

$$w(p) = exp^{[-(-\ln p)^{\delta}]} \tag{5}$$

Where p and q are le probabilities associated with the outcomes x and y. $w(p)$ is the probability weighting function and δ is a parameter that determines the curvature of the probability weighting function. If $\delta = 1$, we are in presence of absence of probability distortion as $w(p) = p$. On the other hand, if $\delta < 1$, we are in presence of probability distortion characterized by the overweighting of small probabilities and the underweighting of high probabilities. However, if $\delta > 1$, we are still in presence of probability distortion where individuals underweight small probabilities and overweight high probabilities (Bocquého *et al.*, 2014). σ and λ measure respectively the degree of concavity of the value function and the degree of loss aversion. Based on the value of σ , a farmer can be characterized as risk lover $(\sigma > 1)$, risk averse $(\sigma < 1)$ or risk neutral $(\sigma = 1)$ (Bocquého *et al.*, 2014). A higher λ will imply that the farmer is more loss averse (Liu, 2013). Note that the cumulative prospect theory model will reduce to the expected utility model if $\delta = 1$ and $\lambda = 1$.

Three series of couple of lotteries adapted from Tanaka *et al.* (2010) were used to estimate the risk parameters of farmers. The series of couples of lotteries are presented in table 2. The series were designed so as the expected payoff of difference between lotteries A and B (A-B) decreases as one go down. For each series of couples of lotteries, it was successively asked to farmer to choose between two lotteries A and B. In each series, the next couple of lotteries was presented to farmer only if she selected the lottery A in the previous couple of lotteries.

The three series were carefully designed so as any combination of choices made by farmer determine particular values of prospect theory parameters σ, δ and λ (Tanaka *et al.*, 2010). Indeed, for any farmer that switches from lottery A to lottery B at row N, we can conclude that the farmer prefers the lottery A over the lottery B at row (N-1) and the prefers the lottery B over the lottery A at row N. If the farmer switches at row 1 or never switches, we will have only one inequality and the lower/upper bound were arbitrarily determined like in Liu (2013). If for example, a farmer switches at row 5 in both series 1 and 2, we know that the following inequalities should be verified:

$$100^{\sigma} + exp^{[-(-\ln 0.3)^{\delta}]}(400^{\sigma} - 100^{\sigma}) > 50^{\sigma} + exp^{[-(-\ln 0.1)^{\delta}]}(930^{\sigma} - 50^{\sigma}) \tag{6a}$$

$$100^{\sigma} + exp^{[-(-\ln 0.3)^{\delta}]}(400^{\sigma} - 100^{\sigma}) < 50^{\sigma} + exp^{[-(-\ln 0.1)^{\delta}]}(1060^{\sigma} - 50^{\sigma}) \tag{6b}$$

$$300^{\sigma} + exp^{[-(-\ln 0.9)^{\delta}]}(400^{\sigma} - 300^{\sigma}) > 50^{\sigma} + exp^{[-(-\ln 0.7)^{\delta}]}(600^{\sigma} - 50^{\sigma}) \tag{6c}$$

$$300^{\sigma} + exp^{[-(-\ln 0.9)^{\delta}]}(400^{\sigma} - 300^{\sigma}) < 50^{\sigma} + exp^{[-(-\ln 0.7)^{\delta}]}(620^{\sigma} - 50^{\sigma}) \tag{6d}$$

A rational combination of δ and σ (δ, σ) that verifies theses inequalities is (0.7, 0.9). When more than one combination of δ and σ (δ, σ), verify the inequalities, we follow Liu (2013) and approximated δ and σ by the midpoint of interval to one decimal place. Once the parameters σ was calculated, it was then used to determine the loss aversion λ using the choice made by farmer in series 3. Table 3 and table 4 were used to determine the combination of (δ, σ) for the different switching points in series 1 and 2.

Table 2: The series of couples of lotteries

Row	Lottery A		Lottery B		Expected payoff difference (A-B)
			Series 1		
1	30% winning 400 CAD	70% winning 100 CAD	10% winning 680 CAD	90% winning 50 CAD	77
2	30% winning 400 CAD	70% winning 100 CAD	10% winning 750 CAD	90% winning 50 CAD	70
3	30% winning 400 CAD	70% winning 100 CAD	10% winning 830 CAD	90% winning 50 CAD	60
4	30% winning 400 CAD	70% winning 100 CAD	10% winning 930 CAD	90% winning 50 CAD	52
5	30% winning 400 CAD	70% winning 100 CAD	10% winning 1060 CAD	90% winning 50 CAD	39
6	30% winning 400 CAD	70% winning 100 CAD	10% winning 1250 CAD	90% winning 50 CAD	20
7	30% winning 400 CAD	70% winning 100 CAD	10% winning 1500 CAD	90% winning 50 CAD	-5
8	30% winning 400 CAD	70% winning 100 CAD	10% winning 1850 CAD	90% winning 50 CAD	-40
9	30% winning 400 CAD	70% winning 100 CAD	10% winning 2200 CAD	90% winning 50 CAD	-75
10	30% winning 400 CAD	70% winning 100 CAD	10% winning 3000 CAD	90% winning 50 CAD	-155
11	30% winning 400 CAD	70% winning 100 CAD	10% winning 4000 CAD	90% winning 50 CAD	-255
12	30% winning 400 CAD	70% winning 100 CAD	10% winning 6000 CAD	90% winning 50 CAD	-455
13	30% winning 400 CAD	70% winning 100 CAD	10% winning 10000 CAD	90% winning 50 CAD	-855
14	30% winning 400 CAD	70% winning 100 CAD	10% winning 17000 CAD	90% winning 50 CAD	-1555
			Series 2		
1	90% winning 400 CAD	10% winning 300 CAD	70% winning 540 CAD	30% winning 50 CAD	-3
2	90% winning 400 CAD	10% winning 300 CAD	70% winning 560 CAD	30% winning 50 CAD	-17
3	90% winning 400 CAD	10% winning 300 CAD	70% winning 580 CAD	30% winning 50 CAD	-31
4	90% winning 400 CAD	10% winning 300 CAD	70% winning 600 CAD	30% winning 50 CAD	-45
5	90% winning 400 CAD	10% winning 300 CAD	70% winning 620 CAD	30% winning 50 CAD	-59
6	90% winning 400 CAD	10% winning 300 CAD	70% winning 650 CAD	30% winning 50 CAD	-80
7	90% winning 400 CAD	10% winning 300 CAD	70% winning 680 CAD	30% winning 50 CAD	-101
8	90% winning 400 CAD	10% winning 300 CAD	70% winning 720 CAD	30% winning 50 CAD	-129
9	90% winning 400 CAD	10% winning 300 CAD	70% winning 770 CAD	30% winning 50 CAD	-164
10	90% winning 400 CAD	10% winning 300 CAD	70% winning 830 CAD	30% winning 50 CAD	-206
11	90% winning 400 CAD	10% winning 300 CAD	70% winning 900 CAD	30% winning 50 CAD	-255
12	90% winning 400 CAD	10% winning 300 CAD	70% winning 1000 CAD	30% winning 50 CAD	-325
13	90% winning 400 CAD	10% winning 300 CAD	70% winning 1100 CAD	30% winning 50 CAD	-395
14	90% winning 400 CAD	10% winning 300 CAD	70% winning 1300 CAD	30% winning 50 CAD	-535

			Series 3		
1	50% winning 250 CAD	50% losing 40 CAD	50% winning 300 CAD	50% losing 210 CAD	60
2	50% winning 40 CAD	50% losing 40 CAD	50% winning 300 CAD	50% losing 210 CAD	-45
3	50% winning 10 CAD	50% losing 40 CAD	50% winning 300 CAD	50% losing 210 CAD	-60
4	50% winning 10 CAD	50% losing 40 CAD	50% winning 300 CAD	50% losing 160 CAD	-85
5	50% winning 10 CAD	50% losing 80 CAD	50% winning 300 CAD	50% losing 160 CAD	-105
6	50% winning 10 CAD	50% losing 80 CAD	50% winning 300 CAD	50% losing 140 CAD	-115
7	50% winning 10 CAD	50% losing 80 CAD	50% winning 300 CAD	50% losing 110 CAD	-130

Table 3: Switching point in series 1 and approximations of values of δ and σ

	δ: 0	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2
σ: 0.10	5	7	8	9	11	12	13	14	99	99	99	99	99	99	99	99	99	99	99	99	99
0.20	4	5	7	8	9	10	11	12	13	14	99	99	99	99	99	99	99	99	99	99	99
0.30	3	4	5	7	8	9	10	11	12	13	14	99	99	99	99	99	99	99	99	99	99
0.40	2	3	4	5	7	8	9	10	11	12	13	14	14	99	99	99	99	99	99	99	99
0.50	1	2	3	4	6	7	8	9	10	11	12	13	13	14	99	99	99	99	99	99	99
0.60	1	1	2	3	5	6	7	8	9	10	11	12	12	13	14	99	99	99	99	99	99
0.70	1	1	1	2	4	5	6	7	8	9	10	11	12	12	13	14	99	99	99	99	99
0.80	1	1	1	2	3	4	5	6	7	8	9	10	11	12	12	13	14	14	99	99	99
0.90	1	1	1	1	2	3	4	5	6	7	8	9	10	11	12	12	13	14	14	99	99
1	1	1	1	1	1	2	3	4	6	6	7	8	9	10	11	12	12	13	14	14	99
1.10	1	1	1	1	1	2	3	4	5	6	7	8	8	10	10	11	12	12	13	14	14
1.20	1	1	1	1	1	1	2	3	4	5	6	7	8	9	10	10	11	12	13	13	14
1.30	1	1	1	1	1	1	2	2	4	5	6	6	7	8	9	10	11	11	12	13	13
1.40	1	1	1	1	1	1	1	2	3	4	5	6	7	8	8	9	10	11	12	12	13
1.50	1	1	1	1	1	1	1	1	2	3	4	5	6	7	8	9	10	10	11	12	12
1.60	1	1	1	1	1	1	1	1	2	3	4	5	6	7	7	8	9	10	11	11	12
1.70	1	1	1	1	1	1	1	1	2	2	3	4	5	6	7	8	8	10	10	11	12
1.80	1	1	1	1	1	1	1	1	1	2	3	4	5	6	6	7	8	9	10	10	11
1.90	1	1	1	1	1	1	1	1	1	2	3	3	4	5	6	7	8	8	9	10	11
2	1	1	1	1	1	1	1	1	1	1	2	3	4	5	6	7	7	8	9	10	10

99 stands for the case where farmer keeps preferring lottery A over lottery B in all the 14 questions in series 1

Table 4: Switching point in series 2 and approximations of values of δ and σ

	δ																				
σ	0	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2
0.10	99	99	99	99	99	99	14	14	13	12	11	10	9	7	6	5	4	3	2	1	1
0.20	99	99	99	99	99	14	13	12	11	10	9	8	7	6	5	4	3	2	1	1	1
0.30	99	99	99	99	14	13	12	11	10	9	8	7	6	5	4	3	2	1	1	1	1
0.40	99	99	14	14	13	12	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1
0.50	99	14	14	13	12	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1
0.60	14	13	12	12	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1
0.70	13	12	12	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1	1
0.80	12	11	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1	1	1
0.90	11	11	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1	1	1	1
1	10	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1	1	1	1	1
1.10	10	9	8	7	6	5	4	3	2	1	1	1	1	1	1	1	1	1	1	1	1
1.20	9	8	7	6	5	4	3	2	2	1	1	1	1	1	1	1	1	1	1	1	1
1.30	8	7	6	5	4	3	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1
1.40	7	6	5	4	3	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1.50	6	5	4	3	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1.60	6	4	4	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1.70	5	4	3	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1.80	4	3	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1.90	3	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

99 stands for the case where farmer keeps preferring lottery A over lottery B in all the 14 questions in series 2.

2.2.Source of data

Primary data were used to achieve the objective of the study. Data were obtained from an online survey of maize and soybean producers that was carried out from February to April 2021 in Québec. Online survey was retained for the purpose of this study as it permits to survey maize and soybean producers under covid 19 pandemic while maintaining the social distancing rules. A unique questionnaire was used to collect information on maize and soybean producers. The questionnaire collects a variety of information on maize and soybean producers including socio-economic characteristics of farmers, farm characteristics, etc. Out of the 298 maize and soybean producers that participated into survey, 93 respondents filled the risk elicitation section representing 31.2% of the contingent of crops farmers These 93 respondents were therefore retained for computing risk parameters and only 63 were retained for regression analysis because of missing values in other variables used in the model. The description of variables used in this study is presented in table 5.

Table 5: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CIACA	63	0.77	0.26	0	1
Risk aversion (σ)	93	0.88	0.45	0.10	1.5
Probability weighting parameter (δ)	93	0.91	0.34	0.10	1.5
Loss aversion (λ)	93	1.68	2.25	0.12	11.23
Farmer's perception regarding the yield of CA	63	8.74	1.17	6.65	11
Farmer's perception regarding the risk of CA	63	0.70	0.50	0	2.29
Membership to agri-environmental organization	63	0.54	0.50	0	1
Education of the farmer	63	2.95	0.77	2	4
Agricultural training	63	0.65	0.48	0	1
Age of the farmer	63	52.43	12.23	24	72
Off-farm job	63	0.19	0.40	0	1
Logarithm of farm size	63	5.31	0.97	3.22	7.89
Rented farm	63	77.08	263.15	0	2023.47
Farmer's perception regarding the easiness of implementing CA	63	2.71	0.63	1	4

3. Results and discussion

3.1. Risk elicitation results

The distribution of switching points obtained from the risk elicitation experiment is presented in table 6. The table shows the proportion of farmers that switch at the first row is the highest series 2 and 3 with respectively 46,24% and 32,26% while the highest proportion of farmer (21.51%)

never switches in series 1. Based on the combination of switching points of farmers, we computed the risk parameters of farmers using information from table 3 and 4. The results show that risk aversion σ, probability weighting parameter δ and loss aversion λ are respectively 0.88, 0.91 and 1.68. Using the t-test, we found that that the three risk parameters were statistically different form one at 5 percent significance level thereby rejecting the expected utility framework in favor of cumulative prospect theory model. Indeed, the results show that maize and soybean producers in Québec are risk averse (0,88). This result corroborates with previous studies in China (Hou *et al.*, 2020) and France (Bocquého *et al.*, 2014) which also found that farmers are risk averse although the degree of risk aversion were greater in those countries 0.64 in China and 0.51 in France. The results also shows that probability weighting parameter δ is 0.91 meaning that most farmers tend to overweight small probabilities and underweight high probabilities as predicted by the cumulative prospect theory (Tversky et Kahneman, 1992). This result was also obtained in previous studies (Mao *et al.*, 2019; Tanaka *et al.*, 2010). A loss aversion of 1.68 indicates a higher sensitivity of farmers to loss than to equivalent gain.

Table 6: Distribution of switching points.

Switching point	Proportion of farmers		
	Series 1	Series 2	Series 3
1	17.20	46.24	32.26
2	4.30	8.60	31.18
3	4.30	5.38	17.20
4	4.30	7.53	3.23
5	9.68	2.15	6.45
6	4.30	3.23	2.15
7	10.75	3.23	4.30
8	3.23	2.15	
9	6.45	2.15	
10	2.15	6.45	
11	6.45	1.08	
12	2.15	1.08	
13	3.23		
14			
99	21.51	10.75	3.23
Total	100	100	100
Number of observations	93	93	93

3.2.Econometric results

The econometric results are presented in table 7. Models 2 and 1 are respectively the estimation results of the model with and without the control variables. Prior to the estimation of the model, the pairwise correlation matrix was computed to check the existence of multicollinearity between independent variables. This pairwise correlation matrix which is presented in annex 1shows a correlation between independent variables and therefore an absence of multicollinearity issue. This absence of collinearity issue is further confirmed by the lower variance inflation factor (1.34). Model 1 shows that risk aversion, loss aversion and probability weighting distortion does not affect the adoption of conservation agriculture. This result remains unchanged even when we control for other factors of adoption of conservation agriculture (Model 2). The results contradict with previous studies such as Jin *et al.* (2020) who found that risk aversion and loss aversion have a positive effect on adoption of crop rotation in China. This absence of the effect of risk parameters on the adoption of conservation agriculture is in line with Ward *et al.* (2018) in Southern Malawi can be explained by the fact that most maize and soybean producers are already familiar with the conservation agricultural practices in Québec. Indeed, all the 63 surveyed farmers declared to know the conservation agriculture and according to a recent study, most maize and soybean producers (98.61%) are either partial or full adopters of conservation agriculture in Québec (Takam Fongang *et al.*, 2023).

Model 2 shows that only three variables, farmer's perception regarding the yield of CA, off-farm job and farmer's perception regarding the easiness of implementing CA are statistically influencing the adoption of CA. Indeed, the results shows that farmers with favorable perception of the potential yield of CA tend to have higher level of adoption of CA. This is not surprising as several studies have also reported that favorable perception of yield potential of an agricultural innovation tend to increase the level of adoption of that innovation (Ramsey *et al.*, 2019; Takam-Fongang *et al.*, 2019). This is the case of Ramsey *et al.* (2019) who showed in Kansas that farmers who viewed conservation agriculture practices (no-till, crop rotation and cover crops) as yield-risk reducing practices tend to adopt them. The model 2 also shows that farmers with off-farm job tend to have greater level of adoption of CA. This is in contradiction with some previous studies that found a negative effect of off-farm income on adoption of conservation agricultural practices (Manda *et al.*, 2016; Ng'ombe *et al.*, 2014). However, two likely reasons may explain this positive effect of off-farm job on CA adoption. Firstly, off- farm job as a source of income can contribute to finance the acquisition of machinery necessary for implementing CA. Secondly, farmer with off-farm job will tend to adopt CA because it is a labour reducing practice (AFD, 2006). This labour reducing effect has been documented in the literature. For example, Król-Badziak *et al.* (2021) have showed that no-till and reduced tillage require less labour (7.47 and 9.52 hour/ha) than conventionnal tillage (10.80 hour/ha) for the prodcution of maize in poland. However, this latter reason maybe challanged in other context like in Subsaharan Africa where it has been shown that that adoption of CA instead increases farms' labour input requirements (Montt et Luu, 2019). This is certainly why several authors have found a negative effect of off-farm income on adoption of conservation agricultural practices in some Sub-Saharan African countries (Manda *et al.*, 2016; Ng'ombe *et al.*, 2014). The results of model 2 further show that the farmer's perception regarding the easiness of implementing CA has positive and significant effect on the adoption of CA. Farmers who view CA as easy to implement tend to have higher level of adoption of CA. This positive effect which was also emphasized by Abdulai (2016) in Zambia, can be explained by the higher complexity of CA as compared with the traditional conventional tillage. Indeed, CA is made up of three interlink agricultural practices (absence or minimum mechanical soil disturbance, the permanent soil cover by mulch and/or cover crop, and crop rotation) which should be carefully set so that to get the full potential of CA.

One likely problem that might emerge from the above estimations is whether all farmers really understand the risk elicitation experiment. For example, we noted that 8.6% of the 93 farmers that participated into the risk elicitation experiment have chosen either lottery B at the first question in all the three series or lottery A at all the questions in all the three series. So, we questioned ourselves if these latter farmers really understand the operating rule of the risk elicitation experiment. If they did not understand the rule, the inclusion of these farmers in the data may have added un bias in the estimation. Therefore, we followed Liu (2013) and removed these farmers from the sample; and rerun the regressions. The results which are presented in model 3 and 4 are quasi consistent with previous estimations. The sign and significance of all parameters are maintained except for off-farm job which is no longer statistically different from zero. The results still show all the risk parameters do not have any significant effect on adoption of conservation agriculture in Québec. They instead show that the key determinants of adoption of conservation agriculture are the farmer's perception regarding the easiness of implementing CA, farmer's perception regarding the yield of CA and level of education. The results show that farmers with higher level of education tend to have higher level of adoption of conservation agriculture. This positive effect of education on adoption of conservation agriculture is consistent with previous studies (Abdulai, 2016; D'Emden *et al.*, 2008; Ward *et al.*, 2018). The literature explained this positive relationship by the increase in capacity of farmers to acquire and analyse information about agricultural technologies that ultimately help them to make the best decisions (Feder et Slade, 1984). Another reason of the positive effect of education is related to the fact that conservation agriculture is knowledge intensive practice rather than input intensive practice (Wall, 2007) meaning that the success of CA will depends mainly on the good management of the farm rather than on the level of input used by farmers (Wall, 2007). Education can then increase the management skill which can help farmers to adopt complex agricultural practice such as conservation agriculture.

Table 7: Econometrics results

	Model 1	Model 2	Model 3	Model 4
Risk aversion (σ)	-0.139	-0.106	-0.176	-0.158
	(0.116)	(0.1)	(0.122)	(0.103)
Probability weighting parameter (δ)	0.06	0.091	0.1	0.178
	(0.15)	(0.14)	(0.147)	(0.136)
Loss aversion (λ)	0.017	0.017	0.015	0.022
	(0.02)	(0.019)	(0.02)	(0.018)
Farmer's perception regarding the yield of CA		0.098**		0.149***
		(0.04)		(0.041)
Farmer's perception regarding the risk of CA		0.113		0.088
		(.097)		(0.092)
Membership to agri-environmental organization		0.026		-0.044
		(.088)		(0.087)
Education of the farmer		0.072		0.148**
		(0.064)		(0.07)
Agricultural training		-0.02		-0.034
		(0.102)		(0.097)
Age of the farmer		0.004		0.006
		(0.004)		(0.004)
Off-farm job		0.24*		0.217
		(0.134)		(0.14)
Logarithm of farm size		-0.024		-0.021
		(0.053)		(0.054)
Rented farm		0		0
		(0)		(0)
Farmer's perception regarding the easiness of implementing CA		0.238***		0.23**
		(0.077)		(0.09)
Constant	0.89***	-1.12**	0.868***	-1.884***
	(0.189)	(0.544)	(0.18)	(0.592)

Observations	63	63	57	57
Pseudo R^2	0.038	0.342	0.048	0.454

*Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

4. Conclusion

This study uses the recent composite index of adoption of conservation agriculture developed by Takam Fongang *et al.* (2023) to analyse the factors of adoption of conservation agriculture among maize and soybean farmers in Québec. Specifically, the study tests the empirical relationship between risk parameters and adoption of conservation agriculture in Québec. Using data from 63 maize and soybean producers and a Tobit model, the study shows that risk parameters do not have any significant effect on the adoption of conservation agriculture. The study instead identifies (1) farmer's perception regarding the easiness of implementing CA; (2) farmer's perception regarding the yield of CA off-farm job and (3) education as the main factors of adoption of conservation agriculture among maize and soybean farmers in Québec. Thus, the study suggests the government should promote education of farmers if it wants to increase the adoption of conservation agriculture among farmers. This will ultimately improve the farm management skills of farmers which are particularly important for adoption of conservation agriculture as it is a knowledge-intensive practice. The government should also provide technical assistance farmers to boost the adoption of conservation agriculture. Farmer field schools could be a good strategy to shape farmers' perception regarding the yield of CA and to raise the management skills of farmers, which ultimately will impact the adoption of CA among farmers. Performance of farmer field schools in boosting the adoption of agricultural technologies has been well documented in the literature (Cai *et al.*, 2021; Emerick et Dar, 2021). Despite this performance, empirical evidence will be needed to validate or invalidate the efficacy of farmer field schools in boosting adoption of CA in Québec.

References

Abadi Ghadim, A. K. (2005). Risk, uncertainty, and learning in adoption of a crop innovation. *Agricultural Economics*, *33*, 1-9.

Abdulai, A. N. (2016). Impact of conservation agriculture technology on household welfare in Zambia. *Agricultural Economics*, *47*(6), 729-741. doi: 10.1111/agec.12269

AFD. (2006). *Le semis direct sur couverture végétale permanente (SCV)*. France : Agence Française de Développement.

Bavorová, M., Unay-Gailhard, İ., Ponkina, E. V. et Pilařová, T. (2020). How sources of agriculture information shape the adoption of reduced tillage practices? *Journal of Rural Studies*, *79*, 88-101. doi: 10.1016/j.jrurstud.2020.08.034

Bocquého, G., Jacquet, F. et Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, *41*(1), 135-172. doi: 10.1093/erae/jbt006

Cai, J., Hu, R. et Hong, Y. (2021). Impact of farmer field schools on agricultural technology extension—evidence from greenhouse vegetable farms in China. *Applied Economics*, *54*(24), 2727-2736. doi: 10.1080/00036846.2021.1996530

D'Emden, F. H., Llewellyn, R. S. et Burton, M. P. (2008). Factors influencing adoption of conservation tillage in Australian cropping regions. *The Australian Journal of Agricultural and Resource Economics*, *52*(2), 169-182. doi: 10.1111/j.1467-8489.2008.00409.x

Davey, K. A. et Furtan, W. H. (2008). Factors That Affect the Adoption Decision of Conservation Tillage in the Prairie Region of Canada. *Canadian Journal ofAgricultural Economics*, *56*, 1257–1275.

Emerick, K. et Dar, M. H. (2021). Farmer Field Days and Demonstrator Selection for Increasing Technology Adoption. *The Review of Economics and Statistics*, 1-14. doi: 10.1162/rest_a_00917

FAO. (2011). *The state of the world's land and water resources for food and agriculture (SOLAW)-Managing systems at risk*. Rome and Earthscan, London : Food and Agriculture Organization of the United Nations.

Feder, G. et Slade, R. (1984). The Acquisition of Information and the Adoption of New Technology. *American Journal of Agricultural Economics*, *66*(3), 312–320.

Fisher, M., Holden, S. T., Thierfelder, C. et Katengeza, S. P. (2018). Awareness and adoption of conservation agriculture in Malawi: what difference can farmer-to-farmer extension make? *International Journal of Agricultural Sustainability*, *16*(3), 310-325. doi: 10.1080/14735903.2018.1472411

Ghazalian, P. L., Larue, B. et West, G. E. (2009). Best Management Practices to Enhance Water Quality Who is Adopting Them Journal of Agricultural and Applied Economics, 41,3(December 2009).pdf>. *Journal of Agricultural and Applied Economics*, *41*(3), 663–682.

Grabowski, P. P. et Kerr, J. M. (2013). Resource constraints and partial adoption of conservation agriculture by hand-hoe farmers in Mozambique. *International Journal of Agricultural Sustainability*, *12*(1), 37-53. doi: 10.1080/14735903.2013.782703

Hobbs, P. R., Sayre, K. et Gupta, R. (2008, Feb 12). The role of conservation agriculture in sustainable agriculture. *Philos Trans R Soc Lond B Biol Sci*, *363*(1491), 543-555. doi: 10.1098/rstb.2007.2169

Hou, L., Liu, P., Huang, J. et Deng, X. (2020). The influence of risk preferences, knowledge, land consolidation, and landscape diversification on pesticide use. *Agricultural Economics*, *51*(5), 759-776. doi: 10.1111/agec.12590

Jin, J., Xuhong, T., Wan, X., He, R., Kuang, F. et Ning, J. (2020). Farmers' risk aversion, loss aversion and climate change adaptation strategies in Wushen Banner, China. *Journal of Environmental Planning and Management*, 1-14. doi: 10.1080/09640568.2020.1742098

Kagoya, S., Paudel, K. P. et Daniel, N. L. (2018, Feb). Awareness and Adoption of Soil and Water Conservation Technologies in a Developing Country: A Case of Nabajuzi Watershed in Central Uganda. *Environmental Management*, *61*(2), 188-196. doi: 10.1007/s00267-017-0967-4

Kassam, A., Friedrich, T. et Derpsch, R. (2018). Global spread of Conservation Agriculture. *International Journal of Environmental Studies*, *76*(1), 29-51. doi: 10.1080/00207233.2018.1494927

Kassam, A., Friedrich, T. et Derpsch, R. (2022). Successful Experiences and Lessons from Conservation Agriculture Worldwide. *Agronomy*, *12*(4). doi: 10.3390/agronomy12040769

Kassam, A., Friedrich, T., Shaxson, F. et Pretty, J. (2011). The spread of Conservation Agriculture: justification, sustainability and uptake. *International Journal of Agricultural Sustainability*, *7*(4), 292-320. doi: 10.3763/ijas.2009.0477

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M. et Erenstein, O. (2015). Production Risks and Food Security under Alternative Technology Choices in Malawi: Application of a Multinomial Endogenous Switching Regression. *Journal of Agricultural Economics*, *66*(3), 640-659. doi: 10.1111/1477-9552.12099

Khonje, M., Manda, J., Alene, A. D. et Kassie, M. (2015). Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, *66*, 695-706. doi: 10.1016/j.worlddev.2014.09.008

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H. et Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia. *Agricultural Economics*, *49*(5), 599-609. doi: 10.1111/agec.12445

Knowler, D. et Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy*, *32*(1), 25-48. doi: 10.1016/j.foodpol.2006.01.003

Kolady, D., Zhang, W., Wang, T. et Ulrich-Schad, J. (2020). Spatially Mediated Peer Effects in the Adoption of Conservation Agriculture Practices. *Journal of Agricultural and Applied Economics*, *53*(1), 1-20. doi: 10.1017/aae.2020.24

Król-Badziak, A., Pishgar-Komleh, S. H., Rozakis, S. et Księżak, J. (2021). Environmental and socio-economic performance of different tillage systems in maize grain production: Application of Life Cycle Assessment and Multi-Criteria Decision Making. *Journal of Cleaner Production*, *278*. doi: 10.1016/j.jclepro.2020.123792

Lal, R. (2018). Sustainable intensification of China's agroecosystems by conservation agriculture. *International Soil and Water Conservation Research*, *6*(1), 1-12. doi: 10.1016/j.iswcr.2017.11.001

Liu, E. M. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *Review of Economics and Statistics*, *95*(4), 1386-1403. doi: 10.1162/REST_a_00295

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M. et Tembo, G. (2016). Adoption and Impacts of Sustainable Agricultural Practices on Maize Yields and Incomes: Evidence from Rural Zambia. *Journal of Agricultural Economics*, *67*(1), 130-153. doi: 10.1111/1477-9552.12127

Mango, N., Makate, C., Tamene, L., Mponela, P. et Ndengu, G. (2017). Awareness and adoption of land, soil and water conservation practices in the Chinyanja Triangle, Southern Africa. *International Soil and Water Conservation Research*, *5*(2), 122-129. doi: 10.1016/j.iswcr.2017.04.003

Mango, N., Siziba, S. et Makate, C. (2017). The impact of adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. *Agriculture & Food Security*, *6*(1). doi: 10.1186/s40066-017-0109-5

Mao, H., Zhou, L., Ifft, J. et Ying, R. (2019). Risk preferences, production contracts and technology adoption by broiler farmers in China. *China Economic Review*, *54*, 147-159. doi: 10.1016/j.chieco.2018.10.014

Michler, J. D., Baylis, K., Arends-Kuenning, M. et Mazvimavi, K. (2019, Jan). Conservation agriculture and climate resilience. *J Environ Econ Manage*, *93*, 148-169. doi: 10.1016/j.jeem.2018.11.008

Mohan, S. (2020). Risk aversion and certification: Evidence from the Nepali tea fields. *World Development*, *129*. doi: 10.1016/j.worlddev.2020.104903

Montt, G. et Luu, T. (2019). Does Conservation Agriculture Change Labour Requirements? Evidence of Sustainable Intensification in Sub-Saharan Africa. *Journal of Agricultural Economics*, *71*(2), 556-580. doi: 10.1111/1477-9552.12353

Ng'ombe, J., Kalinda, T., Tembo, G. et Kuntashula, E. (2014). Econometric Analysis of the Factors that Affect Adoption of Conservation Farming Practices by Smallholder Farmers in Zambia. *Journal of Sustainable Development*, *7*(4). doi: 10.5539/jsd.v7n4p124

Pittelkow, C. M., Liang, X., Linquist, B. A., van Groenigen, K. J., Lee, J., Lundy, M. E., . . . van Kessel, C. (2015, Jan 15). Productivity limits and potentials of the principles of conservation agriculture. *Nature*, *517*(7534), 365-368. doi: 10.1038/nature13809

Poore, J. et Nemecek, T. (2018). Reducing food’s environmental impacts through producers and consumers. *Science* *360*(6392), 7. doi: 10.1126/science.aaq0216originally

Ramsey, S. M., Bergtold, J. S., Canales, E. et Williams, J. R. (2019). Effects of Farmers’ Yield-Risk Perceptions on Conservation Practice Adoption in Kansas. *Journal ofAgricultural and Resource Economics*, *44*(2), 24.

Sharma, P., Abrol, V. et Sharma, R. K. (2011). Impact of tillage and mulch management on economics, energy requirement and crop performance in maize–wheat rotation in rainfed subhumid inceptisols, India. *European Journal of Agronomy*, *34*(1), 46-51. doi: 10.1016/j.eja.2010.10.003

Shiferaw, B., Kassie, M., Jaleta, M. et Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, *44*, 272-284. doi: 10.1016/j.foodpol.2013.09.012

Takam-Fongang, G. M., Kamdem, C. B. et Kane, G. Q. (2019). Adoption and impact of improved maize varieties on maize yields: Evidence from central Cameroon. *Review of Development Economics*, *23*(1), 172-188. doi: 10.1111/rode.12561

Takam Fongang, G. M., Guay, J.-F. et Séguin, C. (2023). A Composite Index Measuring Adoption of Conservation Agriculture among Maize and Soybean Farmers in Québec. *Agronomy*, *13*(3). doi: 10.3390/agronomy13030777

Tambo, J. A. et Mockshell, J. (2018). Differential Impacts of Conservation Agriculture Technology Options on Household Income in Sub-Saharan Africa. *Ecological Economics*, *151*, 95-105. doi: 10.1016/j.ecolecon.2018.05.005

Tamini, L. D. (2011). A nonparametric analysis of the impact of agri-environmental advisory activities on best management practice adoption: A case study of Québec. *Ecological Economics*, *70*(7), 1363-1374. doi: 10.1016/j.ecolecon.2011.02.012

Tanaka, T., Camerer, C. F. et Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*, *100*(1), 557-571. doi: 10.1257/aer.100.1.557

Teklewold, H., Kassie, M., Shiferaw, B. et Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, *93*, 85-93. doi: 10.1016/j.ecolecon.2013.05.002

Thierfelder, C., Mwila, M. et Rusinamhodzi, L. (2013). Conservation agriculture in eastern and southern provinces of Zambia: Long-term effects on soil quality and maize productivity. *Soil and Tillage Research*, *126*, 246-258. doi: 10.1016/j.still.2012.09.002

Tversky, A. et Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, *5*, 27. doi: https://doi.org/10.1007/BF00122574

Wade, T. et Claassen, R. (2017). Modeling No-Till Adoption by Corn and Soybean Producers: Insights into Sustained Adoption. *Journal of Agricultural and Applied Economics*, *49*(2), 186-210. doi: 10.1017/aae.2016.48

Wall, P. C. (2007). Tailoring Conservation Agriculture to the Needs of Small Farmers in Developing Countries. *Journal of Crop Improvement*, *19*(1-2), 137-155. doi: 10.1300/J411v19n01_07

Ward, P. S., Bell, A. R., Droppelmann, K. et Benton, T. G. (2018). Early adoption of conservation agriculture practices: Understanding partial compliance in programs with multiple adoption decisions. *Land Use Policy*, *70*, 27-37. doi: 10.1016/j.landusepol.2017.10.001

Zeng, D., Alwang, J., Norton, G., Jaleta, M., Shiferaw, B. et Yirga, C. (2018, Mar). Land ownership and technology adoption revisited: Improved maize varieties in Ethiopia. *Land use policy*, *72*, 270-279. doi: 10.1016/j.landusepol.2017.12.047

Zhong, H., Qing, P. et Hu, W. (2015). Farmers' willingness to participate in best management practices in Kentucky. *Journal of Environmental Planning and Management*, *59*(6), 1015-1039. doi: 10.1080/09640568.2015.1052379

Annexes

Annex 1: computation of farmer's perception regarding the yield and risk of conservation agriculture

To compute the variables farmer's perception regarding the yield and risk of conservation agriculture, we have asked to farmers to distribute a total of 20 coins over a series of possible maize yield values that could be obtained by a CA producer. The 20 coins stand here for 20 agricultural campaigns. The series of possible maize yield of CA is presented in table below:

Maize yield (ton/hectare)	6 or less	6.5	7	7.5	8	8.5	9	9.5	10	11 and over
Number of coins										

Farmer's perception regarding the yield of CA is the mean of expected yields.

Farmer's perception regarding the risk of CA is the variance of expected yields.

Annex: correlation matrix

Variables	CIACA	σ	δ	λ	prendac	priskac	agroenv	edu	formagri	age	travail	logsup	flocation	facilac
CIACA	1.000													
σ	-0.140	1.000												
δ	0.048	0.042	1.000											
λ	0.110	-0.197	-0.106	1.000										
prendac	0.303	-0.068	-0.119	-0.042	1.000									
priskac	0.103	-0.103	0.052	0.263	-0.334	1.000								
agroenv	0.142	-0.139	0.016	-0.084	0.116	-0.056	1.000							
edu	0.112	-0.018	-0.122	-0.094	-0.064	-0.039	0.151	1.000						
formagri	0.125	-0.033	-0.144	0.105	0.084	0.120	0.192	0.433	1.000					
age	0.063	-0.043	0.132	0.099	-0.052	0.058	0.009	-0.070	-0.213	1.000				
travail	0.082	0.010	-0.117	-0.077	-0.094	0.161	0.124	0.294	0.271	-0.177	1.000			
logsup	0.104	0.026	0.172	0.044	0.037	0.005	-0.025	-0.060	-0.099	-0.259	-0.094	1.000		
flocation	0.084	-0.032	0.091	0.049	-0.159	-0.106	-0.146	-0.175	-0.109	-0.071	-0.033	0.448	1.000	
facilac	0.350	0.020	0.156	0.068	0.212	-0.092	0.036	-0.028	-0.015	0.022	-0.359	0.036	0.040	1.000