UNIVERSITÉ DE SHERBROOKE

ÉCOLE DE GESTION

Essais sur l'Économie de l'Adaptation aux Changements Climatiques

par

Jean Awé

Thèse présentée à l'École de gestion
en vue de l'obtention du grade de Ph.D.
Doctorat en économie du développement

UNIVERSITÉ DE SHERBROOKE

ÉCOLE DE GESTION

Essais sur l'Économie de l'Adaptation aux Changements Climatiques

par

Jean Awé

Cette thèse est évaluée par un jury composé des personnes suivantes :

P^r Christopher Ksoll	Directeur de thèse
P^r Patrick Richard	Examinateur interne
P^r Keven Bluteau	Examinateur interne
P^r Jean-François Gauthier	Examinateur externe

SOMMAIRE

Cette thèse étudie l'impact de la mise en œuvre de mesures d'adaptation aux changements climatiques dans la province du Québec (Canada) et dans des pays d'Afrique subsaharienne, qui est articulée autour de trois articles. L'adaptation au changement climatique revêt une importance cruciale pour le secteur agricole et les services écosystémiques. Les services écosystémiques jouent un rôle essentiel dans la croissance des plantes et, par conséquent, dans l'amélioration des rendements agricoles. La littérature actuelle suggère que l'agriculture sera fortement et négativement impactée par les changements climatiques. Dans ce contexte, il devient impératif d'adopter des mesures d'adaptation afin de permettre aux agriculteurs de minimiser les pertes potentielles. Quels sont les avantages économiques de ces initiatives, et lesquelles s'avèrent les plus efficaces ? Ces questions trouvent leurs réponses dans cette thèse.

Dans le premier article, j'examine l'impact global de la mise en place de mesures d'adaptation aux changements climatiques sur les rendements agricoles ainsi que l'effet propre de chaque stratégie d'adaptation sur ces rendements. Le deuxième article vise à déterminer si la mise en œuvre de ces mêmes stratégies d'adaptation aux changements climatiques réduit l'exposition des agriculteurs aux risques associés aux aléas climatiques. Le troisième article évalue, quant à lui, les bénéfices économiques découlant de la mise en œuvre de sept mesures d'adaptation aux changements climatiques pour les services écosystémiques du Lac Saint-Pierre.

En résumé, cette thèse analyse la portée de l'adoption de mesures d'adaptation aux changements climatiques dans les domaines de la pêche en eau libre et de l'agriculture. Elle considére les variables climatiques importantes, telles que l'évaporation, la vitesse du vent, et la durée d'ensoleillement ainsi que les volontés à payer des pêcheurs sportifs en eau libre pour une meilleure accessibilité aux sites de pêche.

RÉSUMÉ

Cette recherche examine les effets des mesures d'adaptation au changement climatique sur les services écosystémiques dans la province de Québec (Canada) et dans le domaine agricole en Afrique subsaharienne. Elle comprend trois articles.

Le premier article vise à évaluer l'impact de l'adoption de stratégies d'adaptation climatique sur l'accroissement des rendements agricoles, en analysant l'effet de chaque stratégie individuellement. Pour ce faire, il s'appuie sur des données recueillies auprès de 5 091 ménages agricoles dans quatre pays africains : Burkina Faso, Sao Tomé-et-Principe, Sierra Leone et Ouganda. L'étude inclut également l'analyse de données climatiques spatiales sur une période de 30 ans, couvrant cinq variables climatiques. Les résultats révèlent que l'adaptation augmente significativement les rendements agricoles, grâce notamment à un meilleur accès au crédit et à des informations adéquates. J'ai estimé un modèle d'équations simultanées avec commutation endogène pour tenir compte de l'hétérogénéité dans la décision de s'adapter ou non, ainsi que des caractéristiques non observables des agriculteurs et de leurs exploitations. Les résultats montrent que l'adoption de mesures d'adaptation augmente les rendements agricoles de 281 kg, soit une hausse de 23,3% par rapport au rendement annuel moyen. L'adoption de stratégies d'adaptation, qu'elles soient individuelles ou combinées, accroît significativement les rendements agricoles. Ainsi, la combinaison de l'ajustement des dates de semis et du choix de variétés cultivées est associée aux rendements agricoles les plus élevés, soit 343,3 kg par hectare.

Le deuxième article de cette thèse utilise les mêmes ensembles de données et la même méthodologie que le premier pour examiner l'efficacité des stratégies d'adaptation au changement climatique dans la diminution de la vulnérabilité des agriculteurs aux aléas climatiques. Les résultats indiquent une réduction notable de cette vulnérabilité

grâce à l'application de ces mesures. Cependant, l'impact de l'adaptation sur la réduction des risques climatiques varie d'un pays à l'autre.

Le dernier article de cette recherche examine les bénéfices économiques de sept stratégies d'adaptation destinées à améliorer à la fois les services écosystémiques et la pêche en eau libre dans le Lac Saint-Pierre, au Québec. Pour ce faire, l'analyse s'appuie sur des données collectées lors des visites récentes de 212 pêcheurs répartis sur six sites différents du lac, ainsi que sur les réponses obtenues via des enquêtes de choix discret. Les résultats révèlent que la mise en œuvre de ces mesures pourrait entraîner des gains annuels estimés à environ 9,62 millions de dollars pour la pêche en eau libre. De plus, cette étude offre des perspectives importantes sur l'intégration des données issues des préférences révélées et déclarées, mettant en lumière une divergence notable entre les choix hypothétiques et les décisions prises lors d'activités de pêche concrètes.

ABSTRACT

This research examines the effects of climate change adaptation measures on ecosystem services in the province of Quebec (Canada) and in the agricultural sector in Sub-Saharan Africa. It comprises three articles.

The first article aims to evaluate the impact of adopting climate change adaptation strategies on the increase in agricultural yields, analyzing the effect of each strategy individually. To do this, it relies on data collected from 5,091 agricultural households in four African countries : Burkina Faso, Sao Tome and Principe, Sierra Leone, and Uganda. The study also includes the analysis of spatial climate data over a 30-year period, covering five climate variables. The results reveal that adaptation significantly increases agricultural yields, thanks notably to better access to credit and adequate information. I estimated a simultaneous equations model with endogenous switching to account for the heterogeneity in the decision to adapt or not, as well as for the unobservable characteristics of farmers and their farms. The results show that the adoption of adaptation measures increases agricultural yields by 281 kg, an increase of 23.3% compared to the average annual yield. The adoption of adaptation strategies, whether individual or combined, significantly increases agricultural yields. Thus, the combination of adjusting planting dates and choosing cultivated varieties is associated with the highest agricultural yields, namely 343.3 kg per hectare.

The second article of this thesis uses the same data sets and methodology as the first to examine the effectiveness of climate change adaptation strategies in reducing farmers' vulnerability to climatic hazards. The results indicate a significant reduction in this vulnerability due to the implementation of these measures. However, the impact of adaptation on reducing climate risks varies from country to country.

The final article of this research examines the economic benefits of seven adaptation strategies aimed at improving both ecosystem services and open-water fishing in Lake Saint-Pierre, Quebec. For this, the analysis is based on data collected from recent visits of 212 fishermen across six different sites on the lake, as well as on responses obtained through discrete choice surveys. The results reveal that the implementation of these measures could result in annual gains estimated at about 9.62 million dollars for open-water fishing. Moreover, this study provides important insights into the integration of data from revealed and stated preferences, highlighting a notable divergence between hypothetical choices and decisions made during actual fishing activities.

TABLE DES MATIÈRES

TABLES

FIGURES

LISTE DES ABRÉVIATIONS, DES SIGLES ET DES ACRONYMES

ADÉD	Association des Étudiants au Doctorat en Économie du Développement
ASC	Alternative Specific Constant
ATT	Average Treatment Effects
CV	Contingent valuation
DCE	Discrete Choice Experiment
DÉD	Doctorat en Économie du Développement
FIML	Full Information Maximum Likelihood
GDP	Gross Domestic Products
GRÉDI	Groupe de Recherche en Économie et Développement International
GPS	Global Positioning System
HEC Montréal	Hautes Études Commerciales de Montréal
HP	Hedonic Pricing
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
LR	Likelihood Ratio
MWTP	Marginal Willingess To Pay
MML	Method of Maximum Likelihood
NGOs	Non-Governmental Organizations
OLS	Ordinary Least Squares
PNUD	Programme des Nations Unies pour le Développement
RP	Revealed Preference
SP	Stated Preference
UDS	Université de Sherbrooke
UNICEF	United Nations International Children’s Emergency Fund
UNDP	United Nations Development Programme
USC	University of Southern California
TC	Travel costs
UNCTAD	United Nations Conference on Trade and Development
WTP	Willingess To Pay

DÉDICACE

À mes proches !

REMERCIEMENTS

Je souhaite exprimer ma profonde gratitude à mon directeur de thèse, le Professeur Christopher Ksoll, pour ses conseils avisés, son soutien constant et sa disponibilité sans faille. Je tiens également à remercier chaleureusement les Professeurs Patrick Richard et Keven Bluteau, membres de mon jury, ainsi que Jean-François Gauthier, Professeur adjoint à HEC Montréal et évaluateur interne, pour leurs conseils éclairés et leurs commentaires pertinents qui ont grandement contribué à l'enrichissement de mes articles de thèse. Un merci tout particulier s'adresse au Professeur Jie He pour ses précieux commentaires. Enfin, je suis reconnaissant envers Justin Kakeu, Professeur à l'Université de Prince-Édouard, et Augustin Bergeron, Professeur à l'University of Southern California, pour leurs précieux conseils.

Je suis reconnaissant envers Babatunde Abidoye, Agha Akram, Kehinde Omotoso, Sudha Kannan et Sydney Neeley du Programme des Nations Unies pour le Développement, qui m'ont fourni les données utilisées dans mes deux premiers articles. Mes remerciements s'étendent également à la direction de l'École de gestion, aux professeurs du Département d'économie et aux responsables du Programme de doctorat en économie du développement de l'UDS pour leur précieux soutien financier et académique.

Un grand merci à ma famille, mes collègues des Services Stratégiques de Pêches et Océans Canada, notamment Diego Munoz-Alvarez, avec qui j'ai partagé de précieux conseils, des retours constructifs et de beaux moments lors de mon stage. Je tiens aussi à remercier les doctorants de ma promotion, ainsi que ceux des promotions précédentes, pour les moments chaleureux passés ensemble et pour le soutien mutuel que nous avons toujours partagé.

Je souhaite remercier toutes les personnes qui, de près ou de loin, ont contribué à rendre mon séjour à l'UDS et dans la ville de Québec si agréable. Enfin, ma profonde gratitude va à ma famille et à mes amis pour leur soutien inestimable.

INTRODUCTION

Les variables climatiques, intervenant directement dans le processus agricole, ont un impact majeur sur l'agriculture en raison du changement climatique, comme le démontrent de nombreuses études (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007). Les agriculteurs des pays africains seraient particulièrement affectés du fait de leur accès limité aux technologies et au crédit (Guiteras, 2009). Le changement climatique, en réduisant les rendements agricoles, accentue l'exposition des agriculteurs aux risques associés aux aléas climatiques (Di Falco and Veronesi, 2014), avec des répercussions potentielles sur le bien-être et la santé des ménages agricoles (Burgess et al., 2017).

Adopter des mesures d'adaptation peut aider les agriculteurs à minimiser les impacts du changement climatique sur leurs rendements (Di Falco et al., 2011) et à réduire leur vulnérabilité aux risques climatiques. Par exemple, face à des sols asséchés par des précipitations insuffisantes, les agriculteurs peuvent opter pour des techniques d'irrigation, comme des arroseurs ou des pompes à eau souterraine, afin de favoriser la croissance des cultures. Des recherches récentes indiquent que les agriculteurs adaptent leurs pratiques face au changement climatique afin d'augmenter les rendements et de limiter leur exposition aux aléas environnementaux (Zhang et al., 2017). Néanmoins, ces études traitent souvent l'adaptation comme une boîte noire, sans détailler les mesures spécifiques prises par les agriculteurs ni évaluer leur efficacité, se concentrant davantage sur les conséquences du changement climatique que sur le rôle de l'adaptation.

Bien que certaines études aient analysé l'impact de l'adoption de mesures d'adaptation sur les rendements (Kurukulasuriya et al., 2006) et sur l'exposition aux risques (Di Falco and Veronesi, 2014), il est possible que leurs conclusions soient biaisées, faute de prendre en compte certaines variables climatiques (Nkemdirim, 1991; Lawrence, 2005) et à cause de l'endogénéité potentielle d'un facteur clé de la décision d'adaptation : l'accès aux activités non-agricoles (Donaldson, 2018).

Dans cette thèse, j'analyse l'impact de l'adoption de mesures d'adaptation aux changementz climatiques sur plusieurs facettes de l'activité agricole, tout en prenant soin d'adopter des approches méthodologiques rigoureuses pour garantir la validité des résultats. Le premier article étudie l'effet de ces mesures sur les rendements et détermine les gains associés à chaque stratégie d'adaptation, identifiant ainsi les meilleures. Le second article s'intéresse aux effets des stratégies d'adaptation sur l'exposition aux risques climatiques. Le troisième, quant à lui, évalue les bénéfices économiques associés à la mise en œuvre de sept mesures d'adaptation au Lac Saint-Pierre au Québec, destinées à enrichir les services écosystémiques et bénéficier à la pêche en eau libre. Ces services écosystémiques jouent un rôle crucial pour l'obtention de meilleurs rendements agricoles en contribuant à la fertilité des sols, à la lutte contre les parasites et à la pollinisation. L'analyse des rétombés économiques des mesures d'adaptation aux changements climatiques dans un pays dévélopé (Canada) est ainsi effectuée dans le dernier article.

AVANT-PROPOS (ARTICLE 1) : THE ROLE OF ADAPTATION TO CLIMATE CHANGE IN ENHANCING AGRICULTURAL YIELDS : EVIDENCE FROM AFRICA

L'article 1, dont le titre est "The Role of Adaptation to Climate Change in Enhancing Agricultural Yields : Evidence from Africa", a été rédigé entièrement par l'étudiant. Il sera soumis dans la revue World Development et Journal of Development Studies.

ARTICLE 1

THE ROLE OF ADAPTATION TO CLIMATE CHANGE IN ENHANCING AGRICULTURAL YIELDS : EVIDENCE FROM AFRICA

1 INTRODUCTION

The expanding body of economic literature has increasingly focused on understanding and projecting the impacts of climate change on agriculture. This includes seminal works such as those by Burgess et al. (2017), Burke et al. (2015), Deschênes and Greenstone (2012), Fisher et al. (2012), Mendelsohn et al. (1994), and Schlenker and Roberts (2008), which collectively underscore the critical influence of weather on plant physiology, a topic also explored by Hoffman and Jobes (1978). The extent and nature of climate change implications on agriculture are influenced by a variety of factors. These include regional climatic variations, as discussed in studies by Deschênes and Greenstone (2007) and Zhang et al. (2017), the diversity of crop types as investigated by Di Falco and Veronesi (2013), and the adaptive capacities of agricultural practitioners, a subject of research by Di Falco et al. (2011). Each of these elements plays a vital role in determining how agriculture, as a sector, responds to and is affected by the changing climate.

In Sub-Saharan Africa, a substantial portion of the agricultural population, who often work on small plots of land typically less than a hectare, faces significant challenges related to agricultural productivity. These difficulties, as noted by Di Falco and Chavas (2009), encompass a range of issues from below-optimal land yields to the unpredictability and impact of extreme weather events. Such conditions frequently lead to poor harvests and consequent food shortages. The current discussion in the literature, like that of Kurukulasuriya et al. (2006), places a strong emphasis on food productivity, a crucial factor in the subsistence agricultural sector of Sub-Saharan Africa.

Small-scale farmsteads play a pivotal role in this region, contributing to an estimated 95% of the farm output and thus forming the backbone of food security and access. Hopkins and Hüner (1995) highlight that approximately three-quarters of this agricultural production is destined for consumption within the farming households themselves. This reliance on small-scale, often subsistence farming underlines the critical nature of agricultural productivity in the region. Sub-Saharan Africa's dependence on a mono-crop economy and rain-fed agriculture ties its development prospects closely to climatic variations. This connection is underscored in Lobell et al. (2013), where the critical impact of climate on agriculture in this region is explored. The vulnerability of this agricultural system to climate change underscores the need for adaptive strategies and highlights the region's unique challenges in ensuring food security amidst environmental changes.

This research contributes to contemporary academic discourse by exploring the extent to which climate adaptation measures are adopted and their impact on the yields of six different crops. The study utilizes a distinctive dataset from a survey conducted by the United Nations Development Programme in 2015, covering four African countries. This dataset includes responses from 1,811 households that have implemented climate adaptation measures and 3,280 households that have not. The individual and voluntary nature of climate change adaptation suggests that the practices of farmers who have adapted may significantly differ from those who haven not.

To analyze this data, this study employs endogenous switching regression model approaches. This methodology is augmented by using various information sources—like radio, television, and social media—as instrumental variables for the adaptation decision. These information channels are crucial as they provide farmers with strategic advice designed to counteract the negative impacts of climatic variability on agricultural yields by encouraging adaptation. This research presents prior litterature, and falsification tests to indirectly evaluate the exclusion restriction criterion relevant to these information channels. This approach ensures a robust and reliable analysis of the data.

Furthermore, the study incorporates additional climatic variables such as evaporation, wind velocity, and solar duration into its analysis. Relying solely on temperature and precipitation as indicators, as cautioned by Zhang et al. (2017), might lead to skewed assessments of adaptation outcomes. These climatic factors are intricately connected, as shown in studies by Lawrence (2005) and Wooten (2011), and are subject to changes in distribution patterns due to climate change, as observed by Hartmann et al. (2012). Additionally, these supplementary climatic metrics are crucial in understanding crop physiology and productivity, highlighted in research by Nobel (1981) and Zhang et al. (2017). By considering these broader climatic variables, the study aims to provide a more comprehensive and accurate evaluation of the effects of climate adaptation strategies on agricultural yields.

The results of this study reveal that households implementing climate adaptation measures experience notably higher agricultural yields compared to those that do not. On average, households that have adapted to climate change report a yield of 1,489.7 kilograms per hectare, which is 281.1 kilograms per hectare more—a 23.3% increase—than the average yield of 1,208.6 kilograms per hectare among non-adapted households. This significant difference underscores the effectiveness of adaptation measures in enhancing agricultural productivity. Moreover, the impact of adopting these adaptation measures appears to vary depending on the type of crop and the country in question. The variability in climate, types of crops grown, and agricultural practices in different regions can lead to varying outcomes from the implementation of adaptation measures. Factors such as the availability of resources, existing infrastructure, and the level of government support play a crucial role in the success of these adaptation measures, as discussed in the work of Toensmeier (2016).

Therefore, it is vital to consider the unique circumstances of each country when evaluating the efficacy of climate change adaptation strategies in the agricultural sector. This approach is emphasized in studies by Araújo and Rahbek (2006) and Atube et al. (2021), which suggest that crafting adaptation strategies that are specifically tailored to the distinct climatic conditions and crop varieties of each nation is key to effectively addressing the challenges posed by climate change in agriculture. Such contextualized strategies are essential for optimizing agricultural yields and ensuring food security in the face of changing environmental conditions.

This research investigates two critical factors—access to financial working capital and information sources—that contribute to the disparities in agricultural yields between farmers who have adapted to climate change and those who have not. The study uncovers that farmers who have adapted have better access to working capital compared to those who haven't. Moreover, improved access to information significantly enhances the likelihood of farmers adapting to climate change. These elements are vital as they influence the decision to adapt, yet access to these resources is limited among the participating farmers. It's concerning that only a minority of farmers have access to these crucial resources, highlighting the acute constraints in credit and information accessibility for farmers in developing countries, particularly in Sub-Saharan Africa, as indicated in studies by Burgess et al. (2017) and Guiteras (2009).

The scarcity of credit availability for funding modern agricultural inputs is a notable challenge in developing countries. Research focusing on input financing and the role of credit in Sub-Saharan Africa reveals a dual gap : not only in financial resources but also in knowledge regarding modern agricultural inputs (Di Falco et al., 2011; Guiteras, 2009). This suggests that challenges in both financing and information access need to be addressed. In regions dominated by subsistence farming, farmers often encounter limited cash access and market influence, impeding their ability to drive growth in agriculture, as described in Bjornlund et al. (2020). (2020). The financial markets in developing countries, and particularly in Sub-Saharan Africa, are often underdeveloped and inefficient, which further restricts smallholder farmers' access to formal credit, as highlighted in the work of Chivandire (2019).

This study contributes to the existing literature in several ways. First, it discusses the importance of access to working capital and information sources in farmers' decision-making regarding climate change adaptation. Previous studies (Di Falco et al., 2011; Guiteras, 2009; Mendelsohn and Dinar, 2003) explored the relevance of these factors, but their external validity was limited. This research expands the discourse by examining these drivers of adaptation in four African countries, utilizing a unique dataset. Second, the study evaluates the importance of climate variables beyond temperature and rainfall at a micro-level. Research by Zhang et al. (2017) was the first to scrutinize the relevance of additional climate variables at the county level in China, showing that excluding these variables could lead to biased predictions of climate change impacts on crop yields. By including these additional climate variables, this study's results may offer a less biased perspective. Finally, the research reveals some heterogeneous effects in the causal impact of adaptation on yields.

The paper is structured as follows : it begins with the next section, which delves into the background and context of the countries under study, setting the stage for the research. Section 3 describes the methodological approaches and the econometric models. Section 4 presents the survey design and data description. Section 5 presents the estimation results. Finally, the paper concludes with Section 6, summarizing the key findings and implications.

2 BACKGROUND AND CONTEXT

In this study, I utilize survey data from the United Nations Development Programme (UNDP) collected in four African countries : Burkina Faso, Uganda, Sierra Leone, and Sao Tome and Principe. These countries' development prospects depend heavily on the climate, as they rely on rainfed agriculture and have limited economic diversification. As a result, they are highly vulnerable to the impacts of climate change, with constrained response capacities. Additionally, climate change and environmental degradation have led to increased displacement and migration. Sub-Saharan Africa alone has witnessed 86 million internal climate migrants, according to a 2020 report by the World Bank.

2.1 Burkina Faso

In Burkina Faso, agriculture accounts for approximately 33% of the Gross Domestic Product (GDP). It employs around 80% of the population, according to the Food and Agriculture Organization's 2012 report. The sector is predominantly made up of smallholder farms. It is characterized by low productivity in both crops and livestock, coupled with limited participation from the private sector. The majority of agricultural producction is geared towards self-consumption. Despite facing numerous challenges, the farm sector in Burkina Faso possesses the potential to significantly improve productivity across a variety of crops, as indicated by the World Bank Group in 2017. During the 2014-2015 agricultural season, cereal production was estimated at 5.7 million tons, representing a 17.9% increase from the previous season and a 32.7% increase compared to the average over the preceding five years (INADES, 2013).

2.2 Sao Tomé and Principe

Agriculture plays a crucial role in the economy of Sao Tome and Principe, contributing approximately 20% to its GDP and comprising 80% of its export earnings. It employs around 60% of the population, with a workforce primarily consisting of smallholder farmers (Agence Française de Développement, 2010). Critical agricultural products include cocoa, with an annual production of about 3,000 tons, alongside coffee, pepper, and various food crops like bananas, tubers, and vegetables. Despite its significance, the agricultural sector in Sao Tome and Principe is characterized by low productivity, a lack of structure, and a heavy reliance on external aid (Agence Française de Développement, 2010).

2.3 Sierra Leone

Agriculture is a cornerstone of Sierra Leone's economy, with about two-thirds of the active population engaged in this sector, primarily as smallholder farmers. It accounts for 60% of GDP (US Department of Commerce, 2020). The country's arable land, copious rainfall, temperate climate, and numerous rivers create favorable conditions for plant growth. Despite this, production is mainly subsistence-based, and about 75% of the 5.4 million hectares of fertile arable land remains uncultivated. The primary crops cultivated include rice, cassava, maize, millet, cashew, rubber, ginger, vegetables, fruits, and sugarcane, with significant cash crops such as cocoa, coffee, and oil palm. Livestock rearing is also practiced. In 2014, total crop production was estimated at 2.09 million tonnes, a 5% decrease from the previous year (FAO, 2014).

2.4 Uganda

Approximately 35% of Uganda's land is dedicated to agriculture, which contributes 23.7% to its GDP and employs around 70% of the country's working population. In the fiscal year 2020/2021, agriculture also accounted for 31% of the country's export earnings. The sector's primary agricultural products include coffee, tea, sugar, livestock, fish, edible oils, cotton, tobacco, plantains, corn, beans, cassava, sweet potatoes, millet, sorghum, and groundnuts. Ugandan farmers confront various challenges, such as limited access to inputs like fertilizers and quality seeds, inadequate irrigation infrastructure, susceptibility to climate hazards, insufficient packaging facilities, limited storage capabilities, ineffective post-harvest handling practices, restricted access to working capital, high transportation costs, archaic field management structures, and a lack of current knowledge on agricultural best practices, health, and genetics. Rural farmers struggle with poor transportation infrastructure (U.S. Department of Commerce, 2012). In 2013 and 2014, cereal production was estimated at 3.5 million tonnes, which was roughly 3% above the five-year average (GIEWS Country Brief : Uganda, 2015).

3 METHODOLOGICAL APPROACHES AND ECONOMETRIC MODELS

In this section of the paper, I explore the decisions related to adaptation, the production function in agriculture, and present theoretical and econometric models. Drawing on the foundations of agricultural economic theory (and considering the data at hand), my approach extends the model proposed by Mendelsohn et al. (1994) by integrating the choice of adaptation measures into the decision-making process of farmers. In this expanded model, I define the agricultural yield, denoted as y_j, for a specific farmer j. This yield is conceptualized as a function of a diverse range of elements. These elements encompass the input variables, represented by C_j, and the adaptation strategies chosen by the farmer, indicated by A_j. Additionally, the model takes into account the climatic conditions (W_j), geographic factors (O_j), soil properties (S_j), and various socioeconomic aspects (H_j) facing a farmer that can influence agricultural output.

It is posited in this model that the farmer, in pursuit of maximizing their production, will opt for the most efficient combination of input variables (C_j) and adaptation measures (A_j). This assumption allows for a nuanced understanding of how different factors interact and contribute to the agricultural yield of individual farmers, particularly in the context of adapting to changing climatic conditions.

$$y_j = y_j(C_j, A_j, W_j, S_j, H_j, O_j) \tag{1.1}$$

3.1 The bivariate adaptation decision and agricultural production

3.1.1 Bivariate process of making adaptation decision

In this study, farmers are assumed to make a critical decision : whether to adopt adaptation measures for climate change. This decision-making process involves a careful consideration of the net benefits and potential risks. Farmers are essentially faced with two choices : either adapting to climate change or choosing not to adapt. Each of these choices results in a different yield outcome – an adaptation yield (y_{jA}) if they decide to adapt, and a non-adaptation yield (y_{jN}) if they do not.

The reservation yield, symbolized as ϱ_j, effectively encapsulates a farmer's threshold for adopting climate change adaptation measures. This concept represents the minimum acceptable level at which a farmer is inclined to implement such measures. The decision to adopt adaptation strategies or maintain a non-adaptive approach is influenced by various factors. These include the farmer's personal skills, the specific characteristics of the farm, prevailing climate conditions, the farmer's previous experiences with extreme weather events, characteristics of the farm owner and their household, available assets, experience, alternative income sources, access to credit and sources of information, and the perceived benefits of opting not to adapt (Di Falco et al., 2011).

In this model, farmer j is assumed to opt for adaptation to climate change if the following condition is met :

$$\frac{y_{jA} - y_{jN}}{y_{jN}} > \varrho_j$$

Put simply, the farmer decides in favor of adaptation if the relative increase in yield due to adaptation (the adaptation yield differential) exceeds their reservation yield. This concept of reservation yield, ϱ_j, reflects a farmer's readiness and willingness to undertake adaptation measures. If the potential yield gain from adopting a particular adaptation measure does not meet or exceed the reservation yield, the farmer is likely to decide against adapting.

3.1.2 Reduced-form of the adaptation decision-making process

The decision-making criterion can be formalized using a probit model format. This indicates that if $I_j^* > 0$, farmer j will choose to adapt to climate change ; otherwise, they will not (Di Falco et al., 2011; Lee, 1976). Implicitly, both Lee (1976) and Di Falco et al. (2011) introduce unobserved factors and employ a linear approximation in their models. They also define the variable T_j as those factors that influence both the adaptation decision and yields, and Z_j as variables that influence the adaptation decision but not yields.

$$\begin{aligned} I_j^* &= T_j^{'}\psi + Z_j^{'}\Lambda - \xi_j \\ &= G_j^{'}\pi - \xi_j \end{aligned} \tag{1.2}$$

Where $G_j^{'}\pi = T_j^{'}\psi + Z_j^{'}\Lambda$. In this research, the vector $Z_j^{'}$ comprises nine dummy variables, each representing a different source of information available to the farmer. These sources include government agencies, newspapers, radio, TV, mobile phones, and social media platforms, all of which can provide essential climate-related information to the farmers. Following the approaches of Di Falco et al. (2011) and Guiteras (2009), these variables pertaining to access to information are used as excluded instruments in analyzing the adaptation decision. This approach allows for a more nuanced understanding of how information access influences farmers' decisions to adapt. Finally, the error term in this model, denoted as ξ_j, is assumed to have a mean of zero and a variance represented by σ_ξ^2. This term is designed to capture measurement errors and other unobserved factors that may influence a farmer's decision to adapt or not, as suggested by Lee (1976). This consideration of error term variance is crucial in ensuring the robustness and accuracy of the model's predictions regarding adaptation decisions.

The latent variable I_j^* symbolizes the potential benefit that a farmer could gain by adapting to climate change in addition to how information sources might influence the reservation yield. This variable's observed counterpart, I_j, represents the actual adaptation status, indicating whether the farmer has chosen to adapt or not. The explanatory variables are encompassed within the vector T_j, which includes a diverse range of factors. These factors cover characteristics of the farm household, such as the age and education level of the farmer, access to working capital, and inputs. Additionally, it includes soil characteristics, various assets, and geographic factors like latitude and altitude. Climatic factors are also part of this vector, recognizing their influence on farming decisions.

3.1.3 Reduced-form of the production function

In examining the production function of equation (1.2), there are several functional forms that could be considered. However, the quadratic specification stands out for its robustness, as demonstrated in numerous studies. I replace the original variable A_j, which indicates the presence of adaptation measures, with the dummy variable I_j. Given the uncertainty around the best functional form for these climate variables, I adopt a methodology similar to that used by Mendelsohn et al. (1994).

$$y_j = \beta_1 I_j + T_j^{'} \Theta + \upsilon_j \tag{1.3}$$

3.1.4 Endogenous switching regression models

When applying ordinary least squares (OLS) to equation (1.3), there is a risk of obtaining biased estimates. This is because the OLS method is valid only under the assumption that the decision to adapt to climate change is exogenously determined. In reality, this decision is often endogenous, arising from voluntary and individual self-selection. Farmers who opt to adapt may possess different characteristics compared to those who choose not to. Their decisions are likely influenced by the expected benefits of adaptation. Furthermore, unobserved attributes of the farmers and their farms can simultaneously affect both the decision to adapt and agricultural productivity. This overlap can lead to inconsistent estimates when evaluating the impact of adaptation on food security, as discussed in the research by Di Falco et al. (2011). For example, if adaptation is primarily undertaken by the most capable or motivated farmers, not accounting for these unobserved skills could result in an overestimation of the benefits of adaptation. Additionally, traditional measurement errors in the data could introduce attenuation bias, further complicating the analysis.

To mitigate these selection biases, I utilize the same endogenous switching regression model for agricultural yields as Di Falco et al. (2011) did.This model encompasses two distinct regimes : one for farmers who adapt to climate change, as outlined in Equation (1.4), and another for those who do not, detailed in Equation (1.5). Each regime is defined to specifically account for the unique characteristics and outcomes associated with the respective decision to adapt or not. This approach allows for a more nuanced understanding of the causal relationship between adaptation strategies and agricultural yields, providing a clearer picture of the true impact of climate change adaptation on farming productivity.

$$y_{jA} = T_{jA}^{'}\Theta_A + \upsilon_{jA} \quad , I_j = 1 \tag{1.4}$$

$$y_{jN} = T_{jN}^{'}\Theta_N + \upsilon_{jN} \quad , I_j = 0 \tag{1.5}$$

In the context of Equations (1.4) and (1.5), the symbol T_j is used to denote a vector that includes various determinants affecting agricultural yields. These determinants encompass a range of factors, from inputs and soil properties to socioeconomic and geographic variables. Additionally, υ_j is introduced in these equations to represent the idiosyncratic shock, capturing random effects and unforeseen factors that might impact yields.

As previously discussed, the model incorporates the latent variable I_j^*, which is crucial in understanding the decision-making process of farmers regarding adaptation.

This variable specifically captures the utility or benefit that a farmer anticipates gaining from adapting to climate change. Complementing this, the dichotomous variable I_j is employed to indicate the farmer's observed adaptation status. It serves as a straightforward representation of whether a farmer has actually implemented adaptation measures or not. This dichotomous variable, along with the latent variable, plays a key role in the model, allowing for a deeper analysis of the factors influencing farmers' decisions to adapt and the consequent impact on agricultural yields.

Selectivity bias presents a significant challenge to the consistency of estimates obtained from Equations (1.4) and (1.5). This form of bias typically occurs when the process of selecting for adaptation affects the composition of the sample being observed, a phenomenon highlighted in the research by Lee (1982). As a consequence of this bias, there is a possibility that the error terms υ_{jA} and υ_{jN} in the regression models for these equations might be correlated with the error term ξ_j in the selection equation (1.2). Lee (1982) has demonstrated that such a correlation suggests that conventional estimation methods could produce biased parameter estimates.

Given the likelihood of selectivity bias influencing the decision to adapt to climate change, it is crucial to account for this in the analysis. Lee (1982) proposes a methodology that addresses this bias by considering the correlation between the error terms in the outcome and selection models. By acknowledging and adjusting for this potential correlation, the analysis aims to yield more accurate and reliable estimates of the impact of adaptation measures on agricultural productivity.

This methodological consideration is crucial to ensure that the estimated effects of adaptation strategies are accurately represented and not biased due to the selection process inherent in the farmers' decision-making. It is important to note that the expected values of the error terms, given the states of adaptation, are non-zero, as indicated by $E(\upsilon_{jA}|I_j = 1) \neq 0$, and $E(\upsilon_{jN}|I_j = 0) \neq 0$. This implies that the error terms associated with the decision to adapt (or not) are expected to differ from zero, reflecting the potential influence of unobserved factors in the decision-making process.

In Lee (1982)'s model, and this research, the error terms in Equations (1.2), (1.4), and (1.5) are assumed to follow a trivariate normal distribution. This distribution is characterized by a mean vector of zeros and a covariance matrix, which is denoted by Ω. In mathematical terms, this can be expressed as (ξ, υ_A, υ_N)$\sim$ N(0,Ω). This assumption about the distribution of the error terms is a standard approach in such analyses and helps in simplifying the estimation and interpretation of the model. The variance-covariance matrix is

$$\Omega = \begin{bmatrix} 1 & \sigma_{\xi A} & \sigma_{\xi N} \\ \sigma_{A\xi} & \sigma_A^2 & . \\ \sigma_{N\xi} & . & \sigma_N^2 \end{bmatrix},$$

where the variances of the error terms ξ_j, υ_{jA}, and υ_{jN} are var(ξ) = σ_ξ^2, var(υ_A) = σ_A^2, and var(υ_N) = σ_N^2, respectively. The covariance between ξ_j and υ_{jA} is given by cov(υ_{jA}, ξ_j) = $\sigma_{A\xi}$ = $\rho_{\xi A}\sigma_A$, where $\rho_{\xi A}$ is their correlation coefficient. Similarly, the covariance between ξ_j and υ_N is expressed as cov(υ_N, ξ_j) = $\sigma_{N\xi}$ = $\rho_{\xi N}\sigma_N$, with $\rho_{\xi N}$ being their correlation coefficient. According to Lee (1982), a positive selectivity bias is present when ($\rho_{\xi A} > 0$ and $\rho_{\xi N} < 0$), indicating that the sample of farmers who adapt to climate change tends to have above-average yields. Conversely, a negative selectivity bias occurs when ($\rho_{\xi A} < 0$ and $\rho_{\xi N} > 0$), suggesting that the sample is skewed towards farmers with below-average yields. Since y_A and y_N are not observed simultaneously, cov(υ_A, υ_N) is not defined. I follow Lokshin and Sajaia (2004) and assume that $\sigma_\xi^2 = 1$.

The validity of Lee (1982)'s endogenous switching model relies on one or more exclusion restrictions, which will be discussed in the section on Instruments. Adopting the methodology of Lokshin and Sajaia (2004), I apply the full information maximum likelihood (FIML) method to simultaneously estimate the parameters of Equations (1.2), (1.4), and (1.5). The FIML estimator operates by maximizing the likelihood function, which involves multiplying the density functions for each observation in the sample. This process also takes into account the correlation between the error terms in the equations. Given the normality assumption and a joint covariance structure for the error terms, this estimator is both consistent and efficient, as demonstrated in the work by Lokshin and Sajaia (2004). The corresponding log-likelihood function is designed to provide a comprehensive and statistically robust estimation of the model parameters.

$$\begin{aligned} \ln L_j = \ & \textstyle\sum_j^N \{ I_j [\ln\Phi(\frac{G_j^{'}\pi + \rho_{\xi A}\frac{\upsilon_{jA}}{\sigma_A}}{\sqrt{1-\rho_{A\xi}^2}}) - ln\sigma_A + \ln(\phi(\frac{\upsilon_{jA}}{\sigma_A}))] + \\ & (1 - I_j)[\ln(1 - \Phi(\frac{G_j^{'}\pi + \rho_{\xi N}\frac{\upsilon_{jN}}{\sigma_N}}{\sqrt{1-\rho_{N\xi}^2}})) - \ln\sigma_N + \ln(\phi(\frac{\upsilon_{jN}}{\sigma_N}))] \} \end{aligned} \tag{1.6}$$

The likelihood function described in Equation (1.6) involves various parameters, estimations, and calculations. The parameter π is a vector in the function $G_j^{'}\pi$. The correlation coefficients between ξ and υ_A, and between ξ and υ_N, are denoted by $\rho_{\xi A}$ and $\rho_{\xi N}$, respectively. The terms σ_A and σ_N represent the standard deviations of υ_A and υ_N, with their squared values (σ_A^2 and σ_N^2) indicating the variances of these terms. Additionally, υ_{jA} and υ_{jN} are likely error terms or unobserved variables in the equations for the two different states (A and N) of the model.

The estimation of the parameters of likelihood function (1.6) is carried out using the Full Information Maximum Likelihood (FIML) method, designed to maximize the likelihood function. This maximization process incorporates the product of density functions for each observation within the sample (Maddala and Nelson, 1975). Furthermore, the estimation method also accounts for the correlation between the error terms present in the equations, ensuring a more accurate and reliable analysis.

A farmer, denoted by subscript j and characterized by variables T_j, who adopts adaptation measures is expected to realize yields represented by y_{jA},

$$\begin{aligned} E(y_{jA}|I_j = 1) &= E[(T_{jA}^{'}\Theta_A + \sigma_{A\xi}\gamma_A + \zeta_{jA})|I_j = 1] \\ &= T_{jA}^{'}\Theta_A + \sigma_{A\xi}\gamma_A \end{aligned} \tag{1.7}$$

Where ζ_{jA} is a residual term with the expectation E(ζ_{jA}) = 0. The variance of ζ_{jA} is given by var(ζ_{jA}) = $\sigma_{\xi_{jA}}$. Additionally, $\sigma_{A\xi}$ represents the covariance between υ_{jA} and ξ_j. Furthermore, $\gamma_A = -\frac{\phi(G_j^{'}\pi)}{\Phi(G_j^{'}\pi)}$, where $\phi(\cdot)$ is the standard normal probability density function, and $\Phi(\cdot)$ is the standard normal cumulative density function.

The expected value of y_{jA}, in the counterfactual scenario where the adapted does not adapt, is defined by

$$\begin{aligned} E(y_{jA}|I_j = 0) &= E[(T_{jA}^{'}\Theta_N + \gamma_N\sigma_{A\xi} + \zeta_{jN})|I_j = 0] \\ &= T_{jA}^{'}\Theta_N + \gamma_N\sigma_{A\xi} + E(\zeta_{jN}|I_j = 0) \\ &= T_{jA}^{'}\Theta_N + \gamma_N\sigma_{A\xi} \end{aligned} \tag{1.8}$$

Where ζ_{jN} is a residual term with $E(\zeta_{jN}) = 0$. The variance of ζ_{jN} is given by var(ζ_{jN}) = $\sigma_{\xi_{jN}}$. Moreover, $\sigma_{N\xi}$ represents the covariance between υ_{jN} and ξ_j. The term γ_N is defined as $\frac{\phi(G_j^{'}\pi)}{(1-\Phi(G_j^{'}\pi))}$.

For an adapted farmer, represented as j and characterized by T_j, it is anticipated that the yields will amount to y_{jA} due to the adoption of adaptation measures. These measures are predicted to increase the gains from y_{jN} to y_{jA}. The yield improvement as a result of adaptation, denoted as ($\Delta_j = y_{jA} - y_{jN}$), represents the difference in yields achieved by the farmer with and without adaptation. Hence, Δ_j signifies the expected impact of adaptation on products for a farmer j with characteristics T_j.

$$\begin{aligned} \Delta_j &= E(y_{jA}|I_j = 1) - E(y_{jA}|I_j = 0) \\ &= (T'_{jA}\Theta_A + \gamma_A\sigma_{A\xi}) - (T'_{jA}\Theta_N + \gamma_N\sigma_{A\xi}) \\ &= T'_{jA}(\Theta_A - \Theta_N) + (\gamma_A - \gamma_N)\sigma_{A\xi} \end{aligned} \tag{1.9}$$

3.2 Instruments

In addressing the complexities of selectivity bias and its implications on regression models, this section delves into the use of Instruments as a pivotal aspect of the Endogenous Switching Regression (ESR) models. It particularly focuses on the employment of various sources such as newspapers, radio, and television as instrumental variables in climate change adaptation studies, detailing the process of validation and the critical role they play in ensuring the robustness of statistical inferences.

3.2.1 Comments on the selectivity bias correcting methods

The decision to adapt to climate change undergoes specific selection processes that result in observed samples, thereby generating selectivity bias. Specifically, when disturbances in a regression model correlate with those in the selection equation, selectivity bias emerges given a particular set of exogenous variables. Traditional estimation methods fail to deliver consistent parameter estimates in such contexts (Lee, 1976). To tackle this challenge, I use the Endogenous Switching Regression (ESR) models devised by Lee (1976) and further refined by Lokshin and Sajaia (2004) via the application of the Maximum Likelihood Estimation (MLE) to the endogenous switching regression.

ESR models present a potent remedy to complex econometric challenges by aptly addressing endogeneity and selectivity bias issues, which can undermine the credibility of Ordinary Least Squares (OLS) regression analyses. These models manage endogeneity, where an explanatory variable correlates with the error term. They also handle selectivity bias, which surfaces when the sample selection process correlates with the outcome variable, violating the randomness condition. Moreover, ESR models proficiently capture distinct regimes or states, wherein the outcome variable and its interaction with explanatory variables may fluctuate based on a particular variable's status. Additionally, they enable the estimation of simultaneous equations, allowing outcomes from one equation to influence another, thus providing a comprehensive understanding of the system in question.

However, ESR models also come with their own set of intricacies. They require stringent assumptions such as the normality of error terms and invoke an exclusion restriction for the selection equation. This restriction necessitates the presence of at least one variable that impacts the selection process without directly influencing the outcome.

Drawing from insights gained in previous research, I use information sources like newspapers, radio, and television as instrumental variables for adaptation variable to climate change adaptation. The selection of these instruments is based on the premise that access to information plays a crucial role in a farmer's decision-making process regarding adaptation measures. To ensure the effectiveness of these instruments in the results section, it is essential to validate them thoroughly. This validation involves two key steps. First, I examine the relevance of these instruments through probit estimations and first-step equations. This process helps to establish whether these information sources are significantly associated with the adoption of adaptation measures. It provides a statistical basis for using these sources as instrumental variables.

Second, to further validate the instruments, I assess the validity of the exclusion restriction. This involves applying theoretical arguments to justify why these instruments affect the outcome directly only through (armers' adaptation decisions and not directly or through any other channel (section 3.2.2). In addition to theoretical justifications, I conduct falsification tests. These tests are designed to check for any effects of the instruments on the outcome in a context where the exclusion restriction is not, implies they do not. This is a critical aspect of maintaining the integrity and accuracy of the instrumental variable approach. Through these rigorous validation steps, I aim to establish a robust and credible framework for analyzing the impact of information access on farmers' adaptation decisions.

3.2.2 Theoretical arguments for the exclusion restriction

Media platforms such as radio and television, which have widespread accessibility even in primarily agricultural rural areas, play an essential role in disseminating crucial climate and adaptation information to a broad audience (Popoola et al., 2020). These channels are instrumental in increasing awareness and educating individuals about the impact of climate change on agriculture and the requisite adaptation measures. They offer insights into innovative adaptation techniques, water and soil management practices, and environmentally friendly agricultural methods (Goonetilleke and Vithanage, 2017). Additionally, they provide consistent weather updates and details on current and projected climate conditions, enabling farmers to adjust their agrarian activities accordingly (NASA Climate Change Solutions, 2021).

Information sources facilitate the rapid and real-time relay of climate change data, ensuring that farmers receive prompt weather advice and forecasts, which inform their agricultural decisions (World Bank Feature on Adaptation Principles, 2020). Particularly in developing countries, farmers rely on this information to enhance their yields. Guiteras (2009) emphasizes that access to information is a strong determinant of climate change adaptation, aligning with other research that underscores the pivotal role of information sources in climate change adaptation (Burgess et al., 2017; Di Falco et al., 2011; Di Falco and Veronesi, 2014).

Access to information for farmers can occur through a variety of channels, as highlighted in the literature. These channels range from personal purchases to consultations with relatives, involvement in farmers' associations, interactions with government entities, and collaborations with non-profit organizations, as detailed by West and Bogers (2014). Moreover, farmers can also gather information from their resources if they are financially capable, or through social networks such as friends, family, and acquaintances. Neighbors, particularly other farmers or workers, associations, farmer support organizations, and religious institutions like churches and mosques, serve as additional sources of information, as observed by Yaseen et al. (2016). Furthermore, announcements from local chieftainships, notabilities, or officials also play a role in disseminating information. Interestingly, some studies suggest that access to information may not be directly related to a farmer's income. Mittal and Tripathi (2009) notes that the impetus for seeking various information sources is often driven by farmers' desire to enhance their agricultural outputs, including adopting adaptive techniques. Consequently, farmers who are primarily engaged in agriculture are more likely to actively seek this information.

The nature of information from these sources is typically independent of the individual decisions and actions of farmers, as mentioned by Babu and Glendenning (2019). The content disseminated through these channels often relates to broader issues rather than local factors impacting agricultural production, as explained by Kahan et al. (2008). This is because the content is curated and shared on a larger scale—either nationally or regionally—and thus remains external to specific local conditions, a point emphasized by Vidanapathirana (2012). In a similar vein, Abdulai and Huffman (2014) investigated the factors influencing African farmers' decisions to adopt soil and water conservation technologies and their impact on farm yields and net returns. Their findings indicate that variables representing information sources are valid as selection instruments for decisions to adopt such technologies. This body of research collectively underscores the significance of diverse information channels in influencing farmers' decision-making processes, particularly in the context of adopting new agricultural practices and technologies.

3.2.3 Falsification testing for the exclusion restriction

The exclusion restriction is a foundational assumption for instrumental variable (IV) estimation. It posits that information sources influence agricultural yields exclusively through their effects on adaptation decisions, implying that, after accounting for other covariates, there should be no direct relationship between the information sources and production. Such an assumption is crucial as it ensures that the instruments correlates only with the exogenous variation in the endogenous variable, enabling the consistent estimation of causal effects. Empirical verification of the exclusion restriction is challenging since it often relies on theoretical arguments and domain-specific knowledge, as it involves unobservable counterfactuals (Keele et al., 2019). Nonetheless, one can sometimes indirectly test the exclusion restriction through falsification exercises, which provide instances of refutability (Angrist and Krueger, 1999).

Falsification tests arise from the idea that causal theories can yield predictions not only about the presence of causal effects but also about their absence (Rosenbaum, 2002; Lipsitch et al., 2010). For instance, knowing a subset where the instrument does not affect the exposure allows us to infer that any observed correlation between the instrument and the outcome in that subset likely results from a breach of the exclusion restriction (Altonji et al., 2005; Kang et al., 2013).

In their research, Di Falco et al. (2011) utilized data from 2,807 Ethiopian farmers to explore the factors influencing farm households' decisions to adapt to climate change and the subsequent impact on food productivity. They employed a simple falsification test to validate the use of information sources as selection instruments for the adaptation variable. This test determines whether these instruments influence the adaptation decision without affecting the yields of those farm households that did not adapt. Their results show that information sources are statistically significant drivers of the adaptation decision to climate change (χ^2 = 71.93 ; p=0.00) but do not influence the quantity produced per hectare by non-adapting farm households (F-stat = 1.20, p = 0.35). Later studies (Di Falco and Veronesi, 2013, 2014) corroborated these findings, confirming that information sources are valid selection instruments for climate change adaptation decisions.

In this study, I employ this commonly-used falsification test to indirectly assess the exclusion restriction (Altonji et al., 2005; Kang et al., 2013; Keele et al., 2019; Labrecque and Swanson, 2018; Pizer, 2016; Van Kippersluis and Rietveld, 2018). Applying this falsification test to my data leads to the estimation of an alternative equation, which is denoted as Equation (1.3). This alternative formulation omits the treatment variable I_j but includes Z_j, the variable representing information sources :

$$y_j = Z_j\Theta + T_j\Gamma + \epsilon_j, \text{ for j s.th } I_j = 0 \tag{1.10}$$

In the context of my research, Equation (1.10) is specifically estimated for farmers who have not adapted to climate change. A critical aspect of this estimation involves examining the significance of the estimated parameters ($\hat{\Theta}$) for the information source variables. If these estimated parameters are not jointly significant, it implies that there is no substantial evidence to reject the exclusion restriction. This outcome would suggest that the exclusion restriction—a key assumption in instrumental variable analysis—is likely valid (Altonji et al., 2005; Di Falco et al., 2011; Labrecque and Swanson, 2018; Kang et al., 2013; Pizer, 2016).This test uses the F-statistic to evaluate the null hypothesis, which posits that the information sources (used as instruments) are not correlated with the error term in the yield equation. The alternative hypothesis, in contrast, suggests that the instrument directly influences the yield variable among non-adapters, thereby violating the exclusion restriction.

3.2.4 Analysis of an additional endogeneity issue

Access to nonfarm activities emerges as a significant determinant in farmers' decisions to adapt to climate change, and it is important to consider its potentially endogenous nature. For instance, as Donaldson (2018) demonstrate, having access to railroads can significantly boost trade and subsequently nonfarm activities. In a similar vein, proximity to paved roads may enhance opportunities for engaging in nonfarm activities, especially for farmers located near urban areas. These farmers can benefit from additional income streams, which might reduce their motivation to adapt to climate change.

Given these considerations, it is crucial to treat access to nonfarm activities as a potentially endogenous variable in the analysis. To address this, I follow the methodology proposed by Donaldson (2018) and use 'distance from farmers' residences to major paved or tarred roads' as an instrumental variable for access to nonfarm activities. This choice of instrument is based on the assumption that the distance to major roads is likely to influence the likelihood of engaging in nonfarm activities, yet is exogenous to farmers' individual adaptation decisions. The effectiveness of this instrument can be evaluated through the first-stage F-statistic, which, in this case, is 37.4. This value is significantly above the commonly recommended threshold of 10, suggesting that the instrument is not weak. This finding aligns with the guidelines set forth by Stock and Yogo (2002) on testing for weak instruments. A robust instrument, as indicated by a high F-statistic, ensures that the instrument effectively predicts the endogenous variable (access to nonfarm activities) while not being correlated with the error term in the yield equation, thereby lending greater credibility to the analysis.

3.3 The multivariate adaptation decision and agricultural production

3.3.1 Multivariate process of making adaptation decision

The investigation into how individual adaptation measures affect agricultural yields is critical for farmers, scientists, and governmental organizations. This research provides valuable insights, helping farmers make informed decisions about the most beneficial strategies to employ. These decisions are a delicate balance between cost-effectiveness and yield optimization. Scientists can focus their research on enhancing the most promising adaptation strategies, while governments and organizations can better allocate funding to the most impactful practices. Identifying the most effective adaptation measures is essential in improving agricultural productivity and enhancing resilience against climate change.

To delve deeper into this matter, I propose modifying equation (1.2) by replacing I_j with J_{js}, a latent variable that represents utility. The modified adaptation decision can be modeled as follows :

$$J_{js}^{*} = G_j^{'}\phi_s - \vartheta_{js} \quad \text{with} \quad J_s = \begin{cases} 1 \text{ iff } J_{j1}^{*} > max_{k\neq 1}(J_{js}^{*}) \text{ or } \omega_{j1} < 0 \\ 2 \text{ iff } J_{j2}^{*} > max_{k\neq 2}(J_{js}^{*}) \text{ or } \omega_{j2} < 0 \\ \dots \dots \dots \dots \\ N \text{ iff } J_{jN}^{*} > max_{k\neq N}(J_{js}^{*}) \text{ or } \omega_{jN} < 0 \end{cases} \tag{1.11}$$

Where $\omega_{js} = max_{k\neq 1}(J_{js}^{*})$. The term ω_{js} is defined as the maximum of J_{js}^{*} across all choices except the one in question. The vector G_j, as defined in equation (1.2), includes all the determinants and explanatory variables for each adaptation strategy. The idiosyncratic term ϑ_{js} is assumed to follow a Gumbel distribution and is independent and identically distributed, maintaining the Independence of Irrelevant Alternatives (IIA) assumption. Consequently, the model aligns with a multinomial logit framework, as outlined by McFadden et al. (1973). The probability of a farmer j is denoted by P_{js},

$$P_{js} = P(\omega_{js} < 0 | G_j) = \frac{exp(G_j^{'}\gamma_s)}{\sum_{j=1}^{N} exp(G_j^{'}\gamma_j)} \tag{1.12}$$

3.3.2 Reduced-Form of the production function

Each adaptation measure, denoted as s, is linked to an equation of agricultural output y_{js}. Here, y_{js} signifies the yield outcome for farmer j when they employ the adaptation strategy s. This linkage is crucial as it enables an assessment of the impact that various adaptation strategies have on agricultural productivity. The relationship is represented by the following equation :

$$y_{js} = \Gamma J_s + T_j^{'}\Theta_s + \eta_{js} \tag{1.13}$$

In this equation, the vector variable J_s includes N modalities, each corresponding to a different adaptation measure. This setup facilitates an in-depth evaluation of how different adaptation strategies influence agricultural yields.

3.3.3 Endogenous switching regression models

For each adaptation measure s, there is an associated yield equation y_{js}. Thus,

$$y_{js} = T_j^{'}\Theta_s + \eta_{js} \tag{1.14}$$

The vector T_j, as defined in equation (1.3), represents the determinants of agricultural yields [1].

Building on Bourguignon et al. (2007), I can express the yield equation with the corrected selectivity bias as :

$$y_{js} = T_j^{'}\Theta_s + \sigma_s[r_s^* m(P_{js}) + \sum_{i=1}^{s-1} r_i^* m(P_{ji}) \frac{P_{ji}}{(P_{ji}-1)}] + \xi_{js} \tag{1.15}$$

For farmer j the probability of choosing adaptation measure s is represented by P_{js}. The correlation between the error terms of the yield equation (η_{js}) and the selection equation (ϑ_{js}) is denoted by r_s. A positive value of r_s suggests a positive selection bias, whereas a negative value indicates a negative selection bias. The magnitude of r_s quantifies the extent of the selectivity bias. The bias correction term for each adaptation measure s given by $m(P_{js}) = \int J(\xi - \log P_{js})g(\xi)d\xi$, is defined where $J(.)$ is the inverse of the normal cumulative distribution function and $g(.)$ is the density function for the Gumbel

1. Although various methodologies have been proposed to address selectivity bias in multivariate variables, the correction techniques presented by Heckman (1979), Lee and Trost (1978), Lee (1982), and Mincer (1974) are not suitable for our context because the multivariate variable J_s encompasses more than two categories. Furthermore, these methods assume a univariate transformation. Lee (1983) offered a generalized version of the method in Lee (1982) to tackle selectivity bias. However, the correlation between ϑ_{js} and η_{js} could induce a selectivity bias that the methodology in Lee (1983) does not rectify. Moreover, Lee (1983) assumes that the joint distribution of (ϑ_{js},η_{js}) is independent and identically distributed, much like ϑ_{js} and η_{js} individually, which may not always hold true. Dubin and McFadden (1984) formulated a model to correct selectivity bias in multivariate cases, requiring L categories to generate the $L-1$ selection term. Nevertheless, their approach may not be sufficiently robust for maximum likelihood estimation using full information when the number of alternatives is more than two. Both Dahl (2002) and Schmertmann (1994) proposed selectivity bias correction models for multivariate variables, assuming that $-\eta_{js} - \eta_{j1}$ are independent, identically distributed, and share the same sign. However, this assumption can be considered stringent in empirical research, as noted by Huesca et al. (2010). Bourguignon et al. (2007) introduced a bias correction approach for multivariate scenarios wherein the selection procedures adhere to a polychotomous normal model, allowing for possible correlations between alternatives. Their model contemplates the correlation between the error terms ϑ_{js} and each outcome equation's error terms η_{js}.

distribution. Here, ξ_{js}, the error term, is expressed as $\eta_{js} + \log P_{js}$. Consequently, the number of bias-corrected terms in each equation is equal to the number of choices in the multinomial logit model, denoted by N.By incorporating these bias-corrected terms, Equation (1.15) yields a consistent estimation of yield parameters through maximum likelihood estimation, assuming the model's distributional assumptions are valid.

Following Bourguignon et al. (2007), the expected yield for a farm household j that uses adaptation measure s, with $s = 2, \ldots, N$ (where $s = 1$ serves as the reference strategy of non-adaptation), can be expressed as :

$$E(y_j|J_j = s) = T_j^{'}\Theta_s + \sigma_s[r_s^* m(P_{js}) + \sum_{i \neq s}^{N} r_i^* m(P_{ji}) \frac{P_{ji}}{(P_{ji} - 1)}] \tag{1.16}$$

In the counterfactual case, if the farmer j adopts a strategy q that is different from s (where $q \neq s$), his expected yields would be :

$$E(y_j|J_j = q) = T_j^{'}\Theta_q + \sigma_q[r_q^* m(P_{jq}) + \sum_{i \neq q}^{N} r_i^* m(P_{ji}) \frac{P_{ji}}{(P_{ji} - 1)}] \tag{1.17}$$

The impact of adopting strategy s instead of strategy q can be quantitatively expressed as follows :

$$\begin{aligned}\Delta_{js} &= E(y_{js}|A_j = s) - E(y_{jq}|A_j = q) \\ &= T_j^{'}(\Theta_s - \Theta_q) + [\sigma_s r_s^* m(P_{js}) - \sigma_q r_j^* m(P_{jq})] + [\sigma_s \textstyle\sum_{k \neq s}^{N} r_k^* m(P_{jk}) \frac{P_{jk}}{(P_{jk}-1)} \\ &-\sigma_j \textstyle\sum_{i \neq q}^{N} r_i^* m(P_{ji}) \frac{P_{ji}}{(P_{ji}-1)}]\end{aligned} \tag{1.18}$$

4 SURVEY DESIGN AND DATA DESCRIPTION

Due to the absence of direct measurements of farmers' incomes in my database, I have chosen to use their farm yields as a proxy. This approach enables me to explore the relationship between the adoption of climate change adaptation measures and farm yields. My focus is specifically on farmers whose primary occupation is agriculture and who primarily rely on the sale of agricultural products as their main source of income.

This investigation aims to understand how engagement in agricultural activities and the adoption of various adaptation strategies correlate with the yields they achieve, thereby offering insights into the economic impact of these strategies.

4.1 Survey data

I utilize data from a survey carried out by the United Nations Development Programme (UNDP) in 2016. This survey encompassed 5,091 farmers from four African countries, offering a broad perspective on agricultural practices across different regions. The distribution of the participating farmers was as follows : 2,572 from Burkina Faso, 314 from Sao Tome and Principe, 195 from Sierra Leone, and 2,010 from Uganda. The sampling frame employed by the UNDP was meticulously designed to accurately represent farmers at the district level. This was achieved by covering a range of traditional agroecological zones within these countries, ensuring that the diversity of agricultural conditions was adequately captured. To achieve a representative sample, districts within each country were selected based on their proportional representation within the respective country's stratum. The survey was comprehensive, collecting extensive information on several key areas. Additionally, the survey delved into understanding farmers' perceptions of climate change and the specific adaptation measures they had adopted in response to these changes. This wealth of data provides a valuable foundation for analyzing the impact of various factors on agricultural productivity and adaptation strategies in the context of climate change.

In the areas surveyed for this study, approximately 91% of the land is reliant on rainfed agriculture. Labor is a crucial input in the production process, encompassing activities such as land preparation, planting, and post-harvest processing. To quantify labor inputs, they were categorized into three groups : adult male labor, adult female labor, and children's labor. These were then combined into a single labor input metric using adult equivalents, following the standard conversion factor commonly used in the literature on developing countries. According to this convention, adult female and children's labor were converted to adult male labor equivalents using rates of 0.8 and 0.3, respectively, as noted by Di Falco et al. (2011). The surveyed plots were used to grow a total of sixty-eight different annual crops. Of these, the five primary crops – maize, rice, sorghum, cassava, and millet – constituted 74% of the primary crops cultivated by the farmers in the study.

When it comes to climate perceptions, the majority of farmers in the study noted significant changes in key climate variables. For instance, 67% of farmers observed that temperatures have risen, while 70% reported that rainfall patterns have become less frequent and drier. Specifically, 41% of farmers noted long-term changes in at least one climate variable, such as temperature, rainfall, drought, flooding, agricultural pests and diseases, severe winds, hail storms, and riverine flooding. Among these farmers, 88% reported an increase in temperature, while 76% indicated that rainfall has become less predictable or drier. Additionally, 63% observed an increase in droughts over the past five years, and 58% noticed a rise in the frequency of flooding. Furthermore, 56% reported an increase in severe winds, and 89% observed more frequent riverine flooding. About 46% of farmers noticed more frequent hail storms, and around 15% reported long-term changes in the frequency of landslides.

These observations suggest that farmers are already feeling the effects of climate change, which may be driving them to adopt adaptation strategies to safeguard their livelihoods. As shown in Table 1.1, the main adaptation strategies employed by farm households include altering planting dates (49.2%), changing crop types (15.1%), using different crop varieties (5.1%), adjusting irrigation schedules (4%), modifying fertilizer use patterns (4%), and planting wind-resistant trees (3.4%). Collectively, these strategies represent 80.8% of all adaptation methods adopted by the farmers in the study.

Table 1.1 –
Adaptation strategies to climate change

Strategies	Frequency	Percentage (%)
Changing planting dates	891	49.2
Changing irrigation schedule	73	4
Changing fertilizer use pattern	72	4
Changing crop types	274	15.1
Using different crop varieties	92	5.1
Make irrigation investment	32	1.8
Planting wind-resistant trees	62	3.4
Others	315	17.4

Notes : Awé, 2024. Subsample of farm households that adapted at the plot level (sample size = 1,811).

4.2 Climate data

I sourced climate variables using WorldClim data and ArcMap, a sophisticated geographic information system application. These climate variables were assigned to each farm household based on their specific geographic coordinates, including latitude, longitude, and elevation. It is important to note that while the Thin Plate Spline method is commonly employed in literature for creating spatial climate datasets and assigning household-specific climate values (as detailed in studies by Daly (2006), and Wahba (1990)), this method yields interpolated data that includes a margin of error. In my study, I opted for ArcMap to generate climate data, as it offers higher precision and thus increased accuracy in the analysis.

The literature underscores the sensitivity of crops to seasonal climate variations, as explored in studies by Mendelsohn and Dinar (2003) and Schlenker et al. (2005). In this study, I define four seasons—winter, spring, summer, and fall—based on the crop farm data and the midpoint of key rainy seasons in Africa, following the approach suggested by Kurukulasuriya et al. (2006). These seasonal definitions are crucial for accurately capturing the impacts of each climate variable on agricultural outcomes, such as the regulation of insect pests by winter temperatures, the facilitation of optimal crop growth in moderate summer conditions, and the provision of favorable fall temperatures for crop harvesting.

Table 1.2 presents summary statistics from the 2016 UNDP survey data alongside WorldClim version 2.1 climate data for the period 1970-2000. The table includes seasonal and per farm household averages for temperature, rainfall, solar radiation, wind speed, and evaporation for these years [2]. Additionally, the table reports the average annual production per hectare for crops under adaptation measures and those not adapted in 2016, which were 1,488 kilograms and 1,054 kilograms, respectively. It is worth noting that the climate data covers slightly different periods. The countries included in this study represent a variety of climate zones within Africa, each with unique rainfall patterns. Sections 3 to 6 of Table 1.2 detail the average values of assets, inputs used, and characteristics of the farm household head and household.

2. Temperature measured in degrees Celsius (°C) ; rainfall in millimetres (mm) ; evaporation rate in kilopascals (kPa) ; solar radiation in kilojoules per square meter per day (kJ m^{-2} day^{-1}), indicating the amount of solar energy received on a given surface area during 24 hours ; wind speed in meters per second (m s^{-1}), representing how far the wind travels in one second.

Table 1.2 –
Descriptive statistics of the factors determining agricultural yields

	Total sample		Adapted		Nonadapted	
variable name	mean	std. error	mean	std. error	mean	std. error
adaptation	0.435		1.00		0.00	
yield	1,267.09	1,379.86	1,488.18	1,563.36	1,053.6	955.40
machinery	0.61	.5	.92	.27	.49	.33
labor	186.0	27.84	174.06	33.24	197.70	44.48
inorganic fertilizer	586.58	569.9	832.81	454.15	347.07	569.13
organic fertilizer	844.65	1048.8	1287.48	1061.29	404.31	827.62
pesticide powder	227.40	332.1	327.16	315.71	129.4781	318.38
pesticide liquid	227.3	331.5	329.23	320.58	127.16	310.90
seed	180.24	210.1	279.18	209.54	83.27439	159.34
irrigation	.61	.48	.95	.19	.48	.50
literacy	0.62	0.49	.45	0.45	.68	.47
male	0.82	.38	.89	.31	.80	.40
age	45.8	13.7	47.78	13.50	45.04	13.7
household size	8.1	5.75.7	9.44	7.45	7.61	4.75
relatives	7.31	5.9	8.54	7.47	6.83	5.04
access to credit	0.23	0.41	.28	.42	.20	.40
off-farm job	0.21	0.41	.30	.46	.17	.37
computer	.03	0.17	.01	.10	.04	.19
drought exper.	0.39	.48	.43	.49	.38	.48
flood exper	.05	.22	.04	.20	.05	.22
pests exper	0.26	0.50	.25	.43	.27	.44
wind exper	.18	.38	.10	.30	.21	.40
storms exper	.03	.17	.01	.08	.04	.19
flooding exper	.04	.18	.03	.17	.03	.18
landslides exper	.01	.07	.01	.06	.01	.08
latitude	2.61	.04	6.62	.06	1.06	.04
altitude	517.97	2.28	398.34	2.83	562.17	2.92
access extension	.19	.00	.20	.01	.17	.00
farmer association	.11	.01	.13	.01	.1	.01
sample size	5,091		1,811		3,280	

Notes : Awé, 2024. The sample size references the total number of households. The final dataset includes data from 5,091 agricultural households. All data presented are sourced from the household dataset.

5 RESULTS

Tables 1.4 and A.2 display the estimated results for the simultaneous Equations (1.2), (1.4), and (1.5). These estimates were obtained using the Full Information Maximum Likelihood (FIML) method, with standard errors that are clustered at the district level. This methodological choice is grounded in its ability to handle the complexities and interdependencies inherent in simultaneous equations [3]. For comparison, column (2) presents the Ordinary Least Squares (OLS) estimation of the yield function, which includes the adaptation dummy variable and a range of control variables.

Columns (1), (3), and (4) of the tables provide the estimates obtained using the

3. The FIML estimation was carried out using the "movestay" command in STATA, as recommended by Lokshin and Sajaia (2004), which is specifically designed for this type of econometric analysis.

Full Information Maximum Likelihood (FIML) method for Equations (1.2), (1.4), and (1.5). These columns collectively offer a deep dive into various facets of the model. Specifically, column (1) details the estimated coefficients for the selection equation (1.2), which is crucial in understanding farmers' decisions regarding whether to adapt or not to climate change. Meanwhile, columns (3) and (4) display the estimated coefficients for the yield functions (1.4) and (1.5). Column (3) pertains to farmers who have implemented adaptation measures, while column (4) relates to those who have not adapted. This thorough presentation and analysis of the results provide a comprehensive exploration of how climate change adaptation measures influence agricultural yields.

5.1 Basic correlation : OLS estimates

I estimate equation (1.3) using OLS and present the results in column (2) of Table 1.4. These estimates use standard errors clustered at the district level and include the binary adaptation variable. Column (2) displays the estimates of the equation with the adaptation variable and controls for other factors that affect agricultural yield.

The estimated relationship between adopting adaptation strategies and agricultural yields is positive and statistically significant. Furthermore, the magnitudes of the estimated adaptation effect on agrarian products is statistically significant and economically meaningful. Standardized beta coefficients have been calculated for the estimates, and they suggest that adapting to climate change is associated with an increase in agricultural yields by about 0.39 to 0.41 standard deviations. For instance, interpreting the OLS estimates as causal and using the mean of the estimates, a non-adapted farmer with an initial average yield of 1,054 kg per hectare who adopts at least one adaptation strategy could expect an increase to 1,475 kg per hectare, representing a 40% increase in agricultural yields.

Although the OLS estimates indicate a positive and significant association between climate change adaptation and agricultural yields, the causal relationship is not established by these results. Farmers who are more skilled or have better resources may choose to adapt, which could lead to an upward bias in the estimates if these factors are not adequately controlled for in the analysis. Moreover, farmers with initially higher yields may be more inclined to adopt adaptation strategies and sustain high outputs, potentially leading to an overestimated impact of adaptation on crops.

5.2 Assessing instrument validity : The use of falsification test

My preferred FIML estimation relies on instruments that are assumed to be excluded from the outcome equation. To assess the plausibility of this assumption, I conduct a falsification test equation (1.10), where I assess the predictive power of the instruments for the outcomes of non-adapters.

The results for equation (1.10) are meticulously detailed in Table 1.3. This table includes the F-statistic and its corresponding p-value, which are critical in assessing the validity of the instruments used in the analysis. The F-statistic for this equation is calculated to be 0.78, and the associated p-value is 0.67. These values are indicative of the validity of the information sources as instruments for the adaptation variable in the model. The findings that the information sources are valid instruments align well with previous research (Di Falco et al., 2011; Di Falco and Veronesi, 2013, 2014). This consistency with prior research further reinforces the reliability of the methodology and the robustness of the results obtained in this study.

Table 1.3 –
Parameter estimates – falsification test

	Model 1
	Non-adapted farmers yields
Information sources	
government	36.25 (62.55)
newspaper	134.02 (332.53)
radio	-90.39 (86.77)
television	143.38 (231.76)
local community	-144.98 (162.11)
NGO	150.49 (143.56)
worship temple	50.17 (53.55)
social media info	19.94 (31.14)
constant	1,281.71 (2,131.14)
Wald test	F-stat. = 0.78 (p-value = 0.67)
Sample size	3,280

Notes : Awé, 2024. Model 1 employs ordinary least squares with R^2 = 0.414, estimated at the plot level. Standard errors, clustered at the district level, are provided in parentheses. The F-statistic is used to test the null hypothesis that the information sources are not correlated with the yield equation's error term. The symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% levels, respectively. Coefficients for other variables are not reported.

5.3 Drivers of adaptation decision

Probit estimates of the adaptation decision equation (1.2), considering access to information sources as independent variables, are outlined in column (1) of Table 1.4. The data indicates that access to government agencies and newspapers significantly increases the likelihood of adaptation by 13% and 9%, respectively. Similarly, access to radio, TV, and social media notably elevates the probability of climate change adaptation by 6%, 15%, and 38%, respectively. The first-stage F-statistic associated with these information sources is estimated at 346.2, which is substantially above the threshold of 10, suggesting these instruments are relevant and unlikely to be weak (following the criteria established by Stock and Yogo (2002) and discussed further by Andrews et al. (2019). These results are consistent with the discussion in Section 3.2.

The estimates from the selection equation (1.2) show that the coefficient related to literacy is positive and statistically significant, suggesting that educated farmers are more likely to understand and implement adaptation measures. The variables related to access to extension services and membership in farmers' organizations are also positive and statistically significant, which indicates that such organizations and services play a crucial role in disseminating information, as noted by Abdulai and Huffman (2014) and Bandiera and Rasul (2006).

The coefficient for access to working capital is significant and positive, highlighting that farmers with fewer capital constraints are more inclined to undertake adaptation. Conversely, the nonfarm activity variable shows a positive but not statistically significant effect, suggesting that engagement in nonfarm activities does not significantly influence farmers' decisions to adapt due to limited nonfarm opportunities for rural farmers (Burgess et al., 2017). Furthermore, the experience with adverse climate events like droughts, floods, severe winds, and riverine floods has a positive and significant effect, consistent with Iyigun et al. (2017), who found that such experiences tend to increase farmers' resilience. Lastly, the positive and significant coefficient for the farmer age variable indicates that older farmers may have a greater propensity to adapt due to a wealth of experience in dealing with climatic challenges. The variable representing gender is positive and significant, insinuating that male farmers are more likely to adapt than their female counterparts.

5.4 Determinants of yields for adapters and non-adapters

Columns (3) and (4) of Table 1.4 display the estimated coefficients of the agricultural yield functions (1.4) for adapted farmers and (1.5) for nonadapted farmers, respectively. The regression results indicate that inputs such as seeds, inorganic fertilizers, and labor have positive and statistically significant coefficients for both groups of farmers, suggesting their beneficial impact on yields. For nonadapted farmers, the labor input and use of organic fertilizers also show a positive and significant relationship with output, underscoring the importance of these inputs. However, using powder and liquid pesticides does not affect outcomes for either group significantly. While there is a positive correlation between access to working capital and yields, it is not statistically significant. It is consistent with previous research by Guiteras (2009), reflecting limited financial resources for farmers in developing countries.

As for the influence of climate variables, Table A.2 outlines their seasonal impacts on yields for both adapted and nonadapted farmers. Adapted farmers experience yield benefits from fall and spring temperatures, rainfall, and fall evaporation. In contrast, summer and winter temperatures, along with evaporation and wind speed in those seasons, tend to reduce their yields. For nonadapted farmers, beneficial factors include winter temperature, fall evaporation, and spring wind speed. I incorporate quadratic terms into the regression models to examine potential non-linear relationships between climate variables and agricultural yields. Significant coefficients from several quadratic terms indicate non-linear associations for both adapted and non-adapted farmers. Specifically, positive coefficients for squared terms of temperature, solar radiation, and evaporation point to a threshold effect; yields may be low below these thresholds but tend to increase once surpassed. Conversely, negative coefficients for quadratic terms of certain climate variables suggest the presence of an optimal level beyond which yields could decline. These patterns underscore the importance of considering additional climate variables such as evaporation, solar radiation, and wind speed in determining crops. These findings align with the research conducted by Zhang et al. (2017).

Table 1.4 –
Adaptation decisions and agricultural yields

	FIML	OLS	FIML	
	Adaptation	Yields	Yields	Yields
			Adapted	Nonadapted
	(1)	(2)	(3)	(4)
I		417.4*** (33.2)		
labor	.01*** (.00)	8.1 (9.2)	7.2 (8.2)	8.1*** (2.9)
labor sqr	−.00** (.00)	.0 (.0)	.0 (.1)	-.1 (.1)
inorganic fertilizer	.01*** (.00)	.1 (.1)	.5 (.3)	.2* (.1)
inorganic fertilizer sqr	−.00*** (.00)	-.0 (.0)	-.0 (.0)	−.1* (.0)
organic fertilizer	.01*** (.00)	.8** (.4)	1.1* (.6)	.0 (.1)
organic fertilizer sqr	−.01*** (.00)	−.1* (.0)	-.0 (.00)	-.0 (.00)
pesticide powder	−.01*** (.00)	1.5 (1.3)	-2.2 (2.8)	2.4 (1.6)
pesticide powder sqr	.00*** (.00)	-.0 (.0)	.0 (.0)	-.0 (.0)
pesticide liquid	−.01*** (.00)	−2.6* (1.4)	-1.5 (2.8)	-2.2 (1.6)
pesticide liquid sqr	.00*** (.00)	.1* (.00)	.0 (.00)	.0 (.00)
seed	.01*** (.00)	3.7* (1.8)	9.1** (4.5)	.7* (.4)
seed sqr	−.00* (.00)	−.1* (.00)	−.1*** (.00)	.0 (.00)
literacy	05*** (.01)	-25.2 (16.4)	−48.3* (25.5)	-28.7 (18.2)
male	.03*** (.01)	15.7 (18.4)	28.3 (24.9)	37.9 (31.6)
age	.01*** (.00)	.2 (.4)	.7 (.5)	-.0 (.4)
household size	−.02*** (.00)	4.3 (3.1)	-11.3 (9.2)	1.6 (3.5)
relatives	.02*** (.00)	1.0 (2.7)	13.7 (10.1)	3.4 (3.5)
access to credit	.04*** (.01)	9.7 (21.8)	14.1 (30.3)	23.2 (24.1)
nonfarm job	.01 (.01)	.4*** (.00)	321.4 (210.3)	382.7 (293.4)
drought experience	.02*** (.01)	6.7 (22.8)	−55.6** (23.6)	43.9 (28.5)
flood experience	.03* (.01)	97.9 (104.1)	158.0 (158.8)	48.7* (25.7)
pests experience	.00 (.01)	-9.0 (20.7)	−43.3** (19.9)	-8.5 (21.8)
severe wind exp	.03*** (.00)	11.3 (26.8)	−74.2** (40.6)	18.2 (23.4)
hail storms experience	-.00 (.02)	100.4 (74.7)	89.0 (81.2)	-29.7 (74.4)
riverine flood experience	.03** (.01)	149.0*** (52.1)	1.2 (55.0)	142.0*** (34.4)
landslides experience	-.03 (.03)	42.9 (39.6)	-96.5 (54.0)	29.2 (46.7)
mean labor	.01*** (.00)	.6*** (.1)	.1 (.2)	.2*** (.0)
mean inorganic fertilizer	.00 (.00)	−.1*** (.00)	-.0 (.00)	-.0 (.00)
mean organic fertilizer	.00 (.00)	-.0 (.00)	.0 (.00)	.0 (.00)
mean powder pesticide	-.00 (.00)	-.0 (.00)	.0 (.00)	.0 (.00)
mean pesticide liquid	-.00 (.00)	.0 (.00)	.0 (.1)	-.0 (.00)
mean seed	.00* (.00)	−.1* (.00)	-.1 (.1)	.1** (.00)
machinery	.06*** (.01)	32.1 (27.3)	.0 (40.8)	45.5* (27.4)
computer	.01 (.02)	-41.9 (30.2)	−70.3* (34.7)	-9.6 (62.4)
latitude	−.03*** (.00)	−30.2*** (24.8)	−63.1* (6.2)	20.3 (39.3)
altitude	−.00*** (.00)	-.0 (.00)	.0 (.1)	-.0 (.00)
acces extension	.08*** (.01)	−.2* (.1)	-167.9 (253.3)	207.8 (273.9)
farmer organization	.04*** (.01)	52.4*** (9.4)	30.9 (26.9)	69.6** (33.4)
government info	.13*** (.01)			
newspaper info	.09*** (.03)			
radio info	.06*** (.01)			
TV info	.15*** (.03)			
local community info	-.02(.03)			
ngo info	-.09 (.06)			
temple info	.07 (.06)			
social media info	.38*** (.14)			
constant	1324.2** (457.1)	−705899.1*** (96948.7)	-6725.2 (6894.5)	2601.4 (8580.2)
σ_t			395.5*** (64.7)	268.3*** (36.1)
ρ_t			.2*** (.02)	.01 (.03)
F. stat	346.2			
LR test of indep. eqns. :			$chi2(1) = 28.4$***	$Prob > chi2 = 0.0$
Number obs.		5,091	1,811	3,280

Notes : Awé, 2024. Robust standard errors are clustered at the district level and are shown in parentheses. Column (1) presents the probit estimates of the adaptation decision equation (1.2). Column (2) presents the OLS estimates from Equation (1.3), with errors clustered at the district level. Columns (3) and (4) report the estimates of the endogenous switching regression, derived from Equations (1.4) and (1.5), with errors clustered at the district level for the adapted and non-adapted households, respectively. The term σ_j represents the square root of the variance of the error terms μ_{tj} in the outcome Equations (1.4) and (1.5). Meanwhile, ρ_j indicates the correlation coefficient between the error term μ from the selection equation (1.4) and the error term υ_{tj} from the respective outcome equations. Symbols $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.5 Impact on agricultural yields : An analysis of ATT estimates

Table 1.5 presents the expected production per hectare, comparing actual and counterfactual scenarios in Columns 1 and 2, respectively. The last column highlights the impact of adaptation on yields. Across the analyzed countries, adopting adaptation measures correlates with an average yield increase of 23.3%. Specifically, crops rose from 1,208.57 kilograms (for non-adopters) to 1,489.67 kilograms (for adopters), a significant difference of 281.10 kilograms at the 1% level, which is economically substantial. The OLS estimates indicate a potential 40% yield increase or 421 kilograms per hectare. This estimate is 49.8% greater than the observed increase of 281 kilograms, suggesting the possibility of an upward bias from endogeneity.

The country-specific analysis yields further insights. In Burkina Faso, adaptation strategies led to a 21.6% yield increase, from 1,241.24 to 1,509.77 kilograms, which is significant at the 1% level. In Sao Tome and Principe, the adoption of such measures resulted in a 27.7% increase, with yields growing from 1,112.42 to 1,420.16 kilograms. For Sierra Leone, adaptation is associated with a substantial 51.1% yield increase, from 1,058.71 to 1,600.22 kilograms. However, this finding is significant at the 10% level and warrants further investigation due to relatively high standard errors. In Uganda, farmers experienced a yield increase of 23.8%, from 1,164.11 to 1,441.39 kilograms, significant at the 1% level.

These findings underscore that the impact of climate change adaptation on agriculture can significantly differ across countries. Such variations may stem from diverse climatic conditions, crop types, and agricultural practices specific to each nation. Additionally, the availability of resources, quality of infrastructure, and level of government support play pivotal roles in the effectiveness of adaptation strategies. Therefore, it is essential to consider the unique circumstances of each country when assessing the performance of climate change adaptation initiatives within their agricultural sectors.

Table 1.5 –
Impacts on agricultural yields across countries

Country	Decision stage		Treatment effects
	To adapt	Not to adapt	
	(1)	(2)	(3)
All countries	1,489.67	1,208.57	281.10***
	(1.82)	(12.33)	(12.47)
Burkina Faso	1,509.77	1,241.24	268.53***
	(2.11)	(3.98)	(4.79)
Sao Tome and Principe	1,420.16	1,112.42	307.74***
	(10.32)	(17.60)	(20.40)
Siera Leone	1,600.22	1,058.71	541.51*
	(14.09)	(317.86)	(317.13)
Uganda	1,441.39	1,164.11	277.28***
	(2.53)	(24.20)	(24.32)

Notes : Awé, 2024. Columns (1) and (2) display the expected quantity produced per hectare under actual conditions and counterfactual situations, respectively. Column (3) presents the treatment effects of adaptation on agricultural outcomes.The symbols $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Owing to heterogeneity, the increase in yield attributable to adaptation varies among countries and crops.

5.6 Impact of climate change adaptation on principal crop yields : a country-specific analysis

Table 1.6 illustrates the effect of climate change adaptation strategies on the yields of six key crops across various countries. The estimates suggest that countries such as Burkina Faso, Sao Tome and Principe, Sierra Leone, and Uganda have experienced enhanced crop yields following the implementation of these measures. For instance, maize yields in these nations have increased by an estimated 197 kg/ha (13.6%) in Burkina Faso, 350.8 kg/ha (24.6%) in Sao Tome and Principe, 403.8 kg/ha (30.4%) in Sierra Leone, and 228.6 kg/ha (16.1%) in Uganda. Similarly, estimates for rice show an increase of 136.6 kg/ha (9.2%) in Burkina Faso, 539.2 kg/ha (30.0%) in Sao Tome and Principe, 760.9 kg/ha (44.5%) in Sierra Leone, and 406.8 kg/ha (28.4%) in Uganda after the introduction of these adaptation strategies. Through strategic implementation, agricultural leaders and policymakers can bolster the resilience of farming systems, not only promoting higher crop yields and contributing to enhanced food security in the affected regions, as highlighted by Adger et al. (2009).

Table 1.6 –
Impact of Adaptation Strategies on Yields of Various Crops

Crop	Decision	Country				
		Burkina Faso	Sao T. and P.	Sierra Leone	Uganda	All countries
maize	Adapted's yield	1450.4 (3.7)	1423.3 (27.4)	1328.4 (40.2)	1424.7 (3.0)	1438.4 (2.4)
	Adaptation impact	197.0*** (7.5)	350.8*** (29.8)	403.8*** (79.3)	228.6*** (29.3)	213.2***(13.9)
rice	Adapted's yield	1486.5 (15.9)	1800.3 (701.2)	1708.1 (15.8)	1430.0 (6.1)	1491.8 (6.4)
	Adaptation impact	136.6*** (33.9)	539.2 (400.1)	760.9 (525.2)	406.8*** (72.7)	446.1*** (115.8)
sorghum	Adapted's yield	1589.4 (3.6)	1622.3 (72.2)	1439.2 (69.4)	1391.9 (6.0)	1584.7 (3.5)
	Adaptation impact	458.9*** (9.3)	132.9* (10.3)	229.4* (124.3)	21.1 (22.9)	447.5*** (9.2)
millet	Adapted's yield	3097 (6.8)	3328.3 (73.6)	3276.8 (87.6)	2928.1 (33.4)	3216.3 (6.6)
	Adaptation impact	522.4*** (15.3)	936.7*** (103.3)	654*** (124.2)	597.4*** (40.6)	530.5*** (15.0)
cassava	Adapted's yield	1808.3 (62.1)	1420.1 (33.9)	1468.8 (19.3)	1374.4 (5.6)	1399.1 (6.2)
	Adaptation impact	163.3*** (57.6)	216.7** (69.7)	263.0*** (29.5)	350.8*** (14.4)	321.7*** (12.7)
beans	Adapted's yield	1606.9 (47.3)	1449.8 (51.4)	1845.2 (43.2)	1378.3 (37.1)	1427.5 (21.6)
	Adaptation impact	405.9*** (84.4)	23.1 (24.8)	55.6 (74.9)	240.6*** (26.3)	227.6*** (25.7)
All crops	Adapted's yield	1509.8 (2.1)	1420.2 (10.3)	1600.2 (14.1)	1441.4 (2.5)	1489.7 (1.8)
	Adaptation impact	268.5*** (4.8)	307.7*** (20.4)	541.5* (317.1)	277.3*** (24.3)	281.1*** (12.5)

Notes : Awé, 2024. This table showcases the distribution of estimates concerning the impact of implementing adaptation measures on the six primary crops cultivated by farmers in four countries. ***, **, and * indicate coefficients significant at the 1%, 5%, and 10% levels, respectively.

5.7 Analysis of individual adaptation measures on crop yields : a crop-specific breakdown

The table detailing adaptation strategies (Table 1.1) reveals that the most prevalent approach farmers adopt is changing planting dates, followed by altering crop types. While these strategies can be adopted individually, farmers also have the flexibility to combine them. For instance, combining two systems out of five can lead to ten possible combinations (using the binomial coefficient for combinations), three strategies out of five lead to ten combinations, and four measures yield five combinations. All five measures together present one comprehensive approach. Considering all possible combinations without repetition, there are a total of sixty-three potential unique strategy combinations.

Table 1.1 indicates that many of these adaptation strategies have been observed fewer than 100 times. Given more than twenty variables in the regression analysis, estimations based on a limited observation set might introduce bias into the parameter estimates due to the risk of overfitting (Steyerberg et al., 2003). For this reason, this analysis prioritizes the most commonly adopted strategies : changing planting dates (adopted by 49.2% of respondents), adjusting fertilizer use patterns (4%), and switching crop types (15.1%). The analysis also explores combining the two predominant strategies : altering planting dates and crop types. Table 1.7 presents the actual and counterfactual yields per hectare for each measure.

Table 1.7 –
Impacts of various adaptation measures on agricultural yields

	Decision stage		
Adaptation measures	Adapted	Non-adapted	Treatment effects
	(1)	(2)	(3)
Changing planting	1466.6	1195.5	271.0***
dates	(8.5)	(9.9)	(5.8)
Changing fertilizer	1381.5	1266.8	114.7
use pattern	(19.3)	(320.1)	(200.8)
Chang crop	1742.1	1304.4	227.7**
typ	(18.6)	(32.2)	(126.8)
Changing planting	1519.9	1076.6	443.3***
date and crop	(14.2)	(96.7)	(84.52)
All measures	1,489.7	1,208.6	281.10***
	(1.8)	(12.3)	(12.5)

Notes : Awé, 2024. Columns (1) and (2) show the anticipated production per hectare based on actual and hypothetical decisions, respectively. Column (3) presents the impact of adaptation measures on agricultural yields. ***, **, and * indicate that the coefficient is significant at the 1%, 5%, and 10% levels, respectively.

Table 1.7 reveals that, on average, farmers adjusting their planting dates saw a yield increase of 271.0 kilograms per hectare, which is statistically significant at the 1% level. In contrast, those who modified their fertilizer use patterns experienced a modest average yield boost of 114.7 kilograms per hectare, which is not statistically significant. Farmers who opted to switch their crop types registered an average significant yield enhancement of 227.7 kilograms per hectare at the 5% level. Significantly, those who altered both their planting dates and crop types experienced the most pronounced average yield increment, amounting to 443.3 kilograms per hectare, statistically significant at the 1% level. These results suggest that implementing various adaptation strategies can positively influence agricultural yields on average, with modifications in planting dates and crop types, individually or in combination, offering the most substantial benefits.

Table 1.8 –
Impacts of individual adaptation measures on the yields of specific crops

Crop	Decision stage	Adaptation measures			
		Changing Plant. dates	Changing Fert. use	Changing crop typ.	Chang. plant. and crop
	Obs.	891	48	274	54
maize	Adapted's yield	1487.4 (15.9)	1462.1 (28.7)	1708.9 (109.8)	1403.5 (12.1)
	Treatment effects	192.2*** (9.9)	100.4 (77.6)	342.8*** (41.1)	523.9*** (6.9)
	Obs.	180	52	36	43
rice	Adapted's yield	1534.7 (72.2)	1465.2 (38.8)	6273.8 (22.1)	1201.3 (84.1)
	Treatment effects	467.4*** (31.4)	102.1 (98.1)	60.3 (32.6)	280.1*** (41.4)
	Obs.	480	42	72	61
sorghum	Adapted's yield	1478.2 (7.9)	1312.8 (2.4)	1514.6 (33.3)	1622.4 (61.9)
	Treatment effects	338.3*** (12.5)	84.1*** (10.2)	229.4* (90.7)	297.1*** (81.3)
	Obs.	528	82	258	84
millet	Adapted's yield	2713.3 (36.6)	3228.3 (177.1)	2928.2 (41.7)	2692.1 (18.7)
	Treatment effects	734.6*** (46.6)	287.6*** (60.7)	405.1*** (57.2)	81.9*** (11.4)
	Obs.	60	36	54	39
cassava	Adapted's yield	1376.5 (34.5)	840.1 (12.6)	1692.9 (64.5)	2113.4 (76.3)
	Treatment effects	324.4*** (74.4)	40.2 (27.3)	470.1*** (29.8)	261.3*** (51.6)
	Obs.	84	32	54	42
beans	Adapted's yield	1317.8 (9.3)	1353.4 (76.5)	1374.8 (51.8)	1775.3 (86.0)
	Treatment effects	17.7 (23.4)	60 (40.2)	136.2 (64.3)	33.4*** (4.1)
	Obs.	891	52	274	61
All crops	Adapted's yield	1466.5 (8.5)	1381.5 (19.3)	1742.1 (18.6)	1519.9 (14.2)
	Treatment effects	271.0*** (5.8)	114.7*** (22.7)	227.7*** (126.8)	443.3*** (84.5)

Notes : Awé, 2024. Table 1.8 displays the influence of specific adaptation strategies on the yields of individual crops. For every crop, the table provides the number of observations (Obs.), the adjusted yield, and the yield's variation due to the adaptation measures. Coefficients marked with symbols ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Table 1.8 delineates the impacts of different adaptation measures on the yields of individual crops. It details the number of observations, outcomes, and the treatment effects of implementing these adaptation measures for each crop. For maize, yield improvements are statistically significant at the 1% level when altering planting dates, changing crop types, or employing both strategies simultaneously—with the combination of both alterations having the most pronounced effect. For rice, yield gains are significant with adjustments to planting dates and the measure combining planting dates and crop types.

Both sorghum and millet exhibit significant yield increases across all adaptation measures, with the most substantial improvements for millet resulting from adjustments to planting dates. For cassava, significant yield boosts are associated with changes in planting dates, crop types, or a combination of both strategies. Beans show a considerable increase in yield when planting dates and crop types are adjusted concurrently. A collective examination of all crops indicates pronounced yield improvements across all adaptation strategies, underscoring that tailored adaptation measures can significantly enhance agricultural yields for various crops.

6 CONCLUSION

This study uses an endogenous switching regression by full information maximum likelihood to investigate the impact of climate change adaptation on farm households' agricultural yields. The results indicate a notable increase in yields, with an enhancement of 281 kg per hectare, or 23.3%. The implementation of adaptation measures, whether individual or combined, significantly improves agricultural productivity. Notably, strategies employed in tandem appear to be the most effective. Key factors driving the adoption of these strategies include access to working capital and informational resources. The research also expands the examination of climatic influences on yields, going beyond the typically analyzed variables of rainfall and temperature. These findings are crucial for informing policy-making focused on effective adaptation methods to counter the negative impacts of climate change.

Government initiatives that facilitate access to credit, disseminate crucial information about climate change, and provide extension services are vital. These services impart essential knowledge and skills, like crop modification and soil conservation techniques, all aimed at enhancing agricultural productivity. Throughout this study, I have uncovered significant insights into the effects of various adaptation strategies on agricultural productivity. It is important to acknowledge, however, that this analysis, while comprehensive, may not encompass all adaptation methods employed globally, which are often customized to specific environmental and economic contexts. The effectiveness of these methods is deeply influenced by regional characteristics and specificities. Despite the detailed insights provided by the observations for each strategy and the extensive variables in the regression models, broader interpretations might be necessary to cater to different crops or regions. This research opens an exciting avenue for future studies. Investigating the effectiveness of diverse adaptation techniques across various global contexts could deepen our understanding and improve agricultural practices worldwide.

AVANT-PROPOS (ARTICLE 2) : ADAPTATION TO CLIMATE CHANGE AND FARMERS' EXPOSURE TO ENVIRONMENTAL RISKS : A STUDY IN FOUR AFRICAN COUNTRIES

L'article 2, dont le titre est "Adaptation to Climate Change and Farmers' Exposure to Environmental Risks : a Study in Four African Countries ", a été rédigé entièrement par l'étudiant. Il sera soumis dans la revue : American Journal of Agricultural Economics.

ARTICLE 2

ADAPTATION TO CLIMATE CHANGE AND FARMERS' EXPOSURE TO ENVIRONMENTAL RISKS : A STUDY IN FOUR AFRICAN COUNTRIES

1 INTRODUCTION

Climate change significantly impacts agricultural productivity and income by altering climatic patterns, as established in seminal works by Deschênes and Greenstone (2007), Deschênes and Greenstone (2012), and Mendelsohn et al. (1994). In Africa, farmers face considerable risks due to climate change, with its economic impact on agriculture estimated to be around 10% of GDP. Notably, the majority of armers exhibit risk-averse behavior, actively seeking strategies to mitigate their vulnerability to climatic uncertainties, as noted in research by Moscardi and De Janvry (1977) and Palis et al. (2006). Adaptation measures emerge as a potential strategy for African farmers to reduce exposure to production variability, extending beyond merely increasing yield, a topic I explored in Chapter One.

Empirical evidence from studies conducted in both developed and non-African developing countries suggests that such strategies can effectively counter vulnerabilities linked to climatic hazards (Burke et al., 2015; Dinar et al., 2012; Trinh et al., 2018). Di Falco and Veronesi (2014) used data from Ethiopian farmers to demonstrate that climate change adaptation can significantly reduce vulnerability to production fluctuations. This finding raises an important question : Are the results from Di Falco and Veronesi (2014)' study reflective of a broader trend, or do they represent isolated instances ?

Since the work of Menezes et al. (1980), the three central moments of agricultural yields – variance (M_2), skewness (M_3), and kurtosis (M_4) – have been used to measure production uncertainty. While the mean and variance provide basic insights into the distribution's center and spread, skewness and kurtosis offer perspectives on its asymmetry and the likelihood of extreme outcomes, respectively (Kim and Chavas, 2003). Farmers, being inherently risk-averse, adopt strategies that influence these moments, especially skewness (M_3), to mitigate external factors like climate change that impact their output, as suggested by Di Falco and Veronesi (2014). These strategies might also affect both the variance (M_2) and kurtosis (M_4) of their yield distributions, as Binswanger and Rosenzweig (1993) point out. In this study, I focus on skewness as the primary measure of production uncertainty, with variance and kurtosis serving as supplementary measures.

Identifying the causal impact of adaptation on production uncertainty is challenging due to potential endogeneity and selectivity bias. To address these issues, I use endogenous switching regression models and the same dataset as in Chapter One, which includes 5,091 farmers from four African countries, primarily growing six types of crops. Of these farmers, 1,811 have adopted adaptation measures (adapters), while 3,280 have not (non-adapters). Diverging from Di Falco and Veronesi (2014), this study employs all three central moments of agricultural yield distribution as measures of uncertainty instead of focusing solely on the third moment. Additionally, it incorporates extra climatic variables such as evaporation, solar radiation, and wind speed to circumvent biases linked to relying solely on temperature and precipitation, as Zhang et al. (2017) recommend.

The results reveal a significant and negative impact of climate change adaptation on the exposure to production uncertainty in agriculture. The magnitude of these effects is both statistically significant and substantial. Specifically, the adoption of adaptation measures is found to increase the skewness of yield distribution by 2.8 units, suggesting that the yields of a farmer who has adapted to climate change are approximately 1.5 times less susceptible to climatic risks compared to a non-adapting farmer. Similar observations are noted for the other two central moments of yield distribution. For instance, adapting to climate change is observed to decrease the variance of yield distribution by 1.2 unitts, which corresponds to a 69.1% reduction in the impact of climatic risks on agricultural yields. Furthermore, the implementation of adaptation measures is associated with a decrease in the kurtosis of yield distribution by 1.5 units, indicating a 35.5% decrease in the climatic risk to farming yields. Additionally, the study uncovers significant variations in these impacts across different countries. Notably, pronounced impacts of adaptation measures are observed in Uganda and Burkina Faso, while the findings in Sao Tome and Principe show minimal significance. In Sierra Leone, the outcomes are somewhat ambiguous.

This research makes a substantial contribution to the existing literature by providing empirical evidence on the potential effectiveness of climate change adaptation measures in reducing farmers' vulnerability to production variability. It offers a detailed analysis of the impact of adaptation on key statistical measures of yield distribution, namely variance, skewness, and kurtosis. A notable aspect of this work is its exploration of how the effects of adaptation vary from one nation to another, highlighting the crucial role of local conditions in determining the success of such initiatives.

The findings carry important policy implications. They stress the need for promoting and financially supporting climate change adaptation strategies to protect farmers' livelihoods and ensure food security in the face of increasing climate challenges. The significant benefits observed in Uganda and Burkina Faso suggest that these countries should continue prioritizing and expanding effective adaptation measures. The modest results in Sao Tome and Principe call for a reassessment of current adaptation strategies to better suit the specific challenges of the country. The ambiguous outcomes in Sierra Leone necessitate further investigation to identify the underlying factors and develop more tailored adaptation strategies. The study emphasizes the importance of developing country-specific adaptation strategies that take into account the unique climatic, socio-economic, and institutional contexts.

The structure of the paper is as follows : Section 2 provides the background and context, focusing on the factors that influence uncertainty in agricultural production and reviewing relevant literature on farmers' responses to climate risks. Section 3 outlines the analytical framework and the econometric models employed in the study. Section 4 describes the data used for the analysis. Section 5 presents the findings and offers an in-depth discussion of the empirical results. Finally, Section 6 concludes the chapter, summarizing the key observations and insights.

2 BACKGROUND AND CONTEXT

Production uncertainty in agricultural economics is multifaceted, rooted in agronomic, climatic, economic, and policy dimensions. For robust risk analysis, one must consider and examine these intertwined sources of risk. Foremost among these determinants are weather and climate variabilities. Factors such as temperature variations, inconsistent rainfall, drought conditions, floods, and other meteorological phenomena can profoundly impact crop yields and livestock well-being (Antle, 2010; Di Falco and Veronesi, 2014). Similarly, the unpredictability associated with outbreaks of pests and diseases poses significant threats to crop yields and livestock health (Horowitz and Lichtenberg, 1993; Perrings et al., 2011).

The agricultural sector is also sensitive to policy shifts. Fluctuations in agricultural policies and regulations can inject layers of uncertainty into production (Babcock, 2015). Additionally, technological progress, characterized by the inception and adoption of innovations like genetically modified organisms (GMOs) or precision agriculture, carries its own set of uncertainties (Marra et al., 2003; Moschini, 2008). The financial dimension, too, plays a cardinal role in shaping agricultural outcomes. Access to financial instruments and avenues such as credit, insurance, and off-farm income sources can significantly affect a farmer's resilience and capability to counteract risks (Sherrick et al., 2004). The intrinsic attributes of a farm, including its size, geographical positioning, infrastructure, and other inherent characteristics, dictate its susceptibility to external shocks (Harwood, 1999). Lastly, farmers' managerial prowess and decisions, from input selection to marketing strategies, remain central in navigating the labyrinth of risks (Hardaker et al., 2004).

Farmers in developing countries require advanced inputs and technologies to improve their agricultural practices. This need is particularly acute for producers in African countries, who face a myriad of challenges : climate irregularities that severely impede their output (Di Falco and Veronesi, 2014), limited public investment in agriculture, constrained access to essential information, fertilizers, financial resources, and inadequate road infrastructure. Moreover, the ongoing challenges of climate change compound these difficulties. Many nations in Sub-Saharan Africa are expected to experience semi-arid conditions, reduced rainfall, desertification, and prolonged droughts (Godfrey and Tunhuma, 2020). Such climatic shifts will likely lead to diminished crop outputs, exacerbating the food insecurity issues that farming households already confront. Projections suggest increased pest and disease activities and decreasing crop yields, threatening local sustenance and the broader food system infrastructure (Godfrey and Tunhuma, 2020).

The literature indicates that risk-averse farmers tend to be wary of this downside yield risk (Dillon and Scandizzo, 1978; Jullien and Salanié, 2000; Lin and Moore, 1974; Moscardi and De Janvry, 1977; Ramaswami, 1992). They are inclined to adopt measures, including adaptation strategies, to mitigate their vulnerability. Moscardi and De Janvry (1977) explored the risk attitudes of Mexican farmers, explicitly examining how risk aversion influenced their demand for fertilizer. The findings suggest that pronounced risk aversion among farmers leads them to reduce fertilizer application. However, off-farm income, land ownership, and access to support networks can decrease risk aversion. Di Falco and Veronesi (2014) found that climate change adaptation measures significantly reduce Ethiopian farmers' exposure to the downside risk of low yields.

3 ANALYSIS FRAMEWORK AND ECONOMETRIC MODEL

The production function $y_j(C_j, A_j, W_j, S_j, H_j, O_j)$, proposed by Mendelsohn et al. (1994) and utilized in Chapter One, lacks an uncertainty component in its formulation, making it insufficient for modeling uncertainty in the production process. To remedy this, I have expanded the model by incorporating u, a stochastic variable that embodies risk, as recommended by previous studies (Chavas, 2004; Di Falco and Veronesi, 2014; Menezes et al., 1980).

The enhanced production function, denoted as $y_j(C_j, A_j, W_j, S_j, H_j, O_j, u_j)$, captures the maximum yield a farmer can achieve given a set of inputs (C_j) and adaptation measures (A_j), a vector of climate variables W_j, a vector of geographic attributes G_j, a vector of soil characteristics S_j, a vector denoting farmer and farm household attributes H_j, and u_j a random variable denoting production uncertainty stemming from climatic variables for farmer, considering the uncertainty reflected by u_j, which assumes a unique value for each observation. Farmers are presumed to have knowledge of this production uncertainty, which is depicted by a subjective probability distribution of the random variable u_j.

3.1 Metrics for assessing production uncertainty

The work of Chavas (2004) demonstrates that exposure to production uncertainty can be quantified by the i-th order central moment, denoted as ω_j^i as :

$$\omega_j^i = [y_j(C_j, A_j, W_j, S_j, H_j, O_j, u_j) - E[y_j(C_j, A_j, W_j, S_j, H_j, O_j, u_j)]^i \tag{2.1}$$

, and

$$M^i = E(\omega_j^i) \tag{2.2}$$

Here, the values of i are 1, 2, 3, and 4, corresponding to the first four central moments of a distribution. Specifically, the first central moment (M^1) is always zero because it represents the expected value of the deviations from the predicted variables; M^2 denotes the variance; M^3 represents the skewness; and M^4 corresponds to the kurtosis.

A value of $\omega_j^3 < 0$ indicates that farmer j faces the downside risk of reduced yields, defined as the risk associated with unexpectedly low outputs (Chavas, 2004; Menezes et al., 1980). The metrics ω_j^2 and ω_j^4 serve as tools for robustness checks. Elevated values of ω_j^2 and ω_j^4 indicate heightened exposure to production uncertainty Chavas (2004).

3.2 Econometric models

Farmer j can select a combination of inputs C and adaptation measures A to enhance expected yields and reduce the risks to these yields from climate-related factors, ultimately resulting in optimal output. The process of minimizing Model (2.1) leads to the reduced form, as shown in Equation (2.3) (Di Falco and Veronesi, 2014).

$$\omega_j^i = \varpi_i I_j + T_j^{'} \Gamma_i + \varepsilon_{ji} \tag{2.3}$$

Where i takes the values of 2, 3, and 4, the term ω_j^i represents the i-th order central moment of production uncertainty for farmer j, capturing the variance, skewness, and kurtosis respectively. The vector T_j encompasses factors influencing production uncertainty, including historical climate data, input variables, farm assets, characteristics of the farm head, attributes of the farm household, and soil properties. Meanwhile, I_j is a binary variable set to one when the farmer has adopted any adaptation measure A_j and set to zero when no such adoption has occurred.

The Ordinary Least Squares (OLS) estimates of Equation (2.3) might be subject to bias and inconsistency, primarily due to potential endogeneity and selection bias. These issues are likely to arise from the decision-making process farmers undergo regarding whether to adapt to climate change. In order to address these concerns, I utilize the simultaneous equations model with endogenous switching introduced in Chapter One, where I also discussed the validity of the excluded instruments.

Within this framework, the decision to adapt or not is comprehensively modeled in the selection equation (2.4), specifically designed to capture the factors influencing a farmer's choice to adopt climate change adaptation measures. Concurrently, the outcomes of interest, which pertain to the impact of these adaptation decisions on the risk associated with agricultural output, are represented by risk exposure equations (2.5) and (2.6),

$$\begin{aligned} I_j^* &= T_j^{'}\psi + Z_j^{'}\Lambda - \xi_j \\ &= G_j^{'}\pi - \xi_j \end{aligned} \tag{2.4}$$

$$\omega_{jA}^i = T_{jA}^{'}\Gamma_{iA} + \varepsilon_{jiA} \tag{2.5}$$

and,

$$\omega_{jN}^i = T_{jN}^{'}\Gamma_{iN} + \varepsilon_{jiN} \tag{2.6}$$

For $i = 2, 3, 4$, $\omega_{jA}^i = [y_{jA} - E(y_{jA})]^i$, and $\omega_{jN}^i = [y_{jN} - E(y_{jN})]^i$. In this context, y_{jA} and y_{jN} represent the yields for farmers who have and have not adapted, respectively. The error terms, namely ε_{jiA} and ε_{jiN}, are assumed to be independent and identically distributed. To regress ω_{jA}^i and ω_{jN}^i on independent variables, I utilize the estimates of $\hat{y}_{jA}$ and $\hat{y_{jN}}$ to predict $E(\hat{y}_{jA})$ and $E(\hat{y}_{jN})$, which are then used to calculate ω_{jA}^i and ω_{jN}^i for $i = 2, 3, 4$.

I apply the correction approach proposed by Lokshin and Sajaia (2004), a methodology I previously utilized in Chapter One, to specifically address the potential selectivity bias that could arise between the error terms of the decision equation (2.4) and the output equations (2.5) and (2.6) [1].

Building on this methodology, I present the modified risk exposure equation for a farmer who has adapted to climate change as follows :

$$\omega_{jA}^i = T_{jA}^{'}\Gamma_{Ai} + \lambda_A\sigma_{iA} + \eta_{jiA} \tag{2.7}$$

where $\lambda_A = \frac{\phi(G_j^{'}\pi)}{\Phi(G_j^{'}\pi)}$, $\phi(.)$ is the standard normal probability density function, and $\Phi(.)$ the standard normalcumulative density function. Additionally, $\lambda_A\sigma_{iA}$ captures the impact of the potential selectivity bias on the risk exposure, ensuring that the estimates are not skewed by unobserved factors that influence both the adaptation decision and risk exposure. Lastly, η_{jiA} denotes the idiosyncratic error term specific to the adapted farmer.

The analogous adjusted risk exposure equation for a non-adapted farmer is given

1. For those interested in a more in-depth understanding of this approach, the 'Econometric Models' section in Chapter One offers comprehensive details about the empirical specifications and the methodology employed for this correction. This section provides a thorough explanation of the approach, contributing to a clearer understanding of the econometric strategies underpinning the study.

by :

$$\omega_{jN}^{i} = T_{jN}^{'}\Gamma_{iN} + \lambda_N \sigma_{iN} + \eta_{jiN} \tag{2.8}$$

The term σ_{Ni} signifies the variance of ε_{iN}. With the condition $E(\eta_{jiN}|I_j = 1) = 0$, $\lambda_N = -\frac{\phi(G_j^{'}\pi)}{1-\Phi(G_j^{'}\pi)}$. Using the Full Information Maximum Likelihood (FIML) method, as detailed by Lokshin and Sajaia (2004) and previously introduced in Chapter One, the parameters for Equations (2.4), (2.7), and (2.8) are estimated concurrently. The FIML approach maximizes the likelihood function by considering the product of the density functions across all observations, as well as the correlations between error terms. Under the assumption that the error terms are normally distributed and possess a joint covariance structure, the estimator is both consistent and efficient. The associated logarithmic likelihood function is as follows :

$$\begin{aligned} \ln L_i = \quad & \textstyle\sum_j^M \{ I_j [\ln\Phi(\frac{G_j^{'}\pi + \rho_{i\xi A}\frac{\varepsilon_{jiA}}{\sigma_{iA}}}{\sqrt{1-\rho_{i\xi A}^2}}) - \ln\sigma_{iA} + \ln(\phi(\frac{\varepsilon_{jiA}}{\sigma_{iA}}))] + (1 - I_j)[\\ & \ln(1 - \Phi(\frac{G_j^{'}\pi + \rho_{i\xi N}\frac{\varepsilon_{jiN}}{\sigma_{iN}}}{\sqrt{1-\rho_{i\xi N}^2}})) - \ln\sigma_{iN} + \ln(\phi(\frac{\varepsilon_{jiN}}{\sigma_{iN}}))]\} \end{aligned} \tag{2.9}$$

Where $i = 2, 3, 4$; $\rho_{A\xi i}$ represents the correlation coefficient between ε_{iA} and ξ; $\rho_{\xi iN}$ is the correlation coefficient between ε_{iN} and ξ.

For an individual characterized by the vector T_{jA} who has chosen to adapt to climate change, the expected value of the outcome ω_{jA}^{i} can be calculated using the following equation :

$$E(\omega_{jA}^{i}|Ij = 1) = T_{jA}^{'}\Gamma_{iA} + \sigma_{iA}\lambda_A \tag{2.10}$$

In the counterfactual scenario, where a farmer who has otherwise adapted to climate change chooses not to adapt, the expected value of ω_{jA}^{i} is characterized by a different equation. This scenario is essential for understanding the potential impacts of not adapting and provides a comparison against the actual adaptation scenario. The expected value in this counterfactual situation is given by :

$$E(\omega_{jA}^{i}|I_j = 0) = T_{jA}^{'}\Gamma_{iN} + \sigma_{iA}\lambda_N \tag{2.11}$$

The reduction in climate risks due to adaptation is represented by Δ_j :

$$\begin{aligned}\Delta_{ji} &= E(\omega^i_{jA}|I_j = 1) - E(\omega^i_{jA}|I_j = 0)\\ &= [T'_{jA}\Gamma_{iA} + \sigma_{iA}\lambda_A] - [T'_{jA}\Gamma_{iN} + \sigma_{iA}\lambda_N]\\ &= T'_{jA}(\Gamma_{iA} - \Gamma_{iN}) + (\lambda_A - \lambda_N)\sigma_{iA}\end{aligned} \tag{2.12}$$

4 DATA

This investigation extends the data exploration initiated in Chapter One, utilizing a dataset encompassing 5,091 farmers from four African nations. These farmers are primarily engaged in the cultivation of six crop varieties. Within this cohort, 1,811 individuals have implemented adaptive practices to cope with changing climate conditions. These individuals are henceforth referred to as 'adapters.' Conversely, the remaining 3,280 farmers have not undertaken such measures.

Table 2.1 presents comprehensive descriptive statistics for the variables incorporated in the analysis. Notably, adapters—those who have adopted climate-adaptive measures—exhibit an average of the variance of yield distribution of 0.29, considerably lower than the average of .76 observed for non-adapters. This significant difference of -0.47 suggests that adopting adaptive measures may contribute to a more stable yield among farmers. Additionally, the skewness of yield distribution differs markedly between the two groups : adapters have an average skewness of 0.88, indicative of a distribution with fewer low-yield outliers, while non-adapters have a negative skewness of -0.54, revealing a tendency towards unexpected low yields as outlined by Chavas (2004). Moreover, the kurtosis of yield distribution for adapters averages at 2.68, in contrast to the significantly higher kurtosis of 6.60 for non-adapters, resulting in a substantial disparity of -3.92, meaning that non-adapters experience more extreme yield variations, both high and low, which can indicate higher production risk.

Table 2.1 –
Descriptive statistics of the factors determining exposure to climate risks

	Total sample		Adapters		Non-adapters	
variable name	mean	SD	mean	SD	mean	SD
Adaptation	0.435		1		0	
Variance of yield distribution	.48	8.9	.29	.61	.76	6.87
Skewness of yield distribution	.17	.02	.88	.02	-.54	.02
Kurtosis of yield distribution	4.49	8.54	2.68	9.91	6.60	10.07
sample size	5,091		1,811		3,280	

Notes : Awé, 2024. The sample size references the total number of plots. The final dataset includes data from 5,091 agricultural households. All data presented are sourced from the household dataset. SD stands for Standard Deviation.

Continuing with the methodological approach established in Chapter One, I utilize an endogenous switching regression model in conjunction with the full information maximum likelihood (FIML) method to control for potential endogeneity biases. As in Chapter One, the analysis clusters standard errors at the district level to account for intra-district correlation, thus yielding more robust estimates of standard errors.

5 FINDINGS

Table 2.2 displays the estimates derived from endogenous switching regression models for Equations (2.5) and (2.6), which examine the relationship between the distribution of moments of agricultural yields and the binary adaptation variable. These findings utilize the same dataset and variables in Chapter One of the thesis. The table features six columns—Columns 1 through 6—all reporting the Full Information Maximum Likelihood (FIML) results. These FIML results are divided to show the effects on skewness (M_3), variance (M_2), and kurtosis (M_4), with separate subsections for adapted and non-adapted farms.

5.1 Determinants of production uncertainty for adapters and non-adapters

The FIML estimates reveal that climate variables have distinct effects on the risk exposure (M_3) of adapted and non-adapted farmers.[2] Beneficial impacts on yield skewness for adapted farmers (positive coefficients imply less downside risk) are associated with fall and spring temperatures, fall solar radiation, and evaporation levels. Labor and

2. The outcomes regarding yields' kurtosis and variance are consistent with the yield skewness results. Due to their similar nature, further discussion of these results is omitted here. For these results refer to columns (3) to (6) in Table 2.2

fertilizers significantly enhance yield skewness for both adapted and non-adapted farmers, suggesting that increased labor and fertilizer use can reduce the likelihood of unpredictably low yields. The correlation between labor and yield skewness also likely point to an endogeneity concern around labor, as noted by Fafchamps (1993). Pesticide powder has a positive and significant effect on the yield skewness for non-adapted farmers but is less impactful for adapted farmers.

Conversely, seed application does not significantly affect either group, exhibiting that both adapted and non-adapted farmers might benefit from more strategic seed distribution across their plots. Additionally, the impact of seeds on yield skewness could be contingent on their interaction with fertilizers. The interplay between seed quality and fertilizer effectiveness is a crucial determinant in the asymmetry of yield distribution, which affects the potential for above-average agricultural outputs. For both groups, applying fertilizers and liquid pesticides enhances yield skewness, suggesting that these inputs effectively manage production risks.

The coefficient for the literacy variable is positive and significant, suggesting that farmers with better education are more effectively equipped to mitigate their vulnerability to risks of decreased yields. For non-adapted farmers, the non-farm activity variable is also positive and statistically significant, implying that income from such activities could be used to invest in agricultural inputs, thus reducing their vulnerability to lower yield risks. However, this variable does not have a significant effect on adapted farmers. Membership in a farmers' association and access to extension services both have a positive and significant impact on yield skewness for both adapted and non-adapted farmers. The variable representing the number of household relatives exerts a positive and significant effect on adapted farmers. However, it does not significantly influence non-adapted farmers, highlighting that adapted farmers, with more supportive household relatives, have a greater capacity to cope with and manage their exposure to climate risks than non-adapted farmers.

Delving into farm (or plot-level) attributes, it is clear that they have a significant influence on yield skewness. In particular, the irrigation variable shows a positive and significant impact on the yield skewness for both categories of farmers. This finding aligns with numerous studies in the existing literature, which highlight irrigation as a critical determinant of crop growth and, consequently, a factor in reducing yield skewness (Field et al., 2012). In contrast, temperature, rainfall, and solar radiation during the winter and summer harm yield skewness (see Table A.3). For non-adapted farmers, spring temperature is the only significant climatic factor affecting yield skewness. Moreover, the relationships between climate variables and yield skewness exhibit non-linearity, indicating that climate variables affect yield skewness across different seasons.

Table 2.2 –
Adaptation decisions and farmer's exposure to climate risks

Dependent Variables : Variance, Skewness, and Kurtosis of Yield Distribution						
	Skewness (M_3)		Variance (M_2)		Kurtosis (M_4)	
	Adapters	Non-adapters	Adapters	Non-adapters	Adapters	Non-adapters
	(1)	(2)	(3)	(4)	(5)	(6)
labor	.02*** (.00)	.01***	−.01*** (.00)	.01*** (.00)	−.01*** (.00)	.00 (.00)
labor sqr	-.00 (.00)	-.00 (.00)	.02*** (.00)	−.01*** (.00)	.00*** (.00)	-.00 (.00)
inorganic fertilizer	.21** (.00)	.01** (.00)	.00 (.00)	.02*** (.00)	.01* (.00)	.01** (.00)
inorganic fertilizer sqr	-.00 (.00)	−.01** (.00)	-.00 (.00)	-.00 (.00)	−.00** (.00)	-.00 (.00)
organic fertilizer	.04* (.00)	.01* (.00)	.00 (.00)	.00 (.00)	.00 (.00)	.00 (.00)
organic fertilizer sqr	-.00 (.00)	-.00 (.00)	-.00 (.00)	−.01* (.00)	-.00 (.00)	-.00 (.00)
pesticide powder	-.00 (.00)	.01** (.00)	.01* (.00)	.00 (.00)	.01 (.01)	-.01 (.01)
pesticide powder sqr	-.00 (.00)	-.00 (.00)	−.00* (.00)	-.00 (.00)	-.00 (.00)	.00 (.00)
pesticide liquid	-.01 (.01)	-.00 (.00)	-.00 (.00)	-.00 (.00)	-.01 (.00)	-.02 (.01)
pesticide liquid sqr	.00 (.00)	.00 (.00)	.00 (.00)	.00 (.00)	.00	.00 (.00)
seed	.01 (.01)	-.00 (.00)	−.01** (.00)	-.00 (.00)	-.01 (.01)	-.01 (.01)
seed sqr	−.01** (.00)	-.00 (.00)	.00 (.00)	.00 (.00)	-.00 (.00)	-.00 (.00)
literacy	.26** (.12)	.02** (.00)	-.02 (.05)	.13***(.05)	-.45 (.40)	.18 (.18)
male	.06 (.09)	.37** (.17)	.22*** (.07)	.02 (.04)	.78* (.45)	.10 (.19)
age	.00 (.00)	.00 (.00)	.00 (.00)	-.00 (.00)	.01 (.01)	-.01 (.01)
household size	.21*** (.05)	.03*** (.00)	-.01 (.01)	.08*** (.02)	.02 (.11)	.28** (.11)
relatives	.22*** (.05)	.06 (.05)	.01 (.01)	−.08*** (.02)	.09 (.10)	−.285*** (.11)
access to credit	.45*** (.09)	.15 (.21)	.12 (.08)	-.02 (.04)	-.08 (.58)	-.14 (.17)
nonfarm job	2.71 (1.90)	4.80** (1.62)	.02 (.05)	.00 (.03)	-.42 (.47)	.20 (.27)
drought experience	-.14 (.12)	.19 (.15)	.07 (.05)	-.08 (.05)	.34 (.65)	−.49* (.25)
flood experience	-.22 (.15)	.61 (.37)	.09 (.14)	.13 (.09)	1.59** (.92)	.14 (.29)
pests experience	.39** (.15)	.24 (.20)	-.05 (.06)	.08 (.07)	.26 (.60)	.32 (.27)
severe wind exp	-.11 (.10)	.27 (.17)	.18** (.08)	−.13** (.06)	-.05 (.56)	-.26 (.18)
hail storms exp	.28 (.45)	.06 (.37)	.12 (.21)	.08 (.16)	.19 (.79)	.52 (.59)
riverine flood exp	-.43 (.28)	.44 (.63)	.33* (.18)	-.13 (.11)	2.97* (1.76)	-.54 (.39)
landslides experience	-.07 (.34)	-.68 (.50)	-.22 (.27)	-.13 (.25)	-1.29 (1.31)	−2.29* (1.24)
maize	.04 (.10)	.51** (.23)	.05 (.08)	.18*** (.06)	2.04*** (.77)	.18 (.22)
rice	-.16 (.27)	.46 (.47)	.19 (.15)	-.09 (.10)	1.9 (1.24)	.03 (.34)
sorghum	-.07 (.17)	.46** (.24)	.06 (.07)	-.04 (.06)	1.17 (.81)	-.37 (.27)
millet	.20 (.22)	.62** (.26)	-.02 (.09)	.07 (.08)	2.01** (.80)	-.19 (.24)
finger millet	.85** (.34)	.22 (.24)	-.09 (.10)	.06 (.15)	.08 (.68)	−.88* (.48)
cassava	.17 (.13)	.68 (.50)	.18 (.21)	-.20 (.12)	.81 (1.08)	.18 (.25)
beans	-.18 (.11)	-.32 (.46)	-.19 (.19)	-.06 (.05)	-.10 (.99)	-.05 (.20)
mean labor	.01** (.00)	.02** (.00)	.00** (.00)	.00 (.00)	.00 (.00)	.00 (.00)
mean inorganic fertilizer	-.00 (.00)	.00 (.00)	-.00 (.00)	.00*** (.00)	.00 (.00)	.00 (.00)
mean organic fertilizer	.09*** (.00)	.10** (.01)	.00 (.00)	.00** (.00)	-.00 (.00)	-.00 (.00)
mean pesticide liquid	.08*** (.02)	.01*** (.00)	-.00 (.00)	-.00 (.00)	.00 (.00)	-.00 (.00)
mean seed	.00 (.00)	.01* (.00)	-.00 (.00)	.00 (.00)	-.00 (.00)	.00 (.00)
machinery	-.01 (.28)	.38** (.18)	.05 (.07)	-.05 (.12)	-.76 (.99)	-.34 (.44)
computer	.08 (.09)	-.71 (.52)	-.171 (.23)	.09 (.09)	-1.46 (1.15)	-.24 (.20)
irrigation	.89** (.36)	.50*** (.17)	-.23 (.21)	.23*** (.13)	-.38 (1.04)	.28 (.55)
latitude	−.33** (.15)	.13 (.30)	.28*** (.12)	.29*** (.07)	1.29 (.96)	.09 (.36)
altitude	-.00 (.00)	.00 (.00)	.00 (.00)	−.01*** (.00)	.01* (.00)	-.00 (.00)
acces extension	6.77*** (2.11)	2.65** (.63)	.16** (.07)	.06 (.05)	.27 (.60)	-.37 (.26)
farmer organization	.16*** (.03)	.14* (.04)	-.11 (.09)	-.07 (.13)	-.40 (.94)	.18 (.25)
σ_j	1.28*** (.13)	2.32*** (.16)	−.79*** (.04)	−.56*** (.04)	−7.88*** (.79)	−2.71*** (.52)
ρ_j	.12*** (.01)	.02 (.03)	-.09 (.04)	-.01 (.04)	.68*** (.07)	.06 (.13)
LR test of indep. eqns.	$chi2(2) = 23.56^{***}$ $pvalue = 0.00$	$Prob > chi2 = 0.00$	$chi2(2) = 53.95^{***}$ $pvalue = 0.00$	$Prob > chi2 = 0.00$	$chi2(2) = 67.26^{***}$ $pvalue = 0.00$	$Prob > chi2 = 0.00$
Number obs.	1,811	3,280	1,811	3,280	1,811	3,280

Notes : Awé, 2024. Robust standard errors are clustered at the district level and are presented in parentheses. Columns (1), (3), and (5) report the estimates of the endogenous switching regression, derived from Equation (2.5) for adapters. Meanwhile, Columns (2), (4), and (6) report estimates derived from equation (2.6) for non-adapters, with errors also clustered at the district level. The term σ_j signifies the square root of the variance of the error terms μ_{jj} in the outcome equations (2.5) and (2.6). Meanwhile, ρ_j represents the correlation coefficient between the error term η_i in the selection equation (2.4) and the error term ϵ_{ji} in the respective outcome equations. The symbols $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2 Effects of adaptation on production uncertainty : ATT estimates

Table 2.3 displays the average treatment effects on the treated (ATT) of climate change adaptation strategies, specifically examining their impact on the variance, skewness, and kurtosis of agricultural yields, which are key indicators of production uncertainty. This comprehensive analysis includes both aggregated and individual country-level data from Burkina Faso, Sao Tome and Principe, Sierra Leone, and Uganda. The table is structured into three columns. Notably, columns (1), (2), and (3) provide detailed insights into the ATT for the moments M_2 (variance), M_3 (skewness), and M_4 (kurtosis) respectively, thereby offering a deeper understanding of the diverse impacts on agricultural yield distribution.

Overall, implementing adaptation strategies significantly increases yield skewness (M_3) by 2.8 units. This shift signifies a notable decrease in downside risk exposure for adapters, thus lowering the probability of crop failure. Consequently, farmers who adopt climate change adaptation practices have agricultural yields that are less vulnerable to climatic risks. This positive change in skewness is consistent with the effects observed on other central moments of the distribution. In particular, adopting these strategies is linked to a reduction in the estimated variance of yield distribution (M_2) by 1.2 units. Similarly, adapting to climate change measures generates a 1.5 unit decline in the kurtosis of yield distribution (M_4). These results demonstrate that adaptation to climate change significantly reduces the likelihood of crop failure.

In Burkina Faso, adopting climate adaptation measures is associated with a significant 2.6-unit increase in yield skewness. Similarly, implementing climate change adaptation strategies leads to a notable decrease in yield distribution variance by 1.1 units. Additionally, adapting to climate change corresponds to a 1.5-unit reduction in the kurtosis of yield distribution. These findings suggest that the yields of adapters in Burkina Faso are more resilient to climatic risks, as they exhibit lower variability and are less prone to extreme deviations.

In Sao Tome and Principe, the adaptation to climate change exhibits a marginal increase in the skewness of yield distribution of 0.04 units. This figure, however, lacks statistical significance, which aligns with the results for yield kurtosis, which also shows an insignificant downward shift. However, a contrasting significant decrease in the variance of yield distribution by 2.11. The impacts of climate change adaptation on production uncertainty in Sao Tome and Principe present a complex picture, indicating that while certain aspects of production uncertainty are markedly improved, others remain largely unaffected. These nuanced findings underscore the necessity for a more comprehensive analysis to understand the full scope of adaptation benefits in this context.

Table 2.3 –
Effects of climate change adaptation on agricultural yield risk exposure

	Average Treatment Effects on the Treated (ATT)		
Country	M_2	M_3	M_4
	(1)	(2)	(3)
Burkina Faso	-1.1^{***} (.01)		
		2.56^{***} (.02)	
			-1.53^{***} (.05)
Sao Tome and Principe	-1.91^{***} (.03)		
		.04 (.09)	
			-.10 (.11)
Sierra Leone	-1.88^{***} (.21)		
		2^{***} (.16)	
			-5.44^{***} (.83)
Uganda	-1.14^{***} (.03)		
		4.42^{***} (.04)	
			-2.50^{***} (.12)
All countries	-1.21^{***} (.02)		
		2.79^{***} (.15)	
			-1.50^{***} (.05)

Notes : Awé, 2024. Columns (1), (2), and (3) detail the average treatment effects (ATT) of adaptation strategies on production uncertainty, quantified by the moments M_2, M_3, and M_4, corresponding to variance, skewness, and kurtosis of yield distribution, respectively. The symbols $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively, providing a clear indication of the robustness of the findings.

In Sierra Leone, the implementation of climate adaptation strategies has led to a significant two-unit increase in the skewness of yield distribution. Additionally, these measures have decreased the variance in yield distribution by 1.9 units. Moreover, the integration of such strategies has resulted in a substantial 5.4-units reduction in the kurtosis of yield distribution. Overall, these findings highlight the pivotal role of climate adaptation strategies in enhancing the resilience of agricultural production against climate variability in Sierra Leone.

In Uganda, the adoption of climate adaptation strategies is significantly correlated with a 4.4-unit increase in the skewness of yield distribution, indicating enhanced resilience to climatic disruptions among adapters. Furthermore, these strategies have resulted in a 1.14-unit reduction in the variance of yield distribution. Additionally, a notable 2.5-unit decrease in yield kurtosis has been observed. Collectively, these findings underscore the efficacy of adaptation strategies in fortifying the resilience of agricultural production against climate-related challenges in Uganda.

Overall, Table 2.3 provides a comprehensive overview of the substantial decrease in exposure to crop failure due to climate change adaptation measures across various countries. These measures have significantly enhanced the stability of yield distribution by increasing its skewness while simultaneously reducing its variance and kurtosis. Consequently, adapters experience more robust yields against climate risks. The impact of these measures, however, varies from country to country. Notably, there is pronounced success in Uganda and Burkina Faso, a more moderate effect in Sao Tome and Principe, and mixed outcomes in Sierra Leone.

6 CONCLUSION

This study investigates the effects of adopting climate change adaptation measures on the vulnerability of agricultural yields to climate uncertainties. Utilizing endogenous switching regression with Full Information Maximum Likelihood estimates, the research consistently demonstrates that farmers who have adapted to climate change are more effectively equipped to handle climate risks. This benefit is reflected in a lower probability of unfavorable variations in their agricultural yields. This significant observation is consistent across three key indicators of climate risk : the variance, skewness, and kurtosis of yield distribution. Therefore, the study offers crucial empirical evidence on the efficacy of climate change adaptation strategies in diminishing uncertainties in agricultural yields, with a specific focus on these three statistical metrics for evaluation.

Furthermore, the research sheds light on the varying responses to adaptation measures in different countries, underscoring the significance of local context in shaping these outcomes. The heterogeneous effects observed in Sao Tome and Principe, Uganda and Burkina Faso, as well as the mixed results in Sierra Leone, highlight the necessity for climate change adaptation strategies that are specifically tailored to the unique conditions and challenges of each country.

Despite the methodological rigor of this study, potential criticisms may arise regarding the use of endogenous switching regression models and the validity of the instruments used. Such concerns are acknowledged even in light of the theoretical justifications and falsification tests employed for exclusion restrictions. While these models and instruments are effective in addressing endogeneity and selection bias, their validity hinges on the correct model specification and the robustness of the instruments.

Looking ahead, future research should endeavor to develop more comprehensive indicators that capture the interactions among various climate variables. The current study's approach of examining each climate variable in isolation might not fully reveal their collective impact on agricultural yields. For instance, the combined effects of drought, high temperatures, or irregular rainfall patterns may have a different impact on agricultural yields than when these factors are considered individually. Such an approach would offer a more holistic understanding of the complex and multifaceted nature of climate change impacts on agriculture.

AVANT-PROPOS (ARTICLE 3) : ENVIRONMENTAL BENEFITS OF ADAPTATION TO CLIMATE CHANGE : COMBINING REVEALED AND STATED PREFERENCE APPROACHES

L'article 3, dont le titre est "Environmental benefits of adaptation to climate change : combining revealed and stated preference approaches", a été rédigé par l'étudiant en tenant compte des commentaires, suggestions et relectures de son directeur (Christopher Ksoll) et de la professeure Jie He. Il sera soumis dans la revue Journal of Environmental Economics and Management.

ARTICLE 3

ENVIRONMENTAL BENEFITS OF ADAPTATION TO CLIMATE CHANGE : COMBINING REVEALED AND STATED PREFERENCE APPROACHES

1 INTRODUCTION

This research combines Revealed Preference (RP) and Stated Preference (SP) methodologies to assess the potential economic benefits of enacting seven climate change adaptation strategies for open-water fishing at Lake Saint-Pierre in Quebec. These strategies include : the revitalization of riparian zones ; adaptation of agricultural practices in areas vulnerable to flooding ; improvement of municipal wastewater treatment efficiency ; safeguarding and rejuvenation of endangered species habitats ; a prohibition on future dredging activities ; the launch of public education and awareness initiatives ; and more rigorous enforcement of existing laws and regulations.

In this study, I combine RP and SP data within a cohesive econometric model, leveraging the unique strengths of each data type (Louviere et al., 2000). This approach provides a thorough assessment of the economic benefits arising from implementing seven climate adaptation strategies. Specifically, the methodology merges real decision-making data up to 2015 (henceforth RP data) with choices in hypothetical situations (henceforth SP data). RP data, sourced from actual decisions in real-world situations, is valued for its authenticity. However, its dependence on past events may reduce its relevance for new initiatives Train (2009). In contrast, SP data captures individuals' expressed willingness to support new projects, making it a widely used tool for valuing non-market goods and services or those not yet realized. This feature is particularly useful for flexible policy analysis and future planning. Nevertheless, it's important to acknowledge the potential for hypothetical bias within SP data (List et al., 2006). This bias arises from the possible differences between what individuals claim they would do in hypothetical scenarios and their actions in real-life situations. The integration of RP and SP data presents a balanced methodology, capitalizing on the merits of both data types while mitigating their respective drawbacks. This method effectively resolves issues such as observable and unobservable preference heterogeneity, multicollinearity, endogeneity, and the confines of small choice sets associated with RP techniques while simultaneously countering the hypothetical bias observed in SP methods (List et al., 2006; Taylor et al., 2010). Combining RP and SP approaches is an effective method to mitigate hypothetical bias, primarily because it integrates actual behavior data with hypothetical scenarios.

In conducting this research, I utilize two distinct datasets. The primary dataset includes information on the most recent fishing trips of 212 recreational fishermen, detailing which of the six fishing sites at Lake Saint-Pierre was visited, along with their responses to a series of choice experiment questions (stated preference, or SP, data). While comprehensive, this dataset lacks information necessary to measure five key site attributes : catch rate per hour, size of the fish caught, quality of fish habitats, ease of site access, and the level of fisherman traffic. To address these missing attributes, I incorporated a secondary dataset comprising 515 records from Lake Saint-Pierre patrol activities, which also contribute to the RP data. This supplemental data allowed for the calculation of average values for the aforementioned attributes across six fishing sites for the year 2015. However, it is important to note that merging these two datasets at an individual level is not feasible due to the anonymity of the fishers in the patrol records.

This research advances the RP/SP method initially devised by Von Haefen and Phaneuf (2008), introducing a novel aspect : allowing the ratio scales of RP and SP data to differ across various fishing site attributes. This modification diverges from the constant ratio scale employed in the prior study by Von Haefen and Phaneuf (2008), improving the model's accuracy and accounting for potential learning and fatigue effects among participants. To the best of my knowledge, my study is the first to merge RP and SP methodologies for examining the site preferences of open-water anglers and the economic impact of these preferences within the context of climate change adaptation strategies.

The results of this study suggest significant economic benefits from implementing the proposed seven adaptation strategies at Lake Saint-Pierre. The estimated annual advantage for open-water fishing activities is approximately \$9.62 million, culminating in \$216.27 million from 2015 to 2064.

Methodological comparisons between RP and SP data, conducted through statistical tests on similar parameters, indicate notable differences. These discrepancies suggest variations in fishers' decision-making in actual versus hypothetical scenarios. This echoes the findings of Von Haefen and Phaneuf (2008) while offering a contrast to List et al. (2006).

Using the same dataset as He et al. (2016), this study further extends their research, which separately utilized RP methods, such as the travel cost method, and SP methods, including contingent valuation and choice experiments, to assess the socio-economic benefits of ice fishing at Lake Saint-Pierre for the same adaptation strategies. Their research projected annual costs of these strategies to range from $348 million to $1.01 billion, while estimating the benefits for ice fishing between $1.23 billion and $3.27 billion per year. By integrating my findings with those of He et al. (2016), it becomes evident that the combined annual benefits for both ice and open-water fishing significantly outweigh the implementation costs, with estimates roughly ranging from $1.24 billion to $3.28 billion.

The organization of this paper is as follows : Section 2 provides an overview of the background, detailing the benefits and constraints associated with the RP, SP, and the combined RP/SP methodologies. Section 3 outlines the data sources utilized in this study. Section 4 discusses the identification process and the econometric models applied to both RP and SP . Section 5 is dedicated to presenting the findings of the study. In Section 6, we delve deeper into the implications of employing a combined RP/SP approach, along with associated policy recommendations. Finally, Section 7 offers concluding remarks.

2 BACKGROUND

In this section, I delineate the advantages and limitations of both the RP and SP approaches individually. Additionally, I explore the benefits and challenges associated with integrating these two methodologies into a combined RP and SP approach.

2.1 RP approach

Revealed Preference method is a method used to analyze individuals' choices based on their observable behaviour. It is a valuable tool in economics, especially in consumer behaviour and welfare economics.

2.1.1 Advantages

Revealed Preference data derived from the actual choices individuals make in real-world settings, often hold an edge in reliability and accuracy over hypothetical scenarios. They capture individuals' genuine trade-offs when confronted with actual costs (Train, 2009).

Moreover, because RP data capture decisions made in reality, they avoid the hypothetical bias that can occur with stated preference methods, where individuals might declare a specific behavior in a hypothetical situation but act differently when faced with the actual decision (Hausman, 2012). For policy impact analysis, RP data are paramount. They provide insights into individuals' responses to past policy changes like those being analyzed (McFadden, 2001). RP data, often sourced from market transactions, encapsulate the influence of market forces and their constraints on individual decisions (Bockstael and McConnell, 2007).

2.1.2 Limitations

While RP methods offer valuable insights, they are not without their limitations. RP techniques are inherently linked to existing market transactions, which narrows their applicability to goods and services currently available and traded in the market. Consequently, they are less suitable for evaluating non-market goods or services or those not yet in existence (Bockstael and McConnell, 2007). Since RP methods depend on observed behavior under current market and policy conditions, they may struggle to accurately predict behavior when those circumstances change (Train, 2009).

Data collection presents another hurdle; gathering data on actual behavior can take time and effort. RP often relies on data concerning prices and income, which may only sometimes be readily available or accurate (Hausman, 2012). Furthermore, RP methods assume that individuals' choices accurately reflect their preferences. However, various external factors, such as marketing campaigns or social pressures, can influence these choices and may distort the accurate representation of their preferences (McFadden, 2001).

2.2 SP approach

Stated Preference (SP) methods are survey-based techniques used to elicit individuals' preferences by asking them to articulate their choices in hypothetical situations.

2.2.1 Advantages

Stated Preference (SP) methods present several advantages, making them a versatile tool for diverse applications. A standout benefit is their adaptability : they can estimate the value of non-market goods and services, including those not yet in existence, rendering them especially pertinent for policy analysis and planning (Bateman et al., 2002). SP methods adeptly capture non-use values — for instance, the importance individuals place on conserving a species or a natural region for future generations. Since these values do not manifest in market transactions, RP approaches cannot capture them (Carson, 2000). Additionally, SP methods give researchers the autonomy to structure the hypothetical scenarios in surveys, isolating the impacts of distinct elements on individuals' decisions and leading to a deeper understanding of decision-making dynamics (Louviere et al., 2000). Lastly, SP procedures are instrumental in simulating the impacts of policies before their actual implementation, providing invaluable insights for policymakers (Adamowicz et al., 1994).

2.2.2 Limitations

Although SP methods bring many benefits, they have limitations. A primary concern is hypothetical bias, as SP methods rely on hypothetical scenarios. There can be a discrepancy between what individuals say they would do in a simulated setting and their actual behavior when faced with the situation (Hausman, 2012). Another issue is strategic bias, where participants may overstate or understate their willingness to pay if they believe their response could influence policy or the provision of the proposed good or service (Carson, 2000).

Designing and conducting SP surveys also presents challenges. These include creating realistic hypothetical scenarios, choosing an elicitation format, and phrasing questions—all of which can significantly influence responses (Bateman et al., 2002). Finally, there is the potential for information bias : if participants lack sufficient knowledge or understanding of the good or service in question, the validity of their responses may be compromised. When respondents face unfamiliar hypothetical situations, their feedback may not accurately reflect their preferences (Louviere et al., 2000).

2.3 Combining RP and SP approaches

Combining RP with SP approaches entails integrating both methodologies within a single study framework. This synergy is designed to capitalize on the strengths of each method, providing a more comprehensive understanding of individuals' preferences and behaviors.

2.3.1 Advantages

Combining RP and SP methods provides a comprehensive valuation approach, capturing a wide range of values. RP techniques are robust in assessing goods and services with a current market presence and available historical data. At the same time, SP methods are adept at valuing non-market commodities and those not yet available (Louviere et al., 2000). Combining RP with SP offers a strategic remedy for the biases inherent to each approach. SP methods may be prone to hypothetical bias. In contrast, RP's reliance on historical data may only partially capture changing preferences or behaviors.

This integration allows researchers to leverage the advantages of both, mitigating their respective limitations (Hensher, 2010). The amalgamation of RP and SP data enhances the predictive accuracy of models. This hybrid dataset provides a more nuanced representation of individuals' preferences and behaviors (Adamowicz et al., 1994). The merger of RP and SP data strengthens the reliability of policy simulations. While RP data provide insights based on historical trends and past policy changes, SP data allow exploring potential policy impacts at the proposal stage (Train, 2009).

2.3.2 Challenges

While offering a comprehensive perspective on individual behaviors and preferences, uniting RP and SP methodologies does present specific challenges. A primary concern is data compatibility. Since RP and SP data originate from different contexts — actual versus hypothetical — they may reflect divergent preferences, such as observed versus reported. This discrepancy requires researchers to ensure methodological consistency, safeguarding the compatibility of data collected from both sources (Hensher, 2010).

The integration of these methods also adds complexity to modelling. Combining RP and SP data calls for advanced econometric models that appropriately handle both data types. These models are complex in construction and estimation and require substantial statistical expertise (Train, 2009). Designing surveys to gather both RP and SP data poses unique challenges. Researchers must create SP hypothetical scenarios that are realistic and comprehensible while simultaneously obtaining accurate behavioral data for the RP aspect (Louviere et al., 2000). Although merging RP and SP can mitigate biases inherent to each method, it does not completely eliminate them. Researchers must proceed with caution when interpreting results, always considering potential biases that may color their findings (Adamowicz et al., 1994).

3 DATA

This study utilizes two primary data sources to analyze the preferences and decision-making of open-water fishermen in Quebec : an in-depth survey and monitoring datasets [1].

3.1 Survey data

At the heart of this research is an in-depth survey conducted with 212 open-water fishermen in Quebec. The survey aims to explore their preferences and decision-making regarding visits to six distinct fishing locations around Lake Saint-Pierre. The survey categorizes various attributes as follows :

- Individual-specific attribute : travel costs to the six distinct fishing site [2] ;
- Site-specific attributes : These include catch rate per hour, length of the fish caught, quality of fish habitats, site accessibility, and the density of fishermen on-site [3].

The survey not only gathers information on recent fishing trips to these locations but also includes responses to a set of choice experiment questions. These questions

1. I extend my gratitude to Professor Jie He for their provision
2. Travel costs encompass all expenditures associated with the fishing trip, such as fuel, bait, and other miscellaneous expenses.
3. Catch rate per hour represents the average number of fish caught within an hour. Fish length, measured in millimetres, acts as an indicator of habitat quality. Site accessibility refers to the time needed to reach a fishing location. Conversely, on-site fisherman density denotes the number of fishermen at a particular site at any given time.

present participants with hypothetical scenarios involving two generic fishing sites and an option to opt out, with attributes reflective of those mentioned above. While the survey is comprehensive, it falls short in directly measuring the site-specific characteristics. To bridge this gap, I have supplemented the survey data with monitoring records from Lake Patrol activities, collected concurrently with the survey. This additional dataset enriches our understanding of the fishing conditions and angler preferences at these sites.

3.2 Monitoring data from fishing patrols

The monitoring dataset encompasses 515 unique entries, each corresponding to a distinct visit by a fisherman to one of the six designated fishing sites around Lake Saint-Pierre. For a detailed visual depiction of these fishing sites, please refer to Figure 3.1.

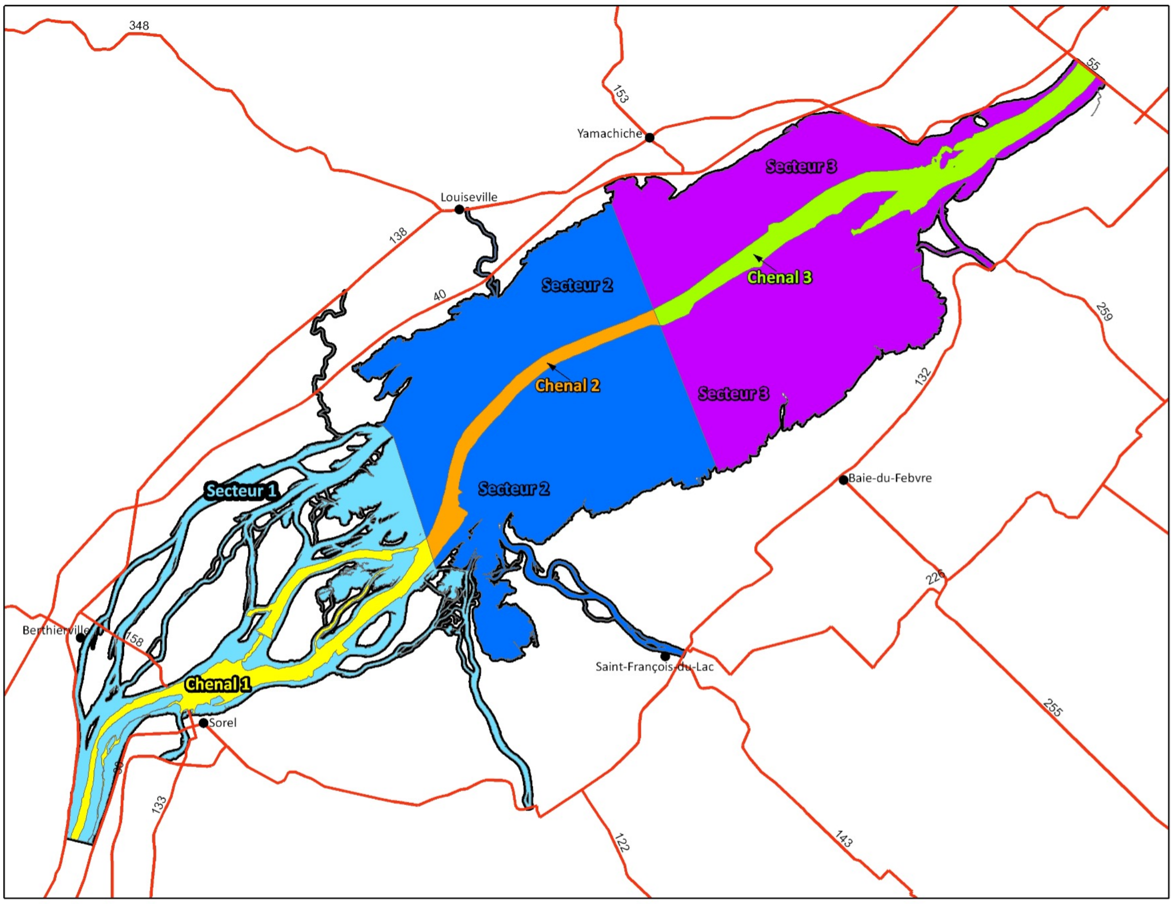

Figure 3.1 – Note : Fishing sites of Lake Saint-Pierre. Figure sourced from the 2015 survey conducted by He et al. (2016).

This dataset is instrumental in providing detailed measurements for several critical site-specific attributes, which include :

— The average catch rate per hour ;

— The typical length of the fish caught ;

— The overall quality of the fish habitats ;

— The accessibility of each fishing site ;

— The density of fishermen present at each site.

However, due to the anonymized nature of the monitoring data, which does not reveal the identities of the fishermen, it is not possible to directly integrate this dataset with the survey data. As such, I utilize the monitoring data to ascertain average values for the five aforementioned site-specific attributes, thereby enhancing the comprehensiveness of the study's findings.

3.3 Descriptive statistics of the factors influencing fishing site choices

Table 3.1 presents descriptive statistics of these two data sources and two types of data (RP and SP). The RP data includes Information from the monitoring records of 515 anonymous fishers, as well as survey data from 212 fishermen regarding their most recent visits to the fishing sites of Lake Saint-Pierre (RP data). The monitoring records capture five site-specific attributes : catch rate per hour, length of fish caught, quality of fishing habitats, site accessibility, and on-site traffic, while the survey data measures the travel costs to these fishing sites. The table also displays descriptive statistics derived from the responses of the 212 fishermen to a series of up to nine choice experiment questions, soliciting hypothetical choices among two generic fishing sites and an 'opt-out' option (SP data). Additionally, the table includes demographic information such as the urban or rural residence status and educational levels of the fishermen, thereby offering a more comprehensive profile of the survey participants.

3.3.1 Recent visit data (RP data)

The monitoring data for 515 anonymous fishers, detailed in column (1) of Table 3.1, yield the following average metrics : a fisherman catches approximately 2.39 fish per hour, with the average fish length being around 416.66 millimeters. The overall catch rate among all fishermen averages about 268.5 fish per hour. The average time to reach a fishing site, a measure known as 'accessibility,' is roughly 138 minutes. In addition, the sites show an average fisherman density of about 2.24 individuals. Meanwhile, survey data (also RP) from 212 fishermen on their most recent trip, as shown in column (2), reveals that the average travel cost for a fishing trip is $477.13.

3.3.2 Hypothetical data (SP data)

The Stated Preference (SP) data, as shown in column (3) of Table 3.1, captures the average values based on hypothetical scenarios presented to the fishermen. In these scenarios, the average travel cost to a fishing site is observed to be higher, at $525.56. Furthermore, the average catch rate per hour is also higher, with an average of 2.98 fish. Fish in these hypothetical scenarios are typically larger, with an average length of 466.92 millimeters. The overall catch quantity per hour shows an increase, averaging at 287.1. This figure may either reflect a combined average across all hypothetical fishing trips or an optimistic perception of fishing success within these scenarios. In terms of accessibility, the average time needed to reach a fishing site is shorter, recorded at 118 minutes. Additionally, the average number of fishermen at these sites is marginally lower, with an average density of 2.1 individuals.

3.3.3 Demographic Information

The survey data from 212 fishermen, presented in column (2), indicates that on average, each fisherman undertakes roughly six fishing excursions annually and typically has around 10 years of fishing experience. Approximately 38% of them reside in urban areas, as reflected by the average of the binary variable for urban residency. Furthermore, the data reveals that about 74% of these fishermen have attained an educational level at least equivalent to a high school diploma, as shown by the mean value of the binary variable for educational background.

Table 3.1 –
Descriptive statistics of the factors influencing fishing site choices

Variable name	RP mean		SP mean
	(1)	(2)	(3)
Site characteristics			
Travel costs per trip		477.13	525.56
		(21.67)	(6.88)
Number of fish caught in one hour	2.39		2.98
	(.54)		(.26)
Length of fish caught (in millimeter)	416.66		466.92
	(.12)		(.89)
Habitat quality (total number of fish caught)	268.45		287.06
	(.85)		(1.52)
Accessibility to fishing sites (minutes)	138		116
	(.001)		(.003)
Traffic (on-site fishermen density)	2.24		2.08
	(.00)		(.01)
Demographic information			
Total trips		5.74	
		(1.22)	
Years of fishing experience		10.37	
		(2.49)	
Urban		.38	
		(.15)	
HS diploma		.74	
		(.27)	
Obs.	515	212	

Notes : Awé, 2024. Table 3.1 displays mean values for Revealed Preferences (RP) and Stated Preferences (SP), summarizing the average characteristics of all fishing sites around Lake Saint-Pierre (LSP). Column (1) lists the averages of five specific site attributes gathered from the monitoring data of 515 anonymous fishers. Column (2) shows the average travel costs per trip and demographic details—such as total trips, years of fishing experience, and binary variables for urban residency ('Urban') and high school diploma attainment ('HS diploma')—as derived from the survey data of 212 fishers. Column (3) consolidates the average responses of these 212 fishermen to choice experiment questions.

4 IDENTIFICATION AND ECONOMETRIC SPECIFICATION WITH RP AND SP DATA

In this section, the analysis utilizes a general discrete choice econometric model to examine the identification challenges associated with RP data, SP data, and the combined RP/SP dataset. This approach is designed to provide a deeper understanding of the nuances and potential complexities inherent in each data type and their combined use.

4.1 Identification and econometric specification with RP data only

In my analysis, I follow a notation system similar to that introduced by Berry (1994), who were trailblazers in tackling the identification issues that are central to my study, particularly in the context of Revealed Preference (RP) applications. The core of my investigation concentrates on scenarios where an individual chooses one of the six fishing sites of Lake Saint-Pierre (LSP) for their most recent fishing trip. This analysis is grounded in the application of travel cost models to understand the dynamics influencing choices of fishing sites. In line with this approach, I define the indirect utility, denoted as U_{kl}, to represent the utility that fisher k derives from choosing fishing site l during his most recent trip. This relationship is articulated in Equation (3.1).

$$U_{kl} = \varphi_{kl}^{RP}\tilde{\delta}_k + y_l^{RP}\tilde{\alpha}_k + \zeta_l + \nu\varepsilon_{kl} \tag{3.1}$$

The indirect utility function U_{kl} in this study is composed of several intricate components. It includes factors that vary both across individuals and fishing sites, such as travel costs represented in the RP data (φ_{kl}^{RP}). Additionally, there is a vector of factors, denoted as y_l^{RP}, which are unique to each fishing site. An alternative-specific constant (ASC), symbolized by ζ_l, is incorporated to account for unobserved attributes of fishing site l. Furthermore, the model includes an unobserved idiosyncratic error term, $\nu\varepsilon_{kl}$, which varies across both fishers and fishing sites and is normalized to facilitate the identification process. To prevent multicollinearity with the ASC, the term ζ_1 is specifically normalized to zero.

Following this, the study introduces two specific equations, represented in Equations (3.2) and (3.3), for $\tilde{\delta}k$ and $\tilde{\alpha}k$, respectively. These equations are crucial as they capture not only the main and interaction effects within the model but also include random effects that are independent of the individual characteristics denoted as x_k.

$$\tilde{\delta}_k = \bar{\delta} + x_k\delta^0 + \psi_k\delta^\psi \tag{3.2}$$

$$\tilde{\alpha}_k = \bar{\alpha} + x_k\alpha^0 + \omega_k\alpha^\omega \tag{3.3}$$

The parameters $(\bar{\delta}, \bar{\alpha})$ in the model are set to capture the primary or average effects, where x_k acts as a vector encompassing specific attributes of interest. On the other hand, the interaction effects, which are crucial for illustrating non-linear relationships between various variables, are represented by the parameter matrices (δ^0, α^0). These interaction effects play a pivotal role as they enable the impact of one variable on the fishing site choice to vary depending on the level of another variable.

Additionally, the model includes normalized random effects, which are independent of x_k and are represented by (ψ_k, ω_k). These random effects are specifically tailored to capture the nuances of the decision-making process that are not directly related to the observed attributes x_k. The specific parameters associated with these random effects are denoted as $(\delta^{\psi}, \alpha^{\omega})$.

To fully articulate the indirect utility function U_{kl}, Equations (3.2) and (3.3) are integrated into Equation (3.1). This integration allows for U_{kl} to be defined as a function of the factors x_k, encompassing both the primary effects and the more complex interaction and random effects, thereby providing a comprehensive and nuanced understanding of the factors influencing the choices of the fishermen.

$$U_{kl} = \varphi_{kl}^{RP}\bar{\delta} + \varphi_{kl}^{RP}x_k\delta^0 + y_l^{RP}x_k\alpha^0 + \gamma_l + \varphi_{kl}^{RP}\psi_k\delta^{\psi} + y_l^{RP}\omega_k\alpha^{\omega} + \nu\varepsilon_{kl} \tag{3.4}$$

and

$$\gamma_l = y_l^{RP}\bar{\alpha} + \zeta_l, \quad 1 = 1, 2, ..., 6 \tag{3.5}$$

Fisher k is inclined to opt for fishing site l when his anticipated utility from this site, denoted as U_{kl}, surpasses the expected utility he associates with any of the other sites within the five sites in Lake Saint-Pierre (LSP). This scenario occurs when the utility U_{kl} from choosing site l is the highest among all available options. Therefore, the probability of a fisher deciding to fish at site l can be articulated as follows :

$$Pr(Z_k = l) = Pr\left(\max U_{k1}, U_{k2}, \ldots, U_{k6} = U_{kl}\right) \tag{3.6}$$

In estimating the likelihood function for fisher k choosing site I, it is assumed that the unobserved error term ε_{kl} adheres to a Type I extreme value distribution and is independently and identically distributed across observations. This assumption is crucial for the model's validity. Additionally, the normalized random effects, denoted as (ψ_k, ω_k), are also presumed to follow a standard normal distribution, maintaining independence and identical distribution throughout the dataset.

Building on these assumptions, the probability of a fisher opting to fish at site l is formulated using a conditional logit model. This model, represented in Equation (3.4), effectively incorporates the specified distributions and assumptions.

$$Pr(Z_k = l) = \frac{exp(U_{kl})}{\sum_{j=1}^{6} exp(U_{kj})} \tag{3.7}$$

and the likelihood function for the fisher k from equation (3.8) is

$$f(k) = \prod_{l=1}^{6} \left[\frac{\exp(U_{kl})}{\sum_{j=1}^{6} \exp(U_{kj})} \right] \tag{3.8}$$

In this study, the method of maximum likelihood is utilized to estimate the coefficients $(\bar{\delta}, \delta^0, \alpha^0, \delta^\psi, \alpha^\omega, \gamma_l)$, which are instrumental in modeling the behavior of the fishers. However, it is important to note that within the framework of revealed preference (RP) data, the parameters $\bar{\alpha}$ and ζ_l cannot be estimated distinctly. Instead, what can be effectively evaluated is the parameter γ_j, which represents a linear combination of $\bar{\alpha}$ and ζ_l.

To estimate the parameter $\bar{\alpha}$ accurately, a regression of the estimated values of γ_l on the observed attributes y_l^{RP} is required. This regression, however, may face several practical challenges, particularly in environmental applications. One such challenge is ensuring that the rank condition is met, which necessitates that none of the observed attributes are linear combinations of other characteristics. Additionally, the number of Alternative-Specific Constants (ASCs)—which should equal the number of sites minus one—must exceed the dimension of y_l^{RP} (Von Haefen and Phaneuf, 2008).

Furthermore, based on prior experiences, it is observed that a significantly larger number of γ_l values, in comparison to the dimension of y_l^{RP}, is necessary for accurate parameter estimation. Another challenge arises when correlations exist between the unobserved site attributes, ζ_l, and the observed attributes y_l^{RP}. In such scenarios, the use of instrumental variables becomes essential. The discrete choice model structure provides a basis for developing instruments for observed attributes that are influenced by social interactions, such as congestion (Bayer et al., 2009). The application of instrumental variables in the second stage of analysis may further necessitate a substantial choice set for accurately estimating structural parameters, especially when the instruments have limited identifying power (Taylor et al., 2006).

These complexities highlight the challenges in achieving identification in environmental applications that rely exclusively on RP data, as pointed out by Von Haefen and

Phaneuf (2008). Theoretically, Stated Preference (SP) data can be used to identify the parameters $\bar{\alpha}$ and ζ_l, offering a potential solution to these challenges.

4.2 Identifying and specifying econometric models with SP data only

Within the context of Stated Preference (SP) data, the representation of indirect utility is articulated as shown in Equation (3.9) :

$$U_{kld} = \varphi_{kld}^{SP}\tilde{\delta}k + y_{kld}^{SP}\tilde{\alpha}k + \nu^{*}\epsilon_{kld} \tag{3.9}$$

Here, k serves as an index representing an individual, l denotes a specific fishing site, and d identifies a particular choice set. The formulation in Equation (3.9) diverges from that in Equation (3.1) in three key respects :

1. In the SP framework, the choices of fishers are driven exclusively by hypothetical attributes (y_{kld}^{SP}), which contrasts with RP data, where choices are influenced by both observed (y_l^{RP}) and unobserved (ζ_l) attributes ;
2. The parameter y_{kld}^{SP} exhibits variability across individuals and fishing sites due to the inherent random assignment and exogenous variation of the experimental design, contrasting with y_l^{RP}, which does not have this variability. The variation in y_{kld}^{SP} facilitates the estimation of all primary and interaction effects in $\tilde{\gamma}k$ and $\tilde{\alpha}k$;
3. The scale parameters ν^{*} and ν may possess different values, which can notably influence the integration of RP and SP data (Swait and Louviere, 1993).

For alternative l to be the selected option, its utility must be higher than the expected utilities of the other alternatives in the same choice set. This means that the utility of l, U_{kld}, should exceed those of U_{k1d}, U_{k2d}, and U_{k3d}. The probabilistic nature of this choice and the comparison of utilities are encapsulated in Equation (3.10) :

$$Pr(Y_{kd} = l) = Pr\left(\max\{U_{k1d}, U_{k2d}, U_{k3d}\} = U_{kld}\right) \tag{3.10}$$

In this analysis, the assumptions made about the error term ε_{kl} in the Revealed Preference (RP) data section also applied to ε_{kld} in the Stated Preference (SP) data. Both error terms are treated as draws from a Type I extreme value distribution and are considered to be independently and identically distributed across observations. Similarly, the normalized random effects, represented by (ψ_k, ω_k), are presumed to follow a standard normal distribution, with the same independent and identical distribution across the dataset.

The decision-making process of fishers, which is influenced by a variety of factors and stochastic elements, is thus characterized by a specific functional form. This form accounts for the complexities and uncertainties inherent in choosing fishing sites, integrating both the predictable and random aspects of the decision-making process :

$$Pr(Z_{kd} = l) = \frac{exp(U_{kld})}{\sum_{j=1}^{3} exp(U_{kld})} \tag{3.11}$$

and

$$f(k) = \prod_{d=1}^{9} \prod_{l=1}^{3} \left[\frac{exp(U_{kld})}{\sum_{j=1}^{3} exp(U_{klj})} \right] \tag{3.12}$$

Equation (3.12) provides a detailed outline of the likelihood function for fisher k. This function accounts for the probabilities of selecting each site l within each choice set d. This formulation operates under the assumption that the normalized random effects, denoted as (ψ_k, ω_k), are independently and identically distributed standard normal variables. This approach contrasts with the Revealed Preference (RP) data, where both observed attributes and potentially correlated unobserved attributes are considered. On the other hand, Stated Preference (SP) data is restricted to only observed characteristics. This key difference highlights the limitation of SP data in terms of unobserved features. Specifically, the unobserved attributes, represented by ζ_l in Equation (3.1), cannot be effectively identified using SP data alone. As a result, without incorporating RP data into the analysis, the ability to fully comprehend and accurately reconstruct the preferences of fishers would be significantly compromised. This underscores the importance of integrating both RP and SP data for a more complete and nuanced understanding of fisher preferences and behaviors.

4.3 Assessing the parameters of common variables in RP and SP data

Recent empirical research indicates that the hypothetical decisions made by experienced individuals tend to closely align with their actual choices in the real world. However, there are noteworthy exceptions, such as a more pronounced inclination towards selecting the 'opt-out' or 'no trip' option in hypothetical scenarios (List et al., 2006; Taylor et al., 2010). This observation suggests that there should be a consistency in the parameters of shared variables between Revealed Preference (RP) and Stated Preference (SP) data. Essentially, this implies a harmonious relationship between revealed and stated preferences among the fishermen. Based on this understanding, the study proposes two principal hypotheses that stem from the apparent alignment between fishermen's hypothetical and actual choices in the context of fishing site selection.

1. $H_0^1 : \varphi_{kl}^{RP}\bar{\delta}RP = \varphi kld^{SP}\bar{\delta}SP \Longleftrightarrow H0^1 : t_{kl} = \frac{\varphi_{kl}^{RP}\bar{\delta}RP}{\varphi kld^{SP}\bar{\delta}_{SP}} = 1$ (1);
2. $H_0^2 : y_l^{RP}x_k\alpha_{RP}^0 = y_{kld}^{SP}x_k\alpha_{SP}^0 \Longleftrightarrow H_0^3 : t_l = \frac{y_l^{RP}x_k\alpha_{RP}^0}{y_{kld}^{SP}x_k\alpha_{SP}^0} = 1$ (2).

In this study, I conduct tests on the hypotheses, labeled as H_0^1 and H_0^2, employing likelihood ratio tests that follow a chi-squared (χ^2) distribution. These tests are specifically focused on the attributes of the fishing sites. The critical metrics in this testing process are the ratios t_{kl} and t_l, which represent the RP/SP scale ratios.

If the values of these ratios, t_{kl} or t_l, exhibit significant deviations from one, it implies a disparity between the factors influencing individuals' real-world decisions (as captured in Revealed Preference, or RP data) and those affecting their stated preferences in hypothetical scenarios (as captured in Stated Preference, or SP data). This potential divergence in influencing factors is crucial as it can provide insights into how real-world choices might differ from those made in hypothetical situations, a concept explored in depth by Von Haefen and Phaneuf (2008). Therefore, the analysis of these ratios is pivotal in understanding the consistency—or lack thereof—between Revealed and Stated Preferences in the context of fishing site selection.

4.4 Synthesis model : Combining RP and SP data

In this subsection, the focus is on leveraging the synergistic potential of Revealed Preference (RP) and Stated Preference (SP) data. By merging RP and SP datasets, precise estimation of all parameters in Equations (3.1) and (3.6) becomes feasible. For example, the parameter $\bar{\alpha}$ is ascertainable through SP data, while the parameter γ_j can be determined using RP data. Once these parameters are estimated, ζ_l, a key variable in the model, can be derived by calculating $\zeta_l = \gamma_j - y_l^{RP}\bar{\alpha}$. This integrative approach ensures a thorough estimation of all model parameters, thereby enriching our understanding of the factors influencing fishers' site selection choices.

It is important to emphasize that the effectiveness of the experimental design used in the Stated Preference (SP) choice experiments, and the subsequent identification in combined Revealed Preference RP/SP data, hinges crucially on the assumption of a shared data-generating process underlying both RP and SP choices (Von Haefen and Phaneuf, 2008). The inherent cross-equation restrictions stemming from this common data-generating process can be modified in certain ways. For instance, we can introduce variations in the RP and SP scale for the idiosyncratic error term, and manage the frequency of choosing the 'opt-out' option in SP choice experiments by adjusting RP/SP scale ratios.

To align the SP parameters within the combined model, I utilize RP/SP scale ratios. These per-attribute scale ratios, t_{kl} and t_l, are essential for recalibrating the SP parameters to be consistent with the RP data. The calculated values of these scale ratios are detailed in Table 3.2. The convergence of RP and SP data is effectively achieved through the implementation of a specific likelihood function, which embodies this integration and enables a comprehensive analysis of fisher preferences and behaviors.

$$l(k) = \prod_{d=1}^{9} \prod_{l=1}^{3} \left[\frac{\exp(t_{kl}\varphi_{kld}^{SP}\tilde{\delta}k + t_l y_{kld}^{SP}\tilde{\alpha}k + \zeta l)}{\sum_{q=1}^{3} \exp(t_{kq}\varphi_{kqd}^{SP}\tilde{\delta}k + tq y_{kqd}^{SP}\tilde{\alpha}k + \zeta q)} \right] \tag{3.13}$$

In the specified likelihood function, $l(k)$ symbolizes the likelihood of a data observation contingent upon the parameters. This function incorporates the term $t_{kl}\varphi_{kld}^{SP}$, which signifies the rescaled SP parameter for the l-th attribute. Concurrently, $t_l y_{kld}^{SP}$ represents the rescaled SP parameter for other observed attributes in the model. The vectors of parameters, $\tilde{\delta}k$ and $\tilde{\alpha}k$, as elucidated in Equations (3.2) and (3.3), are integral to the function. Additionally, ζ_l functions as a dummy variable, representing the fishing site l within the model.

In their research, Von Haefen and Phaneuf (2008) advocate for a constant RP/SP scale ratio. However, they also highlight that accommodating variations in the scale ratio across different SP choice scenarios can significantly enhance the model's accuracy and fit, particularly within a framework that combines Revealed Preference (RP) and SP data. This insight underscores the potential benefits of allowing for such variability in the scale ratio, thereby enabling a more nuanced and accurate representation of preferences and decision-making processes in the combined RP/SP model.

4.5 Estimating the marginal willingness to pay for attribute improvements

Upon completing the estimation of the combined RP/SP model, a significant finding is the calculation of the Marginal Willingness to Pay (MWTP) for a single unit improvement in an attribute, which is represented by $y_{kl}^{RP/SP}$. MWTP is an essential metric in economic analysis, indicating the additional amount an individual is prepared to pay for a marginal improvement in a specific attribute. This metric is especially valuable as it provides insight into how individuals value incremental changes in various attributes.

MWTP is determined by the ratio of the marginal utility of the attribute to the marginal utility of cost. This calculation is important as it reveals the trade-off an individual is willing to make between an improvement in the attribute and the associated cost. It essentially captures the economic value that individuals assign to small enhancements in attributes. The equation to compute MWTP for the attribute $y_{kl}^{RP/SP}$ is as follows :

$$\begin{aligned} MWTPy_{kl}^{RP/SP} &= \frac{\partial U_{kl}^{RP/SP}/\partial y_{kl}^{RP/SP}}{\partial U_{kl}^{RP/SP}/\partial C_{kl}^{RP/SP}} \\ &= -\frac{t_{y_{kl}}(\overline{\alpha}+x_k\alpha^0)}{t_{\varphi_{kl}}\overline{\delta}} \end{aligned} \tag{3.14}$$

This equation allows for a quantitative understanding of the value that individuals place on a unit improvement of a given attribute, providing crucial insights for economic analysis and decision-making. In Equation (3.14), $MWTPy_{kl}^{RP/SP}$ symbolizes the marginal willingness to pay for a unitary improvement in the attribute $y_{kl}^{RP/SP}$. In this context, $U_{kl}^{RP/SP}$ is the conditional indirect utility function denoting the individual's derived utility from the attribute ; $y_{kl}^{RP/SP}$ represents the value of the l-th attribute. The term $C_{kl}^{RP/SP}$ corresponds to the cost linked with the attribute. The symbols t_{kl} and t_l indicate scale ratios obtained from the integrated RP/SP model. Meanwhile, $\overline{\alpha}$ and α^0 are parameters linked to fisher l. The variable x_k represents a vector of demographics, and $\overline{\delta}$ is a parameter associated with the cost.

The negative sign in the equation for $MWTPy_{kl}^{RP/SP}$ (Equation (3.14)) indicates that an increase in cost leads to a decrease in willingness to pay, which aligns with the law of demand. Practically, MWTP is used to quantify the economic value of various goods, services, or attributes, including those that are non-market in nature, such as environmental quality, health improvements, and other intangible benefits. These valuations are crucial for policymakers and businesses as they aid in making informed decisions regarding resource allocation, pricing strategies, and policy interventions.

To transform the conditional choice likelihoods into the unconditional probabilities required for the estimation process, I employ the simulation methods outlined by Train (2009). The parameters in Equations (3.4) and (3.9) are then estimated using the maximum likelihood method. I estimate the Revealed Preferences (RP) and Stated Preferences (SP) models separately before examining whether at least one RP/SP scale ratio equals one. Lastly, I estimate the combined RP/SP model. The results are summarized in Table 3.3 for side-by-side comparison.

5 RESULTS

This section of the study presents a comprehensive analysis of the findings derived from both Revealed Preferences (RP) and Stated Preferences (SP) data, including their integration. Detailed examination of various attributes, interaction effects, and their implications for fishing site selection are discussed. The results provide valuable insights into the factors influencing fishermen's choices and the potential economic impacts of these choices.

5.1 Discussion of the main results from the RP estimation only

In this subsection, I delve into the standalone estimation using RP data only, employing the maximum likelihood method specifically for Equation (3.4). The results from this estimation are presented in column (1) of Table 3.3. Analyzing the RP data offers crucial insights into the determinants influencing the selection of a fishing site. The travel costs estimate is -0.01, statistically significant at the 1% level, indicating that travel costs negatively affect the fishing site choice. Likewise, the forecast for the Number of Fish Catches (NFC) is 5.12, statistically significant at the 1% level, highlighting the vital role that the number of fish catches plays in influencing choices.

Various interaction terms are also statistically significant. For instance, the coefficient for the interaction between NFC and general fishing experience is 0.70, significant at the 1% level. The interaction term for NFC and Urban Residence is valued at 0.91, significant at the 5% level. The interaction between NFC and possession of a High School Diploma is quantified as -1.7, marked at the 1% level. Furthermore, the interaction coefficient between NFC and Random Effect is -0.17, significant at the 1% level. The model includes a heterogeneity test, which yields a chi-square statistic of 838.78, significant at the 1% level with a p-value of 0.00, leading to the rejection of the null hypothesis of no interaction and confirming significant interaction effects within the model. However, several parameters, such as Accessibility to Fishing Sites (AFS) and its various interactions with General Fishing Experience, Urban Residence, High School Diploma, and Random Effect, are not included in the model due to multicollinearity issues.

5.2 Analysis of key outcomes from the SP estimation only

In this subsection, I focus exclusively on estimating the model using SP data only, employing the maximum likelihood method for Equation (3.9). The results are in column (2) of Table 3.3. Analyzing the Stated Preferences (SP) data reveals several crucial insights into behaviors or choices associated with fishing activities. Travel costs are identified as a critical determinant, with an estimate of -0.01, statistically significant at the 1% level, suggesting that travel costs have a pronounced negative influence on fishing site choices. The number of fish catches also emerges as a significant factor, with an estimated 0.35, significant at the 1% level.

Various interaction terms within the model further underscore their significance. The interaction between the number of fish catches and general fishing experience is an estimated -0.014, significant at the 1% level. The interaction between the number of fish caught per hour and having a high school diploma is essential at the 1% level, with an estimated -0.32. The interaction term between the number of fish caught per hour and a random effect is not statistically significant, with an estimate of -0.001, contrasting with the findings from the RP data.

The robustness of the model is supported by the chi-square statistics related to interaction and random effects. The chi-square statistic for interaction effects is 43.71 with a p-value of 0.00, allowing for rejecting the null hypothesis of no interaction at the 1% significance level. Conversely, the chi-square statistic for random effects is 17.62 with a p-value of 0.06, significant at the 10% level, which leads to the rejection of the null hypothesis of no random effects. The SP data highlight the importance of travel costs, the number of fish caught, and various interaction terms in influencing the behaviors or choices under study. Unlike the RP data, the SP data do not reveal the impact of unobserved attributes specific to the fishing sites, and the random effect associated with the number of fish catches is insignificant.

5.3 Testing of parameters of common variables in RP and SP data

The RP/SP scale ratios derived from this process are shown in Table 3.2.

Table 3.2 –
RP/SP scale ratio per attribute

Attribute	ratio scale	Estimate	χ^2
		(2)	(3)
Travel costs	t_{kl}	.478	9.98***
		(.003)	(0.002)
Number of fish caught in one hour	t_l^1	.103	44.75***
		(.0005)	(0.000)
Length of fish caught	t_l^2	.311	835.07***
		(.00002)	(0.000)
Habitat quality for fish	t_l^3	.287	83.99***
		(.004)	(0.000)
Traffic	t_l^4	.521	606.71***
		(5.37e-06)	(0.000)

Notes : Awé, 2024 for reference. The symbols ***, **, and * indicate that a coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively. Column (2) displays each attribute's RP to SP estimate ratios. The standard errors for these estimates appear in parentheses below the ratios. Column (3) lists the χ^2 values, which test the equality of the RP and SP parameters for each attribute. The p-values for these tests are provided in parentheses beneath the χ^2 values. The null hypothesis, H_0, posits that these ratios equal one.

Table 3.2 displays significant differences between the Revealed Preferences (RP) and Stated Preferences (SP) estimates for the attributes of the fishing sites. All estimated RP/SP scale ratios are less than one, with the associated p-values from the chi-square test estimates consistently below 0.05. This evidence strongly indicates that the RP/SP scale ratios significantly deviate from one, suggesting a notable disparity between the factors that influence individuals' actual decisions (RP) and those that guide their stated preferences in hypothetical scenarios (SP).

The presence of scale ratios less than one may imply that individuals are more precise or consistent in their actual choices than in their hypothetical ones, possibly due to hypothetical biases or the differing contexts within which real and hypothetical decisions are made (Von Haefen and Phaneuf, 2008). Acknowledging these observed discrepancies is crucial as they highlight the unique dynamics underlying RP and SP data. Subsequently, I utilize these estimated RP/SP scale ratios through the maximum likelihood method to assess Equation (3.13).

5.4 Analysis of principal findings from the combined RP/SP estimation

In this subsection, I use the maximum likelihood method to estimate the combined RP/SP data for Equation (3.13). The results are in column (3) of Table 3.3. Analyzing the combined RP and SP data provides critical insights into the factors influencing fishing site selection. A consistent finding across the RP, SP, and combined RP/SP estimation is the significant negative impact of travel costs on site selection. The parameter's estimate is $-.01^{***}$, indicating statistical significance at the 1% level for all three datasets. However, the combined RP/SP data highlights differences from the separate RP and SP datasets. For example, the influence of the Number of Fish Catches (NFC) and specific interaction terms differ. In the combined data, the NFC estimate is 0.39, which is not statistically significant, contrasting with its essential role in the individual RP and SP datasets.

Additionally, interaction terms, such as NFC and General Fishing Experience or NFC and High School Diploma, lack statistical significance in the combined data despite their importance in the individual RP or SP models. The chi-square statistics for testing interaction and random effects merit attention. In the combined RP/SP dataset, the chi-square statistic for interaction effects is $\chi^2 = 31.52$ with a p-value of 0.00, which is significant at the 1% level. The chi-square statistic for random effects is $\chi^2 = 34.13^{***}$ with a p-value of 0.00, indicating significance at the 1% level. These figures align with the results from the individual RP and SP datasets, reinforcing the importance of interaction and random effects.

Table 3.3 –
Determinants of fishing site selection

	RP data	SP data	RP/SP data
	(1)	(2)	(3)
Log-likelihood	-3519.06	-1959.93	-1961.1441
Travel costs	$-.01^{***}$ (.00)	$-.01^{***}$ (.00)	$-.01^{***}$ (.00)
Number of fish catches (NFC)	5.12^{***} (.70)	$.35^{***}$ (.11)	.39 (.33)
NFC * Gen fish exp.	$.70^{***}$ (.04)	$-.014^{***}$ (.01)	-.024 (.02)
NFC * Urban	$.91^{**}$ (.36)	$-.15^{*}$ (.08)	-.25 (.26)
NFC * HS diploma	-1.7^{***} (.64)	$-.32^{***}$ (.09)	-.28 (.27)
NFC * Random effect	$-.17^{***}$ (.04)	-.001 (.04)	-.002 (.122)
Length of fish caught (LFC)	$.54^{***}$ (.03)	$.00^{***}$ (.00)	$.01^{***}$ (.03)
LFC * Gen fish exp.	$-.03^{***}$ (.00)	$-.00^{***}$ (.00)	$-.00^{**}$ (.00)
LFC * Urban	$-.62^{***}$ (.03)	-.00 (.0)	-.00 (.0)
LFC * HS diploma	$.12^{***}$ (.02)	.00 (.00)	$-.00^{*}$ (.00)
LFC * Random effect	.00 (.00)	-.00 (.00)	-.00 (.00)
Quality of fish habitat (QFH)	$.02^{***}$ (.00)	$.00^{***}$ (.00)	$.00^{***}$ (.00)
QFH * Gen fish exp.	$-.01^{***}$ (.00)	-.00 (.00)	9.53e-07 (.00)
QFH * Urban	.00 (.00)	-.00 (.00)	-.00 (.00)
QFH * HS diploma	$.02^{***}$ (.00)	.00 (.00)	.00 (.00)
QFH * Random effect	.00 (.00)	-.00 (.00)	-.00 (.00)
Accessibility to fishing sites (AFS)	-	-.04 (.19)	-.58 (.44)
AFS * Gen fish exp.	-	.000 (.00)	.02 (.02)
AFS * Urban	-	-.23 (.15)	-.26 (.34)
AFS * HS diploma	-	-.06 (.16)	.22 (.38)
AFS * Random effect	-	$-.06^{***}$ (.01)	$-.10^{***}$ (.03)
Fishers number (FN)	-194.02^{***} (10.24)	$-.53^{***}$ (.14)	-1.22^{***} (.31)
FN * Gen fish exp.	4.44^{***} (.27)	.01 (.01)	$.04^{**}$ (.02)
FN * Urban	114.81^{***} (5.14)	.14 (.11)	.17 (.22)
FN * HS diploma	-23.74^{***} (2.78)	.17 (.12)	$.56^{**}$ (.27)
FN * Random effect	$.07^{***}$ (.00)	$.01^{***}$ (.00)	$.11^{***}$ (.01)
SP outside dummy (ASC)		21.79 (580.77)	40.49 (900.96)
ASC * Gen fish exp.		$.20^{***}$ (.06)	$.03^{***}$ (.01)
ASC * Urban		2.47^{**} (.97)	$.44^{**}$ (.20)
ASC * HS diploma		2.21^{**} (1.12)	.17 (.19)
ASC * Random effec		-.31 (.46)	.12 (.09)
Sectors of the Lake Saint-Pierre			
Sector 2	-8.16^{***} (.56)		-.11 (.07)
Sector 3	.10 (.11)		$.16^{***}$ (.05)
Channel 1	.28 (.22)		-.06 (.17)
Channel 2	-6.07^{***} (1.11)		.11 (.18)
Channel 3	-.12 (.40)		$.76^{***}$ (.14)
Constant	209.67^{***} (13.63)		-1.5^{***} (.20)
Heterogeneity test			
H_0 : Interact. = 0	$\chi^2 = 838.78^{***}$	$\chi^2 = 43.71^{***}$	$\chi^2 = 31.52^{**}$
	$p.value = 0.000$	$p.value = 0.000$	$p.value = 0.048$
H_0 : Random eff. = 0	$\chi^2 = 25.60^{***}$	$\chi^2 = 17.62^{*}$	$\chi^2 = 34.13^{***}$
	$p.value = 0.000$	$p.value = 0.06$	$p.value = 0.000$
H_0 : ASCs = 0	$\chi^2 = 295.29^{***}$		$\chi^2 = 63.01^{***}$
	$p.value = 0.000$		$p.value = 0.000$

Notes : Awé, 2024. The estimates for Equation (3.1), using only RP data, are shown in column (1). Column (2) displays the estimates for Equation (3.9) based on SP data alone. Column (3) presents the estimates of Equation (3.13) derived from the combined RP/SP data set. The table encompasses estimations for various parameters including 'Travel Costs,' 'Number of Fish Catches (NFC),' 'Length of Fish Caught (LFC),' 'Quality of Fish Habitat (QFH),' 'Accessibility to Fishing Sites (AFS),' and 'Fishers' Number (FN).' Some parameters are presented in interaction with variables such as 'General Fishing Experience,' 'Urban Residence,' and 'High School Diploma.' At the table's lower section, a heterogeneity test assesses the significance of interaction effects, random effects, and alternative specific constants (ASCs). The chi-square statistic and p-value of this test are also included, with a low p-value suggesting rejection of the null hypothesis, thereby indicating significant heterogeneity. The table further details parameters for different sectors and channels of Lake Saint-Pierre, with symbols $***$, $**$, and $*$ indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

5.5 Marginal willingness to pay for attribute improvement

Table 3.4 presents the Marginal Willingness to Pay (MWTP) for various attributes related to fishing activities. The MWTP indicates the monetary value individuals assign to a one-unit increase in a particular characteristic. Additionally, the table shows the relative importance of each attribute, quantifying the proportion that each MWTP contributes to the total MWTP for all features considered.

Table 3.4 –
Marginal willingness to pay (MWTP)

Attributes	Marginal WTP ($)	Relative importance (%)
Number of fish caught in one hour	45.18	13.94
	(2.56)	
Length of fish caught	7.76	2.39
	(.02)	
Habitat quality for fish	4.8	1.48
	(.001)	
Accessibility to fishing sites	227.43	70.16
	(2.29)	
Traffic	38.99	12.03
	(2.83)	
Total	324.16	

Notes : Awé, 2024. Standard errors are given in parentheses.

The MWTP for site accessibility stands at $227.43, with this attribute holding the highest relative importance at 70.16%, indicating that individuals greatly value their ease of access to fishing sites and are prepared to pay a considerable amount for reduced travel time. Such a preference might arise because easy access significantly enhances the convenience and overall enjoyment of fishing. In contrast, the MWTP for the number of fish caught per hour is $45.18, with a relative importance of 13.94%. Individuals value the opportunity to catch more fish within a set period, likely because it increases the satisfaction and perceived efficiency of their fishing excursions. Traffic, referring to the number of fishers per trip at a fishing site, has an MWTP of $38.99, with a relative importance of 12.03%.

The MWTP for the length of fish caught is slightly lower at $7.76 and holds a relative significance of 2.39%, indicating that while individuals appreciate catching larger fish, they do not value this attribute as highly as others. The preference for larger catches could stem from the desire for more significant hauls or the perceived prestige of landing larger fish. The quality of fish habitat has an MWTP of $4.80 and relative importance of 1.48%, the least among the attributes discussed. Although individuals do value the habitat's quality, which likely affects the health and abundance of fish, they give higher priority to other features. The total MWTP, representing the aggregate monetary value individuals are prepared to pay for enhancements across all the attributes mentioned, is $324.16. In 2009, Dulude (2017) estimated the number of open-water fishers at Lake Saint-Pierre (LSP) to be 29,673. By applying the MWTP per fisher to the total number of fishers, these climate change adaptation measures could yield an annual benefit of approximately $9.62 million for open water fishing.

6 EVALUATION OF THE COMBINED RP/SP METHOD AND POLITICAL IMPLICATIONS

The climate change adaptation strategies slated for implementation at Lake Saint-Pierre encompass various interventions. These include the restoration of riparian zones, shifts in agricultural practices in flood-prone areas, and enhancing municipal wastewater treatment efficiency. Collectively, these measures aim to mitigate the negative impacts of human activities on the Lake's ecosystem, bolster its resilience to the effects of climate change, and promote sustainable utilization of its resources.

In their study, He et al. (2016) utilize several non-market valuation methods to assess the socioeconomic benefits of ice fishing and ecosystem services at Lake Saint-Pierre (LSP) due to the same adaptation measures. Their findings suggest that the annual costs for these adaptive measures may range from $348 million to $1,010 million, contingent on the scenario chosen. However, the projected yearly benefits derived from the enhanced ecosystem services of the Lake, attributable to these efforts, are estimated to outweigh the costs, ranging from $1,227 million to $3,271 million. The present study indicates that the economic benefits of open-water fishing alone are approximately $9.62 million annually. Integrating these results with those of He et al. (2016), it can be inferred that the annual economic returns from the adoption of the seven adaptation strategies at LSP could range from $1,236.62 million to $3,280.62 million, translating to a net benefit of between $888.62 million and $2,270.62 million. This underscores that the economic advantages of the proposed interventions substantially outweigh their associated costs.

These findings have numerous policy implications. Investments in climate adaptation measures at Lake Saint-Pierre (LSP) are economically sound. They may yield policy benefits for public officials. Such investments also encourage the private sector to adopt sustainable practices that preserve and enhance the ecosystem. To further promote sustainability, policymakers could design initiatives that incentivize eco-friendly practices, such as offering tax incentives or subsidies to compliant businesses. The significant economic contributions of LSP to fisheries and ecosystem services underscore the importance of the Lake to many livelihoods. Policymakers can present compelling arguments for preserving these livelihoods through the sustainable management of LSP, a task of particular relevance to local representatives.

Moreover, policymakers should consider endorsing these adaptation measures, enhancing their credentials in environmental stewardship and garnering support from constituents who prioritize ecological conservation and climate change mitigation. Such endorsement could be strategically advantageous. By aligning with climate adaptation initiatives, politicians demonstrate leadership in the global effort to combat climate change. Environmentally-focused industries have the potential to be engines of economic growth and job creation. Employment opportunities could arise directly within these sectors, such as roles in renewable energy or sustainable agriculture, and indirectly through supporting services. This includes positions in local enterprises catering to eco-tourism or the service sector supporting the renewable energy industry. Thus, climate change adaptation measures could improve the socioeconomic fabric of the region. The development of green industries could promote a more sustainable and resilient economy. The substantial economic prospects highlight the opportunity for collaborative governance at local, provincial, and national levels. Such collaboration can pool resources and integrate diverse expertise to maximize the efficacy and reach of these initiatives. Moreover, their successful implementation could serve as a model for other regions or countries facing similar environmental challenges, potentially leading to international alliances or partnerships that extend the reach and impact of these actions.

Concerning methodological insights, this study rejects the hypothesis that the ratios of common Revealed Preferences and Stated Preferences parameters equal one at a 99% confidence level, suggesting that the process by which experienced fishers choose fishing sites in hypothetical situations differs from how they have chosen sites during their recent visits. This outcome aligns with the findings of Von Haefen and Phaneuf (2008). However, it contradicts other studies (Taylor et al., 2010). Von Haefen and Phaneuf (2008) use the ratio of travel costs in RP and SP data to estimate the scale parameter ratio. In this study, I apply a scale ratio for each attribute, using the average levels across the characteristics of the fishing sites. Based on the RP/SP scale ratios, I adjust the SP parameters in the combined RP/SP model. Von Haefen and Phaneuf (2008) highlight that estimations made with variable ratios improve model fits. A key takeaway from both the findings of Von Haefen and Phaneuf (2008) and my own research is that, when both stated preference (SP) and revealed preference (RP) data are available, researchers should ensure that the common variables in Revealed and Stated Preferences originate from the same process. Statistical tests can then be used to assess the equality between the shared parameters of Revealed and Stated Preferences.

7 CONCLUSION

This study utilizes survey data from 212 open-water fishermen to conduct a comprehensive cost-benefit analysis of implementing seven climate change adaptation measures at Lake Saint-Pierre in Quebec. The research methodology integrates both Revealed Preference and Stated Preference approaches to accurately estimate the marginal willingness to pay (MWTP) for enhancements in various attributes of fishing sites. The results of the study reveal specific MWTP values for different attributes : accessibility is valued at $227.40, the catch rate (number of fish caught per hour) at $45.20, traffic at the site at $39.00, the quality of fish habitats at $4.80, and the average length of fish caught within an hour at $7.80. The aggregate MWTP across these attributes amounts to approximately $324.20, translating into an estimated annual benefit of around $9.62 million for open-water fishing activities.

When these findings are combined with those from the research conducted by He et al. (2016), the annual economic benefits derived from implementing the seven adaptation measures at Lake Saint-Pierre are estimated to range between $1,236.62 million and $3,280.62 million. This leads to a net benefit ranging from $888.62 million to $2,270.62 million. Such figures underscore that the economic advantages of the proposed adaptation measures significantly exceed their associated costs.

Furthermore, this study uncovers a significant difference in the decision-making patterns of experienced fishermen. It appears that the way fishermen select fishing sites in hypothetical scenarios does not always align with their choices in actual, recent fishing trips. This discrepancy suggests that the data derived from Revealed Preference (RP) and

Stated Preference (SP) methodologies originate from distinct decision-making processes. This finding highlights the complexity and multifaceted nature of fishermen's site selection behavior.

CONCLUSION

Cette thèse a étudié l'impact de l'adoption de mesures d'adaptation aux changements climatiques sur l'agriculture en Afrique subsaharienne. Pour ce faire, j'ai intégré des variables climatiques supplémentaires, au-delà de la température et des précipitations, et j'ai corrigé l'endogénéité de la variable d'adaptation. Les données utilisées proviennent de quatre pays d'Afrique subsaharienne. Les résultats montrent que l'accès au crédit et aux sources d'information sont des déterminants importants de la décision d'adaptation aux changements climatiques.

Le premier article a démontré que la mise en œuvre de stratégies d'adaptation entraîne une augmentation statistiquement significative des rendements agricoles d'environ 281 kg par hectare, soit une hausse de 23,3% du rendement annuel par hectare. De plus, selon que les mesures d'adaptation soient adoptées séparément ou combinées, elles génèrent des rendements de magnitudes différentes. Le deuxième article révèle que l'adoption de stratégies d'adaptation aux changements climatiques est associée à une baisse significative de l'exposition des agriculteurs aux risques environnementaux. Toutefois, cette réduction est hétérogène selon les pays, due à des inégalités dans l'accès au crédit et aux sources d'information.

Le dernier article associe les méthodes de préférences révélées (coûts de transport) et de préférences déclarées (choix multi-attributs) pour estimer les bénéfices annuels liés à l'adoption de sept mesures d'adaptation au Lac Saint-Pierre, au Québec. Les résultats suggèrent que ces bénéfices pourraient atteindre 9,62 millions de dollars. Ils montrent aussi une divergence dans les données produites par ces deux méthodes, indiquant que la façon dont les pêcheurs ont choisi les sites de pêche lors de leurs dernières visites diffère de celle adoptée lors des scénarios hypothétiques qui leur ont été présentés. Ces deux méthodes ne génèrent pas les mêmes types de données, rendant leur combinaison complexe.

Bibliographie

Abdulai, A. and Huffman, W. (2014). The adoption and impact of soil and water conservation technology : An endogenous switching regression application. *Land Economics*, 90(1) :26–43.

Adamowicz, W., Louviere, J., and Williams, M. (1994). Combining revealed and stated preference methods for valuing environmental amenities. *Journal of Environmental Economics and Management*, 26(3) :271–292.

Adger, W. N., Lorenzoni, I., and O'Brien, K. L. (2009). *Adapting to climate change : Thresholds, values, governance*. Cambridge University Press, UK.

Altonji, J. G., Elder, T. E., and Taber, C. R. (2005). An evaluation of instrumental variable strategies for estimating the effects of Catholic schooling. *Journal of Human Resources*, 40(4) :791–821.

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak instruments in instrumental variables regression : Theory and Practice. *Annual Review of Economics*, 11 :727–753.

Angrist, J. D. and Krueger, A. B. (1999). Empirical strategies in labor economics. *Handbook of Labor Economics*, 3 :1277–1366.

Antle, J. M. (2010). Asymmetry, partial moments, and production risk. *American Journal of Agricultural Economics*, 92(5) :1294–1309.

Araújo, M. B. and Rahbek, C. (2006). How does climate change affect biodiversity ? *Science*, 313(5792) :1396–1397.

Atube, F., Malinga, G. M., Nyeko, M., Okello, D. M., Alarakol, S. P., and Okello-Uma, I. (2021). Determinants of smallholder farmers' adaptation strategies to the effects of climate change : Evidence from Northern Uganda. *Agriculture & Food Security*, 10(1) :1–14.

Babcock, B. A. (2015). Using cumulative prospect theory to explain anomalous crop insurance coverage choice. *American Journal of Agricultural Economics*, 97(5) :1371–1384.

Babu, S. C. and Glendenning, C. J. (2019). Information needs of farmers : A systemic study based on farmer surveys. *Annals of Economic and Social Measurement*, 1(2) :101–139.

Bandiera, O. and Rasul, I. (2006). Social networks and technology adoption in Northern Mozambique. *Oxford University Press Oxford, UK*, 116(514) :869–902.

Bateman, I., Carson, R., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., and Pearce, D. (2002). Economic valuation with stated preference techniques. *Ecological Economics*, 3(1) :19–45.

Bayer, P., Keohane, N., and Timmins, C. (2009). Migration and hedonic valuation : The case of air quality. *Journal of Environmental Economics and Management*, 58(1) :1–14.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 60(2) :242–262.

Binswanger, H. and Rosenzweig, M. (1993). Wealth, weather risk and the composition and profitability of agricultural investments. *Economic Journal*, 103(416) :56–78.

Bjornlund, V., Bjornlund, H., and Van Rooyen, A. F. (2020). Why agricultural production in Sub-Saharan Africa remains low compared to the rest of the world : A historical perspective. *International Journal of Water Resources Development*, 36(1) :20–53.

Bockstael, N. E. and McConnell, K. E. (2007). *Environmental and resource valuation with revealed preferences : A theoretical guide to empirical models*. Science and Business Media.

Bourguignon, F., Fournier, M., and Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model : Monte Carlo comparisons. *Journal of Economic Surveys*, 21(1) :174–205.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2017). Weather, climate change and death in India. *University of Chicago, USA*.

Burke, M. Dykema, J., Lobell, D. B., Miguel, E., and Satyanath, S. (2015). Incorporating climate uncertainty into estimates of climate change impacts. *Review of Economics and Statistics*, 97(2) :461–471.

Carson, R. T. (2000). *Contingent valuation : A user's guide*. American Chemical Society, USA.

Chavas, J.-P. (2004). *Risk analysis in theory and practice*. Academic Press Advanced Finance, USA.

Chivandire, L. (2019). Determinants of smallholder farmers' access to formal credit : The case of Chivi District. *Stellenbosch University, South Africa*.

Dahl, G. B. (2002). Mobility and the return to education : Testing a Roy model with multiple markets. *Econometrica*, 70(6) :2367–2420.

Daly, C. (2006). Guidelines for assessing the suitability of spatial climate data sets. *International Journal of Climatology*, 26(6) :707–721.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change : Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1) :354–385.

Deschênes, O. and Greenstone, M. (2012). The economic impacts of climate change : Evidence from agricultural output and random fluctuations in weather : Reply. *American Economic Review*, 102(7) :3761–73.

Di Falco, S. and Chavas, J. (2009). On crop biodiversity, risk exposure, and food security in the Highlands of Ethiopia. *American Journal of Agricultural Economics*, 91(3) :599–611.

Di Falco, S. and Veronesi, M. (2013). How can African agriculture adapt to climate change ? A counterfactual analysis from Ethiopia. *Land Economics*, 89(4) :743–766.

Di Falco, S. and Veronesi, M. (2014). Managing environmental risk in presence of climate change : The role of adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics*, 57(4) :553–577.

Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security ? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3) :829–846.

Dillon, J. L. and Scandizzo, P. L. (1978). Risk attitudes of subsistence farmers in Northeast Brazil : A sampling approach. *American Journal of Agricultural Economics*, 60(3) :425–435.

Dinar, A., Hassan, R., Mendelsohn, R., Benhin, J., et al. (2012). *Climate change and agriculture in Africa : Impact assessment and adaptation strategies*. Routledge, UK.

Donaldson, D. (2018). Railroads of the raj : Estimating the impact of transportation infrastructure. *American Economic Review*, 108(4-5) :899–934.

Dubin, J. A. and McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica*, 4(2) :345–362.

Dulude, A.-M. (2017). La chasse et la pêche au Lac Saint-Pierre.

Fafchamps, M. (1993). Sequential labor decisions under uncertainty : An estimable household model of west-african farmers. *Econometrica*, (5) :1173–1197.

Field, C. B., Barros, V., Stocker, T. F., and Dahe, Q. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. *Cambridge University Press, UK*, 2(3) :1–23.

Fisher, A. C., Hanemann, W. M., Roberts, M. J., and Schlenker, W. (2012). The economic impacts of climate change : Evidence from agricultural output and random fluctuations in weather : Comment. *American Economic Review*, 102(7) :3749–60.

Godfrey, S. and Tunhuma, F. A. (2020). *The climate crisis : Climate change impacts, trends and vulnerabilities of children in Sub-Sahara Africa*. United Nations Children's Fund Eastern and Southern Africa Regional Office, Nairobi, Kenya.

Goonetilleke, A. and Vithanage, M. (2017). Water resources management : Innovation and challenges in a changing world. *Water*, 9(4) :281.

Guiteras, R. (2009). The impact of climate change on Indian agriculture. *University of Maryland, USA*.

Hardaker, J. B., Richardson, J. W., Lien, G., and Schumann, K. D. (2004). Stochastic efficiency analysis with risk aversion bounds : A simplified approach. *Australian Journal of Agricultural and Resource Economics*, 48(2) :253–270.

Hartmann, D., Tank, A. M., Rusticucci, M., Alexander, L., Brönnimann, S., Charabi, Y. A., Dentener, F., Dlugokencky, E., Easterling, D., and Kaplan, A. (2012). Observations : tmosphere and surface. climate change 2013 the physical science basis : Working Group I contribution to the fifth assessment report of the intergovernmental panel on climate change. *Cambridge University Press, UK*, 2(4) :159–254.

Harwood, J. L. (1999). Managing risk in farming : Concepts, research, and analysis. *Cambridge University Press, UK*, (774).

Hausman, J. (2012). Contingent valuation : From dubious to hopeless. *Journal of Economic Perspectives*, 26(4) :43–56.

He, J., Poder, T., Dupras, J., and Enomana, H. (2016). La valeur économique de la pêche blanche et des services écosystémiques au lac Saint-Pierre : Analyse coûts-avantages des stratégies d'adaptation aux changements climatiques. *Groupe de recherche en économie et développement international (GRÉDI), Canada*.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 2(1) :153–161.

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Methodological Research*, 44(6) :735–752.

Hoffman, G. J. and Jobes, J. A. (1978). Growth and water relations of cereal crops as influenced by salinity and relative humidity. *Agronomy Journal*, 7(5) :765–769.

Hopkins, W. G. and Hüner, N. P. (1995). Introduction to plant physiology. *Science*, 1(2) :14–54.

Horowitz, J. K. and Lichtenberg, E. (1993). Insurance, moral hazard, and chemical use in agriculture. *American Journal of Agricultural Economics*, 75(4) :926–935.

Huesca, L., Camberos, M., et al. (2010). *Selection bias correction based on the multinomial logit : An application to the Mexican labour market*. 2nd Stata Users Group Meeting Mexico, Universidad Iberoamericana, Mexico.

Iyigun, M., Nunn, N., and Qian, N. (2017). *The long-run effects of agricultural productivity on conflict, 1400-1900.* National Bureau of Economic Research, USA.

Jullien, B. and Salanié, B. (2000). Estimating preferences under risk : The case of racetrack bettors. *Journal of Political Economy*, 108(3) :503–530.

Kahan, D. et al. (2008). *Managing risk in farming*. Food and Agriculture Organization of the United Nations, Roma, Italy.

Kang, H., Kreuels, B., Adjei, O., Krumkamp, R., May, J., and Small, D. S. (2013). The causal effect of Malaria on stunting : A Mendelian randomization and matching approach. *International Journal of Epidemiology*, 42(5) :1390–1398.

Keele, L., Zhao, Q., Kelz, R. R., and Small, D. (2019). Falsification tests for instrumental variable designs with an application to tendency to operate. *Medical Care*, 57(2) :167.

Kim, K. and Chavas, J.-P. (2003). Technological change and risk management : An application to the economics of corn production. *Agricultural Economics*, 29(2) :125–142.

Koundouri, P., Nauges, C., and Tzouvelekas, V. (2006). Technology adoption under production uncertainty : Theory and application to irrigation technology. *American Journal of Agricultural Economics*, 88(3) :657–670.

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H. M., Fosu, K. Y., Gbetibouo, G., Jain, S., et al. (2006). Will African agriculture survive climate change ? *The World Bank Economic Review*, 20(3) :367–388.

Labrecque, J. and Swanson, S. A. (2018). Understanding the assumptions underlying instrumental variable analyses : A brief review of falsification strategies and related tools. *Epidemiology Reports*, 5 :214–220.

Lawrence, M. G. (2005). The relationship between relative humidity and the dewpoint temperature in moist air : A simple conversion and applications. *Bulletin of the American Meteorological Society*, 86(2) :225–234.

Lee, L.-F. (1976). *Estimation of limited dependent variable models by two-stage method.* University of Rochester, USA.

Lee, L.-F. (1982). Some approaches to the correction of selectivity bias. *Review of Economic Studies*, 49(3) :355–372.

Lee, L.-F. (1983). Generalized econometric models with selectivity. *Econometrica*, 5(2) :507–512.

Lee, L.-F. and Trost, R. P. (1978). Estimation of some limited dependent variable models with application to housing demand. *Journal of Econometrics*, 8(3) :357–382.

Lin, W., G. and Moore, C. V. (1974). An empirical test of utility vsersus profit maximization in agricultural production. *American Journal of Agricultural Economics*, 56(3) :497–508.

Lipsitch, M., Tchetgen, E. T., and Cohen, T. (2010). Negative controls : A tool for detecting confounding and bias in observational studies. *Epidemiology*, 21(3) :383.

List, J. A., Sinha, P., and Taylor, M. H. (2006). Using choice experiments to value non-market goods and services : Evidence from field experiments. *Advances in Economic Analysis and Policy*, 5(2).

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., and Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, 3(5) :497–501.

Lokshin, M. and Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, 4(3) :282–289.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000). *Stated choice methods : Analysis and applications*. Cambridge University Press, UK.

Maddala, G. and Nelson, F. (1975). Switching regression models with exogenous and endogenous regimes. *Proceedindgs of the American Statistical Association*, (5) :423–425.

Marra, M., Pannell, D. J., and Ghadim, A. A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies : Where are we on the learning curve ? *Agricultural Systems*, 75(2-3) :215–234.

McFadden, D. (2001). Economic choices. *American Economic Review*, 91(3) :351–378.

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior. *Institute of Urban and Regional Development*, 7(1) :17–38.

Mendelsohn, R. and Dinar, A. (2003). Climate, water, and agriculture. *Land Economics*, 79(3) :328–341.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture : a ricardian analysis. *American Economic Review*, 1(2) :753–771.

Menezes, C., Geiss, C., and Tressler, J. (1980). Increasing downside risk. *American Economic Review*, 70(5) :921–932.

Mincer, J. (1974). *Schooling, experience, and earnings. Human behavior and social institutions*. Education Resources Information Center, USA.

Mittal, S. and Tripathi, G. (2009). Role of mobile phone technology in improving small farm productivity1. *Agricultural Economics Research Review*, 22(1) :451–459.

Moscardi, E. and De Janvry, A. (1977). Attitudes toward risk among peasants : An econometric approach. *American Journal of Agricultural Economics*, 59(4) :710–716.

Moschini, G. (2008). Biotechnology and the development of food markets : Retrospect and prospects. *European Review of Agricultural Economics*, 35(3) :331–355.

Nkemdirim, L. (1991). An empirical relationship between temperature, vapour pressure deficit and wind speed and evaporation during a winter Chinook. *Theoretical and Applied Climatology*, 43(3) :123–128.

Nobel, P. (1981). Wind as an ecological factor. *Physiological Plant Ecology*, 4(3) :475–500.

Palis, F. G., Flor, R. J., Warburton, H., and Hossain, M. (2006). Our farmers at risk : Behaviour and belief system in pesticide safety. *Journal of Public Health*, 28(1) :43–48.

Perrings, C., Duraiappah, A., Larigauderie, A., and Mooney, H. (2011). The biodiversity and ecosystem services science-policy interface. *Science*, 331(6021) :1139–1140.

Pizer, S. D. (2016). Falsification testing of instrumental variables methods for comparative effectiveness research. *Health Services Research*, 51(2) :790–811.

Popoola, O., Yusuf, S., and Monde, N. (2020). Information sources and constraints to climate change adaptation amongst smallholder farmers in amathole district municipality, eastern cape province, south africa. *Sustainability*, 12(14) :5846.

Ramaswami, B. (1992). Production risk and optimal input decisions. *American Journal of Agricultural Economics*, 74(4) :860–869.

Rosenbaum, P. R. (2002). *Overt bias in observational studies*. Springer, USA.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will US agriculture really benefit from global warming ? Accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1) :395–406.

Schlenker, W. and Roberts, M. J. (2008). *Estimating the impact of climate change on crop yields : The importance of nonlinear temperature effects*. National Bureau of Economic Research, USA.

Schmertmann, C. P. (1994). Selectivity bias correction methods in polychotomous sample selection models. *Journal of Econometrics*, 60(1-2) :101–132.

Sherrick, B. J., Barry, P. J., Ellinger, P. N., and Schnitkey, G. D. (2004). Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics*, 1(4) :103–114.

Steyerberg, E. W., Bleeker, S. E., Moll, H. A., Grobbee, D. E., and Moons, K. G. (2003). Internal and external validation of predictive models : A simulation study of bias and precision in small samples. *Journal of Clinical Epidemiology*, 56(5) :441–447.

Stock, J. H. and Yogo, M. (2002). *Testing for weak instruments in linear IV regression*. National Bureau of Economic Research, Cambridge, USA.

Swait, J. and Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research*, 30(3) :305–314.

Taylor, L., Morrison, M., and Boyle, K. (2006). Markets and the incentive compatibility of choice surveys. *World Bank Policy Research*, 5(2) :45–67.

Taylor, L. O., Morrison, M. D., and Boyle, K. J. (2010). Exchange rules and the incentive compatibility of choice experiments. *Environmental and Resource Economics*, 47(2) :197–220.

Toensmeier, E. (2016). *The carbon farming solution : A global toolkit of perennial crops and regenerative agriculture practices for climate change mitigation and food security*. Chelsea Green Publishing, USA.

Train, K. E. (2009). Discrete choice methods with simulation. *Cambridge University Press, UK*.

Trinh, T. Q., Rañola Jr, R. F., Camacho, L. D., and Simelton, E. (2018). Determinants of farmers' adaptation to climate change in agricultural production in the Central Region of Vietnam. *Land Use Policy*, 70 :224–231.

Van Kippersluis, H. and Rietveld, C. A. (2018). Pleiotropy-robust Mendelian randomization. *International Journal of Epidemiology*, 47(4) :1279–1288.

Vidanapathirana, N. P. (2012). Agricultural information systems and their applications for development of agriculture and rural community : A review study. *IRIS*, 2(3) :1–14.

Von Haefen, R. H. and Phaneuf, D. J. (2008). Identifying demand parameters in the presence of unobservables : A combined revealed and stated preference approach. *Journal of Environmental Economics and Management*, 56(1) :19–32.

Wahba, G. (1990). *Spline models for observational data*. Society for Industrial and Applied Mathematics (SIAM), USA.

West, J. and Bogers, M. (2014). Leveraging external sources of innovation : A review of research on open innovation. *Journal of Product Innovation Management*, 31(4) :814–831.

Wooten, R. (2011). Statistical analysis of the relationship between wind speed, pressure and temperature. *Journal of Applied Sciences*, 11(15) :2712–2722.

Yaseen, M., Xu, S., Yu, W., and Hassan, S. (2016). Farmers' access to agricultural information sources : Evidence from rural Pakistan. *Journal of Agricultural Chemistry and Environment*, 5(1) :12–19.

Zhang, P., Zhang, J., and Chen, M. (2017). Economic impacts of climate change on agriculture : The importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management*, 83 :8–31.

ANNEXE A

ANNEXE ARTICLE 1 et 2

Table A.1 –
A. Variable definitions

Variable name	Definition
adaptation	dummy=1 if the farmer adapted to climate change, 0 otherwise
yield	quantity produced per hectare (kg)
yield skewness	third central moment of the distribution of yields
yield variance	second (variance) of the distribution of yields
yield kurtosis	fourth central moment of the distribution of yields
temperature	average temperatures (°C)
rainfall	average rainfall (mm)
solar	average solar radiation (kJ m^{-2} day^{-1})
evaporation	average evaporation (kPa)
wind	average wind speed s(m s^{-1})
altitude	altitude coordinates
atitude	latitude coordinates
irrigation	dummy=1 if crops are rainfed/water irrigated, 0 otherwise
machinery	dummy=1 if machinery is used, 0 otherwise
labor	labor use per hectare (adult days)
inorganic fertilizer	inorganic fertilizer used per hectare (kg)
organic fertilizer	organic fertilize used per hectare (kg)
pesticide powder	pesticide powder used per hectare (kg)
pesticide liquid	pesticide liquid used per hectare (kg)
seed	Seed used per hectare (kg)
literacy	dummy=1 if the household head is literate, 0 otherwise
male	dummy=1 if the household head is male, 0 otherwise
age	age of the household head
household-size	household size
relatives	number of relatives in the district
access credit	dummy=1 if the farmer accesses to credit, 0 otherwise
offfarm job	dummy=1 if the farmer has an non-farm job, 0 otherwise
computer	dummy=1 if the farmer has at least a computer, 0 otherwise
drought experience	dummy=1 if the farmer experimented drought, 0 otherwise
flood experience	dummy=1 if the farmer experimented a flood, 0 otherwise
pests experience	dummy=1 if the farmer experimented pests, 0 otherwise
severe experience	dummy=1 if the farmer experimented severe winds, 0 otherwise
hail experience	dummy=1 if the farmer experimented hail storms, 0 otherwise
riverine experience	dummy=1 if the farmer experimented riverine flooding, 0 otherwise
landslides experience	dummy=1 if the farmer experimented landslides, 0 otherwise
access extension	dummy=1 if the farmer accessed to extension services, 0 otherwise
farmer organization	dummy=1 if the farmer belongs to a farmer's organization, 0 otherwise
government info	dummy=1 if the farmer has access to government info, 0 otherwise
newspaper info	dummy=1 if the farmer has access to newspaper info, 0 otherwise
radio info	dummy=1 if the farmer has access to radio info, 0 otherwise
tv info	dummy=1 if the farmer has access to tv info, 0 otherwise
community info	dummy=1 if the farmer has access to community info, 0 otherwise
ngo info	dummy=1 if the farmer has access to NGO info, 0 otherwise
temple info	dummy=1 if the farmer has access to temple info, 0 otherwise
social media info	dummy=1 if the farmer has access to social media info, 0 otherwise

Table A.2 –
A. Adaptation decisions and agricultural yields (continued)

	FIML	OLS	FIML	
	Adaptation	Yields		
			Adapted	Nonadapted
	(1)	(2)	(3)	(4)
fall temp	$-.25^{***}$ (.07)	597.4^{**} (270.8)	1329.6^{**} (473.4)	84.0 (531.6)
fall temp sqr	$.01^{***}$ (.00)	-10.7^{**} (5.1)	-21.5^{**} (9.2)	-.6 (9.5)
winter temp	$.41^{***}$ (.03)	-417.3^{**} (160.2)	-319.2 (229.8)	1005.8^{**} (435.1)
winter temp sqr	$-.01^{***}$ (.00)	10.5^{***} (3.5)	8.7^{*} (4.9)	-18.0^{**} (8.1)
spring temp	$-.59^{***}$ (.06)	525.7^{*} (316.7)	139.3 (385.1)	-1395.8^{**} (443.4)
spring temp sqr	$.01^{***}$ (.00)	-10.9 (6.7)	-1.9 (8.6)	29.7^{***} (8.7)
summer temp	$.70^{***}$ (.08)	-621.5^{*} (354.1)	-974.8^{**} (483.4)	-28.4 (546.1)
summer temp sqr	$-.01^{***}$ (.00)	10.9 (7.1)	17.6^{*} (9.7)	-1.3 (10.7)
fall rainfall	.00 (.00)	4.3^{**} (2.2)	5.3^{**} (2.3)	7.9 (5.1)
fall rainfall sqr	$.01^{***}$ (.00)	-.1 (.1)	-.1 (.1)	-.1 (.1)
winter rainfall	$-.00^{***}$ (.00)	.4 (1.1)	.3 (1.1)	-9.1^{***} (3.4)
winter rainfall sqr	$.00^{***}$ (.00)	$-.1^{**}$ (.00)	$-.1^{*}$ (.00)	.1 (.1)
spring rainfall	$-.00^{***}$ (.00)	-.1 (1.8)	-1.6 (2.5)	2.8 (3.2)
spring rainfall sqr	.00 (.00)	$.1^{*}$ (.0)	.1 (.1)	.1 (.1)
summer rainfall	$-.00^{***}$ (.00)	-.7 (2.5)	-1.5 (2.8)	-3.0 (5.6)
summer rainfall sqr	$.00^{***}$ (.00)	-.1 (.1)	.1 (.1)	.1 (.1)
fall solar	$.01^{***}$ (.00)	-64018.3 (96735.1)	.6 (.6)	-1.6^{**} (.7)
fall solar sqr	$.00^{***}$ (.00)	3311.5 (4980.3)	-.0 (.1)	$.1^{***}$ (.0)
winter solar	$.00^{***}$ (.00)	50617.1 (41084.9)	.2 (.4)	.3 (.2)
winter solar sqr	$-.00^{***}$(.00)	-2571.4 (2127.9)	-0.0 (.0)	$-.1^{*}$ (.0)
spring solar	$-.00^{***}$ (.00)	77593.9 (53055.7)	-.1 (.2)	.3 (.3)
spring solar sqr	$.00^{***}$ (.00)	-4089.6 (2716.8)	-.0 (.0)	-.0 (.0)
summer solar	$-.01^{***}$ (.00)	102632.8 (75260.8)	-.4 (.6)	1.0 (1.2)
summer solar sqr	$.00^{***}$ (.00)	-5260.3 (3888.5)	.0 (.0)	-.0 (.0)
fall evaporation	-1.93^{***} (.31)	5263.2^{***} (1542.5)	4400.1^{**} (2005.4)	6747.3^{***} (2560.6)
fall evaporation sqr	$.30^{***}$ (.08)	-1437.2^{***} (391.4)	-1175.1^{***} (490.0)	-1469.9^{**} (701.7)
winter evaporation	.61 (.48)	1673.1 (2191.8)	1975.8 (4065.8)	2268.8 (5358.2)
winter evaporation sqr	-.17 (.12)	-257.8 (565.2)	-313.4 (1075.3)	-741.8 (1206.6)
spring evaporation	-2.49^{***} (.42)	269.4 (1809.7)	-632.8 (3455.8)	-620.3 (4981.7)
spring evaporation sqr	$.97^{***}$ (.11)	-358.3 (521.9)	86.5 (965.2)	188.5 (1154.6)
summer evaporation	1.93^{***} (.31)	-5900.4^{***} (1342.1)	-3982.6 (2493.8)	-7195.4^{**} (1905.0)
summer evaporation sqr	$-.45^{***}$ (.08)	1616.7^{***} (378.0)	1232.6^{*} (592.4)	1592.5^{***} (599.6)
fall wind	$-.55^{***}$ (.09)	82.4 (379.0)	492.4 (440.5)	-722.4 (635.8)
fall wind sqr	$.13^{***}$ (.02)	-53.8 (80.8)	-139.4 (109.0)	113.1 (129.1)
winter wind	$.87^{***}$ (.10)	-1171.8^{***} (379.5)	-405.8 (434.9)	-827.0 (702.6)
winter wind sqr	$-.14^{***}$ (.02)	202.6^{***} (75.8)	79.4 (90.7)	178.0 (126.6)
spring wind	$.17^{**}$ (.07)	857.5^{**} (401.3)	-41.3 (319.1)	907.2^{*} (528.1)
spring wind sqr	$-.07^{***}$ (.01)	-96.9 (55.3)	30.4 (47.9)	-172.9^{*} (101.8)
summer wind	$-.37^{***}$ (.08)	277.6 (374.9)	455.8 (444.8)	60.7 (401.4)
summer wind sqr	$.08^{***}$ (.01)	-59.5 (84.3)	-95.8 (103.6)	-13.8 (79.9)
Number obs.	5,091		3,280	1,811

Notes : Awé, 2024. Robust standard errors are clustered at the district level and are shown in parentheses. The first column present the OLS estimates from equation (1.3), with errors clustered at the district level. In column (1), the quantity produced per hectare (yield) is regressed on the adaptation dummy variable and control variables have been included. The estimates for the endogenous switching regression, derived from equations (1.2), (1.4), and (1.5), with errors clustered at the district level, are also reported. The term σ_j represents the square root of the variance of the error terms μ_{tj} in the outcome equations (1.4) and (1.5). Meanwhile, ρj indicates the correlation coefficient between the error term μ from the selection equation (1.4) and the error term υ_{tj} from the respective outcome equations. Symbols $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.3 –
A. Adaptation decisions and farmer's exposure to climate risks (continued)

FIML	Dependent Variables : Variance, Skewness, and Kurtosis of Yield Distribution					
	Skewness (M_3)		Variance (M_2)		Kurtosis (M_4)	
			Adapted	Nonadapted	Adapted	Nonadapted
	(1)	(2)	(3)	(4)	(5)	(6)
fall temp	9.91^{***}	1.15	.13	-2.91^{**}	.98	3.99
	(3.55)	(4.63)	(1.79)	(1.34)	(11.96)	(5.96)
fall temp sqr	$-.20^{***}$	-.01	.001	$.05^{**}$	-.006	-.09
	(.07)	(.07)	(.03)	(.02)	(.21)	(.11)
winter temp	-1.66	3.96	3.33^{***}	$.96^{**}$	18.55^{**}	-.17
	(1.12)	(3.57)	(1.20)	(.37)	(9.32)	(1.61)
winter temp sqr	.02	-.06	$-.05^{**}$	$-.02^{***}$	$-.32^{*}$	-.009
	(.02)	(.06)	(.02)	(.01)	(.18)	(.036)
spring temp	5.48^{***}	-11.02^{***}	-4.59^{***}	-2.68^{***}	-37.98^{***}	-1.31
	(2.03)	(3.97)	(1.52)	(.84)	(11.62)	(3.23)
spring temp sqr	$-.10^{**}$	$.22^{***}$	$.09^{***}$	$.05^{***}$	$.760^{***}$	.02
	(.04)	(.08)	(.03)	(.01)	(.24)	(.069)
summer temp	-10.39^{***}	4.97	1.12	4.59^{***}	15.75	.79
	(3.23)	(4.39)	(1.43)	(1.27)	(11.79)	(5.14)
summer temp sqr	$.20^{***}$	-.08	-.02	$-.08^{***}$	-.29	.003
	(.06)	(.08)	(.02)	(.02)	(.22)	(.102)
fall rainfall	-.007	.03	$.03^{**}$	-.01	$.14^{*}$	-.011
	(.01)	(.04)	(.01)	(.01)	(.07)	(.023)
fall rainfall sqr	.00	-.00	-.00	.00	-.00	-.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
winter rainfall	.01	-.06	$-.03^{**}$	-.00	$-.14^{***}$	.00
	(.02)	(.05)	(.01)	(.01)	(.05)	(.015)
winter rainfall sqr	-.00	.00	.00	$.01^{***}$	.00	.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
spring rainfall	.01	.05	.00	-.01	-.02	.00
	(.01)	(.04)	(.01)	(.01)	(.06)	(.01)
spring rainfall sqr	-.00	-.00	$.00^{*}$	$-.00^{**}$	$.00^{**}$	$-.00^{**}$
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
summer rainfall	-.01	-.08	.01	.01	.03	.01
	(.01)	(.06)	(.01)	(.01)	(.07)	(.02)
summer rainfall sqr	.00	.00	-.00	.00	-.00	.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
fall solar	$.01^{***}$	.00	-.001	$-.01^{***}$	.01	$-.017^{**}$
	(.00)	(.01)	(.00)	(.00)	(.02)	(.01)
fall solar sqr	$-.04^{**}$	-.01	.00	$.00^{***}$	-.00	$.00^{**}$
	(.01)	(.10)	(.00)	(.00)	(.00)	(.00)
winter solar	$-.01^{***}$	.00	-.00	$.002^{***}$	$.01^{**}$	.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
winter solar sqr	$.02^{***}$	-.00	-.00	$-.01^{***}$	$-.00^{*}$	-.00
	(.00)	(.01)	(.00)	(.00)	(.00)	(.00)
spring solar	$.01^{*}$	.00	$.00^{***}$	$-.01^{***}$	-.00	-.00
	(.00)	(.00)	(.001)	(.00)	(.00)	(.00)
spring solar sqr	$-.01^{**}$	-.00	$-.01^{***}$	$.01^{***}$	.00	.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

Notes : Awé, 2024. presents the Full Information Maximum Likelihood (FIML) estimates for the variance, skewness, and kurtosis of yield distribution among farmers, categorized into 'Adapted' and 'Nonadapted' groups based on their responses to climate risks. The robust standard errors, presented in parentheses, are clustered at the district level to account for potential intragroup correlations. The estimates are derived from an endogenous switching regression model, as detailed in equations (2.4), (2.5), and (2.6). In these models, σ_j represents the square root of the variance of the error terms (μ_{jj}) in the outcome equations ((2.5) and (2.6)), providing insights into the variability of the yield distribution. The correlation coefficient ρ_j, calculated between the error term η_i in the selection equation ((2.4)) and the error term ϵ_{ji} in the outcome equations, indicates the degree of association between the selection process and the yield outcomes. Statistical significance levels are indicated by asterisks : $***$ (1%), $**$ (5%), and $*$ (10%).

ANNEXE B

ANNEXE ARTICLE 3

Table B.1 –
A. Repartition of RP attributes per fishing sectors

	Sectors					
Attributes	Sector 1	Sector 2	Sector 3	Chenal 1	Chenal 2	Chenal 3
Number of fish caught	2.56	2.94	2.69	2.62	2.09	1.44
	(1.90)	(2.59)	(1.85)	(2.84)	(1.60)	(1.58)
Length of fish caught (mm)	467.86	407.5	440	429.21	405.08	401.67
	(157.35)	(78.29)	(92.27)	(71.36)	(68.14)	(88.37)
Quality of fish habitat	294	458	66	289	278	91
Accessibility to fishing sites (hour)	1.58	1.22	1.44	1.52	1.14	1.55
	(1.73)	(0.69)	(0.51)	(1.75)	(0.53)	(0.52)
Fishers number	2.28	2.17	2.21	2.33	2.15	2.31
	(0.86)	(0.85)	(0.79)	(0.88)	(0.91)	(0.75)

Notes : Awé, 2024.The table presents average values for various attributes across different fishing sectors and channels, with standard errors shown in parentheses. "Number of fish caught" indicates the average catch per hour per fisher; "Length of fish caught" is the average size of the catch in millimeters; "Quality of fish habitat" reflects the total catch in 2015, serving as an indirect measure of habitat quality; "Accessibility to fishing sites" measures the average travel time in hours from home to the fishing location; "Fishers number" denotes the average number of adult fishermen present during a trip. The absence of standard errors for "Quality of fish habitat" is due to its aggregate nature, representing total catch rather than individual variability. This comprehensive data provides insights into the fishing dynamics and environmental conditions of each sector.