[Makara Human Behavior Studies in Asia](https://scholarhub.ui.ac.id/hubsasia)

Volume 24 | Number 2 Article 24

12-31-2020

Origins of Farmers' Adoption of Multiple Climate-Smart Agriculture Management Practices in the Vietnamese Mekong Delta

Dung Tien Luu
Faculty of International Economic Relations, University of Economics and Law, Ho Chi Minh City, 70000, Vietnam; Vietnam National University, Ho Chi Minh City, 70000, Vietnam, dunglt@uel.edu.vn

Recommended Citation

Luu, D. T. (2020). Origins of Farmers' Adoption of Multiple Climate-Smart Agriculture Management Practices in the Vietnamese Mekong Delta. *Makara Human Behavior Studies in Asia, 24*(2), 141-153.
https://doi.org/10.7454/hubs.asia.1030320

Makara Hubs-Asia, 2020, 24(2), 141-153
DOI: 10.7454/hubs.asia.1030320

Origins of Farmers' Adoption of Multiple Climate-Smart Agriculture Management Practices in the Vietnamese Mekong Delta

Dung Tien Luu*[1, 2]

1. Faculty of International Economic Relations, University of Economics and Law, Ho Chi Minh City, 70000, Vietnam
2. Vietnam National University, Ho Chi Minh City, 70000, Vietnam

**E-mail: dunglt@uel.edu.vn*

Abstract

The present study analysed determinants of farm-level climate adaptation measures in Vietnam using a multinomial logit model fitted to data from a cross-sectional survey of 350 rice farmers. The findings show that human capital (farmer's education level), social capital, financial capital (access to credit), farmland size, institutional factors (farmland tenure status), extension service access and constraint to market are the determining factors of climate-smart agricultural technology adoption among farmers. The results demonstrate the need for policymaking designed to improve the probability of households applying climate-smart agricultural technology as the most crucial step in successfully implementing adaptive agricultural production strategies to climate change.

Asal Usul Petani Adopsi Beberapa Praktek Manajemen Pertanian Cerdas Iklim di Delta Mekong Vietnam

Abstrak

Penelitian ini menganalisis faktor-faktor penentu langkah-langkah adaptasi iklim tingkat pertanian di Vietnam menggunakan model multinomial logit yang sesuai dengan data dari survei *cross-sectional* terhadap 350 petani padi. Temuan menunjukkan bahwa modal manusia (tingkat pendidikan petani), modal sosial, modal keuangan (akses ke kredit), ukuran lahan pertanian, faktor kelembagaan (status kepemilikan lahan pertanian), akses layanan penyuluhan dan kendala pasar adalah faktor penentu pertanian cerdas-iklim adopsi teknologi di kalangan petani. Hasilnya menunjukkan perlunya pembuatan kebijakan yang dirancang untuk meningkatkan kemungkinan rumah tangga menerapkan teknologi pertanian cerdas-iklim sebagai langkah paling penting dalam berhasil menerapkan strategi produksi pertanian adaptif terhadap perubahan iklim.

Keywords: climate change, soil and water management, Vietnam, weather-risk management, yield management

Citation:
Luu, D. (2020). Origins of farmers' adoption of multiple climate-smart agriculture management practices in the Vietnamese Mekong Delta. *Makara Human Behavior Studies in Asia, 24*(2), 141-153. doi:10.7454/hubs.asia.1030320

1. Introduction

For the past 30 years (1990-2018), agricultural and rural areas have continued to play an essential role in the Vietnamese economy, employing around 60.0% of the workforce and accounting for 16.3% of GDP (General Statistical Office of Vietnam [GSO], 2019). Nevertheless, the substantial growth in agricultural production has come at a high environmental cost; agriculture being the second-largest source of greenhouse gas (GHG) emissions after the energy sector (World Bank, 2016). As a result, Vietnam is one of the country's most vulnerable to climate change. Among the 84 developing coastal countries profoundly affected by sea-level rise, Vietnam ranks first in terms of the consequences to the population and GDP performance. It ranks second in terms of the influence of climate change on land area and agricultural production (World Bank, 2016). Climate change is expected to reduce the agricultural production area and agricultural productivity in Vietnam (World Bank, 2016).

Furthermore, rising sea levels may inundate most of the Mekong and Red River deltas by 2070 and cause adverse impacts on agriculture. Flooded ponds and lakes could suffer a complete loss of stock. Climate change will probably also reduce the variety of aquatic resources and degrade soil quality (Van Mai & Lovell, 2015). Agriculture is the second-largest source of GHG emissions, contributing to about 33% of total GHG emissions in Vietnam in 2010 (GSO, 2019). Within the agricultural sector, rice cultivation is responsible for significant GHG emissions, accounting for 46.3% of agriculture's total emissions (Food and Agriculture Organization of the United Nations [FAO], 2010). Studies revealed that climate change adaptation response, including climate-smart agriculture participation, played a crucial role in improving technical efficiency, economic benefits, and food security (Hasan, Desiere, D'Haese, & Kumar, 2018; Ho & Shimada, 2019; Khatri-Chhetri, Aryal, Sapkota, & Khurana, 2016; Lipper et al., 2014; Taneja, Pal, Joshi, Aggarwal, & Tyagi, 2019). In the Vietnamese Mekong Delta, many climate-smart agricultural practices have been applied in rice production. One practice is called One Must–Six Reductions ("One Must" recommends that farmers use certified seeds; "Six Reductions" includes reducing seed rate, fertiliser, pesticide, water, post-harvest loss, and GHG emissions). Other climate-smart agricultural practices are system of rice intensification, Viet-GAP, integrated pest management, crop production, alternate wetting and drying, large-field model, and weather-risk insurance (Chi et al., 2013; Dung, Ho, Hiep, & Hoi, 2018; Ho & Shimada, 2019; Lampayan, Rejesus, Singleton, & Bouman, 2015). These technologies are based on soil management, water management, crop management, and risk management against natural disasters that contribute to climate-smart agriculture from several vital perspectives, including productivity, adaptation through short-term risk management, adaptation through longer-term risk management, and mitigation. However, the majority of climate-smart agricultural technologies have a low to average adoption rate in Vietnam of below 30% (GSO, 2019).

Previous studies used farm management models to explain decision making and technology adoption by farmers and focused on microeconomics theory with assumptions of profit maximisation and cost-benefits (Addisu, Fissha, Gediff, & Asmelash, 2016; Asrat & Simane, 2018; Atinkut & Mebrat, 2016; Ayal & Leal Filho, 2017; Dung et al., 2018; Fadina & Barjolle, 2018; Gebrehiwot & Van Der Veen, 2013; Khatri-Chhetri, Aggarwal, Joshi, & Vyas, 2017; Teklewold, Kassie, & Shiferaw, 2013; Tessema, Aweke, & Endris, 2013; Wassie & Pauline, 2018). Nevertheless, these models cannot capture the complexity of farmers' behaviour and attitudes toward climate-smart agricultural technology adoption. They also do not take into account all related constraints on climate-smart agricultural adoption, which include transaction costs, social benefits or costs, the role of social capital with collective actions, and the role of institutions.

Collective action is treated as a significant adaptation decision regarding the management of agricultural and other resources that community livelihoods depend on. It plays an essential role in supporting the community co-adapting to climate change. Collective action involves activities carried out together, such as resource contribution, coordination, information sharing, knowledge sharing, and the formation of institutions to support the community in adopting climate-smart agricultural technologies more effectively. Social networks are relevant in the farmers' decision making about climate-smart agricultural adoption based on their function as centres of technical, moral, and financial support.

Institutions factor as security of land tenure and land ownership is related to adoption is debated in the literature. The land is a critical component of development and, in economic terms, considered one of the critical factors of production. Therefore, land tenure arrangements need an explicit examination to facilitate climate adaptation planning. The importance of formal land tenure to livelihoods has also been strengthened by peri-urbanisation and the increased commoditisation of land, which has led to more intense competition for land. The causal relationship between these factors and climate-smart agricultural technology adoption was rarely evaluated in past empirical studies. Indeed, dependent variables in previous studies were used as specific climate-smart agricultural practices for each case study, which made it difficult to represent all adaptation strategies to climate change situations. Therefore, the results did not predict a model of farmers' behaviour in terms of climate-smart agricultural practices for all research cases. In Vietnam, many studies provided variables that explained the adoption of sustainable technologies among farmers in the Mekong Delta (Dung et al., 2018; Heong, Escalada, & Mai, 1994; Huan, Mai, Escalada, & Heong, 1999; Le Dang, Li, Nuberg, & Bruwer, 2014). However, there is a lack of empirical studies conducted in the context of climate-smart agricultural practices adoption by Vietnam's agriculture, which is one of the Southeast Asian countries most significantly impacted by climate change. In consideration of the utility needs in the literature and climate-smart agricultural practices, this study uses a multinomial regression model to explore the antecedents of farmer's adoption behaviour when it comes to climate-smart agricultural practices, including soil and water management, yield management, and weather-risk management in the Vietnamese Mekong Delta.

Literature review and hypothesis development. The concept of climate-smart agriculture is designed to improve the integration of agricultural development and resilience to climate risks. It aims to achieve food security and social and economic goals under the adverse effects of climate change. Climate-smart agriculture initiatives sustainably increase productivity, enhance resilience, reduce net greenhouse gas emissions (GHGs), and require action planning to address trade-offs and synergies between the three pillars of productivity, adaptation, and mitigation (FAO, 2013). Climate-smart agriculture has many approaches that can be considered at different levels; Climate-smart agriculture should not be considered only a collection of production technologies or practices. Climate-smart agriculture is a process. Its many steps include developing techniques and methods, modelling based on different climate change contexts, integration of information technology, insurance mechanisms to limit risks along the value chain and through institutional arrangements, and policy systems (FAO, 2010). As such, climate-smart agriculture is not only a manufacturing technology but a combination of many interventions in the production systems, landscapes, value chains, or policies that cover a region. Climate-smart agriculture is specific to the location. Successful in one area, it may not be considered intelligent in another area, and no intervention solution is climate-smart at all times or in all places. Interventions need to consider the interaction between different factors at the landscape level, in and between ecosystems, as well as part of the policy and institutional practices (FAO, 2013).

In Vietnam, CSA in rice production aims to provide measures for yield management (e.g., the system of rice intensification, integrated pest management, improved variety for rice, change in land uses with rice-peanuts/crop rotation with rice-shrimp, changing sowing or harvesting date, reducing the number of crop plantings, changing fertiliser and chemical use, changing crop variety, and diversifying crops); soil and water management (e.g., One Must, Six Reductions;1 Three Reductions, Three Gains; Large Field Model; and VietGAP); and weather risk management (e.g., agricultural insurance) (Chi et al. 2013; Dung et al. 2018; Ho and Shimada 2019; Lampayan et al. 2015).

Researchers have proposed many theoretical frameworks to explain the behaviour of individual choice. Based on these behavioural economic theories, several studies of choice behaviour were examined to select variables regarding the adoption of sustainable agricultural practices among farmers.

A farmer’s education level typically correlates positively with technological innovations adoption because of the assumed link between education and knowledge accumulation and a farmer’s decision-making capacity (Addisu et al., 2016; Asrat & Simane, 2018; Dung et al., 2018; Fadina & Barjolle, 2018; Gebrehiwot & Van Der Veen, 2013; Teklewold et al., 2013). Education level might significantly affect the ability to absorb technical information and coherence in applying climate-smart agricultural technologies in practice. A farmer's age has also been regularly assessed in terms of the adoption of climate-smart agricultural technology practices, resulting in a positive correlation (Atinkut & Mebrat, 2016), a negative association (Addisu et al., 2016; Asrat & Simane, 2018; Gebrehiwot & Van Der Veen, 2013; Maguza-Tembo, Mangison, Edris, & Kenamu, 2017), and insignificant correlation (Neill & Lee, 2001). In this study, the age of the household head has both positive and negative impacts on adaptation measures, in which old age is associated with more experience and expect older farmers to adapt to changes in climate. However, young farmers to have a longer planning horizon and to take up long-term adaptation. Gender of the household might affect climate-smart agricultural technology adoption due to financial or resource constraints, availability of information, access to extension services, and available adaptation strategies. These factors tend to be harder to achieve and to create higher labour loads for women farmers (Atinkut & Mebrat, 2016; Jost et al., 2016; Mersha & Van Laerhoven, 2016).

Farm size refers to the total land available to a farmer for agricultural production. Given the uncertainty and the fixed transaction and information costs associated with technologies, there may be a critical lower limit on farm size that prevents smaller farms from making an adoption decision (Dung et al., 2018). Owners of larger farms are more willing to invest in climate-smart agricultural technologies than those who do not have as much land (Atinkut & Mebrat, 2016; Fadina & Barjolle, 2018; Teklewold et al., 2013). The larger the area of productive land, the more motivation for farmers to learn how to apply climate-smart agriculture to keep costs, labour, and care to a minimum.

Agricultural technology adoption requires sufficient economic well-being, especially if new equipment is needed (Dung et al., 2018). Khatri-Chhetri et al. (2017) indicated that technologies and the cost of implementation influence farmers' preferences and willingness-to-pay. The impact of off-farm income or income, access to credit on adoption revealed a positive correlation (Addisu et al., 2016; Asrat & Simane, 2018; Gebrehiwot & Van Der Veen, 2013; Tessema et al., 2013; Teklewold et al., 2013). If a farmer has off-farm income, income, or access to credit, they are willing to invest in technology.

Social capital is a long-lasting network of community acquaintances and identities that can be institutionalised. Social capital includes mutual trust; reciprocity based on rules, exemplary behaviours, and sanctions; and unity to form a social network that governs all human-to-human interactions and thus contributes to economic development (Coleman, 1988; Fukuyama, 1995). Social capital and farmer networks can influence technology adoption decisions (Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Marenya & Barrett, 2007). Social capital represents a combination of variables: membership in a farmers' association, the number of relatives inside and outside the village that a household can rely on for critical support, and the number of traders that a farmer knows inside and outside the town (Asrat & Simane, 2018). Social capital refers to a farmer's social network, including the ability to access information, find jobs, access to credit, insurance against unforeseen risks, exchange of information on prices, reduction of information asymmetry, and the ability to contract in agricultural production (Maertens & Barrett, 2012).

The most critical barriers to climate change adaptation are lack of information and inadequate extension services (Addisu et al., 2016; Asrat & Simane, 2018; Atinkut & Mebrat, 2016; Gebrehiwot & Van Der Veen, 2013; Tessema et al., 2013; Wassie & Pauline, 2018). Information sources that positively influence adoption can include other farmers, media, meetings, and extension. The agricultural extension service is a formal source of information for producers, based on the contact with extension agents and farmer groups (Tessema et al., 2013).

Farmer's changing agricultural practices are due to observations of climatic and environmental change (Jost et al., 2016; Schattman, Conner, & Méndez, 2016). Farmers' perception of the impact of climate change is significantly related to the age and gender of the head of household, income, knowledge of climate change, social capital, and agro-ecological settings (Abrha, 2015; Atinkut & Mebrat, 2016; Ayal & Leal Filho, 2017; Deressa, Hassan, & Ringler, 2011; Schattman et al., 2016).

Land tenure status is a descriptor that differentiates self-owned farmland from property that is rented from a third party (Dung et al., 2018). A farmer is more likely to manage self-owned land than rented property because the benefits of long-term practices like the adoption of climate-smart agriculture accrue over time (Carolan, 2005; Isgin, Ilgic, Forster, & Batte, 2008; Teklewold et al., 2013). Climate-smart agriculture adoption is affected by the land tenure status of the farmer, which has generally been consistent across a range of studies (Dung et al., 2018).

Access to the market is directly associated with the transaction costs that occur when households participate in input and output marketing activities (Dung et al., 2018; Kassie et al., 2013). Transaction costs are barriers to participation by rice farmers and determinants of market failure in developing countries (Addisu et al., 2016; Asrat & Simane, 2018; Atinkut & Mebrat, 2016; Tessema et al., 2013).

2. Methods

The quantitative models adopted in previous studies include the multivariate logit, probit, ordered logit/probit, and multinomial logit model (Addisu et al., 2016; Atinkut & Mebrat, 2016; Deressa et al., 2011; Fadina & Barjolle, 2018; Gebrehiwot & Van Der Veen, 2013; Teklewold et al., 2013; Tessema et al., 2013). The logit model was typically adopted in choice behaviour studies and is based on the theory of maximum likelihood suggested by Ben-Akiva and Lerman (1985). The logit model is classified into two major categories, including the logit model of binary and multinomial models. Multinomial logistic regression was adopted to predict the probability of category membership on a dependent variable based on multiple independent variables (see Table 1). Like binary logistic regression, the multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of definite membership. Tabachnick, Fidell, and Osterlind (2001) argued that the multinomial logistic regression technique has many significant advantages relative to other regression models.

Table 1. Definition of Variables in The Research Model

Variable	Definition	Expected sign
Dependent variable	Dummy, 3 = Yield management adopter; 2 = Soil and Water management adopter; 1 = Weather-risk management adopter; 0 = non-adopter.	
Independent variables		
Gender	Dummy, the gender of household head: 1= male, 0 = female	−
Age	Continuous, age of household head (years)	−/+
Education level	Continuous, the number of formal education year of the household head	+
Farmland size	Continuous, total farmland (1.000m2)	+
Credit access	Dummy, access to credit of household: 1 = yes, 0 = otherwise	+
Social capital	Continuous, the number of traders/ relatives that farmer trust	+
Extension service access	Continuous, the number of agricultural knowledge sources that farmer accesses by an extension (television-radio, agricultural paper-book, smartphone, extension officer, extension-education courses, others)	+
Perceived climate change	Dummy, perceived climate change risks: 1 = yes, 0 = otherwise	+
Farmland tenure status	Dummy, farmland tenure status: 1 = secure, 0 = otherwise	+
Market Constraint	Continuous, access to markets (Distance to input/product market, km)	−

We assumed that farmers choose adoption to maximise their expected utility (Y*ij). The latent model (Y*ij) describes the behaviour of farmer i in adopting climate-smart agricultural technology j rather than adopting any other alternative technologies, which can be expressed as Equation (1):

$$Y^*_{ij} = \beta_i X_i + \varepsilon_{ij} \quad j = 1 \ldots J \qquad (1)$$

Where Xi is a vector of independent variables, namely human capital, farmland size, financial capital, social capital, extension service access, perceived climate change impact, farmland tenure status, and access to input and product factor markets; and εi is a random error term.

The utility to the farmer of choosing a climate-smart agricultural technology is not observed, but the farmer's adoption decision is observable. Let (Y) be an index that denotes the farmer's choice of climate-smart agricultural technology. Thus, the farmer will choose a climate-smart agriculture practice j preference for adopting any other climate-smart agriculture practice m if:

$$Y = \begin{cases} 1 \text{ iff } \delta_{ij} < 0 \text{ or } Y^*_{i1} > \max\limits_{m \neq 1} (Y^*_{im}) \\ j \text{ iff } \delta_{ij} < 0 \text{ or } Y^*_{ij} > \max\limits_{m \neq 1} (Y^*_{im}) \end{cases} \quad \text{for all } m \neq j \ (2)$$

$$\text{Because } \delta_{ij} = Y^*_{i1} > \max\limits_{m \neq j}\left(Y^*_{im} - Y^*_{ij}\right) < 0$$

Equation (2) indicates that farmer i will choose a climate-smart agriculture j to maximise expected profit and obtain greater expected profit than any other technology m ≠ j (Bourguignon, Fournier, & Gurgand, 2007).

The δjs are assumed to be independent and identically Gumbel distributed (Bourguignon et al., 2007). The probability that farmer i with characteristics Xi chooses a j over another climate-smart agricultural technology can be specified by a multinomial logit selection model (McFadden, 1973) as follows:

$$P\left(\delta_{ij} < 0/X_I\right) = \frac{\exp(X_i\beta_j)}{\sum_{m=1}^{J} \exp(X_i\beta_m)}$$

This expression shows that consistent maximum likelihood estimates of δj can be obtained given its cumulative and density functions G(δ) = exp(−e-δ) and g(δ) = exp(−δ −e-δ), respectively. A sample size requirement for the multinomial logistic regression requires a minimum of 10 cases per independent variable (Schwab, 2002).

The Mekong Delta is the largest rice production area in Vietnam, located in southwestern Vietnam. The Delta covers 39.000 km2 with about 600 km of coastline. It is divided into 12 provinces (Long An, Tien Giang, Ben Tre, Tra Vinh, Vinh Long, Dong Thap, An Giang, Kien Giang, Hau Giang, Soc Trang, Bac Lieu, and Ca Mau) and has one central city, Can Tho. Provinces of the Delta are categorised into four groups related to their vulnerability to climate change: high vulnerability level (Tra Vinh and Ca Mau provinces), moderate vulnerability level (Bac Lieu, Soc Trang, and Ben Tre provinces), low vulnerability level (Long An, Tien Giang, Vinh Long, Can Tho, Kien Giang, Vinh Long, and Hau Giang provinces), and the lowest level of vulnerability to climate change (An Giang and Dong Thap provinces) (Ho & Shimada, 2019).

The sample areas included four provinces (An Giang, Long An, Ben Tre, and Tra Vinh) and were randomly chosen from each of the four vulnerability-level groups, respectively. The sample areas also represent three major water resource zones: the highly flooded zone (Long Xuyen and Plain of Reeds), the fresh-water zone (upper-lands between the Tien and Hau rivers), and the saline intrusion zone (East Sea Coastal, Ca Mau Peninsula) (Tuan, Hoanh, Miller, & Sinh, 2007). Cross-sectional data from 350 households collected via face-to-face interviews with a structured questionnaire was used. A stratified random sampling procedure was adopted to select three wards in two districts in each province. The respondents were household heads randomly selected from the official household list of each commune, based on the guidance and support of village leaders. The distribution of sample households is shown in Table 2 and Figure 1.

Table 2. Sample Distribution in the Study Area

Study Area	Sample size
An Giang	
Chau Thanh	30
Thoai Son	30
Long An	
Tan Thanh	40
Can Duoc	40
Ben Tre	
Ba Tri	50
Thanh Phu	50
Tra Vinh	
Tieu Can	60
Tra Cu	50

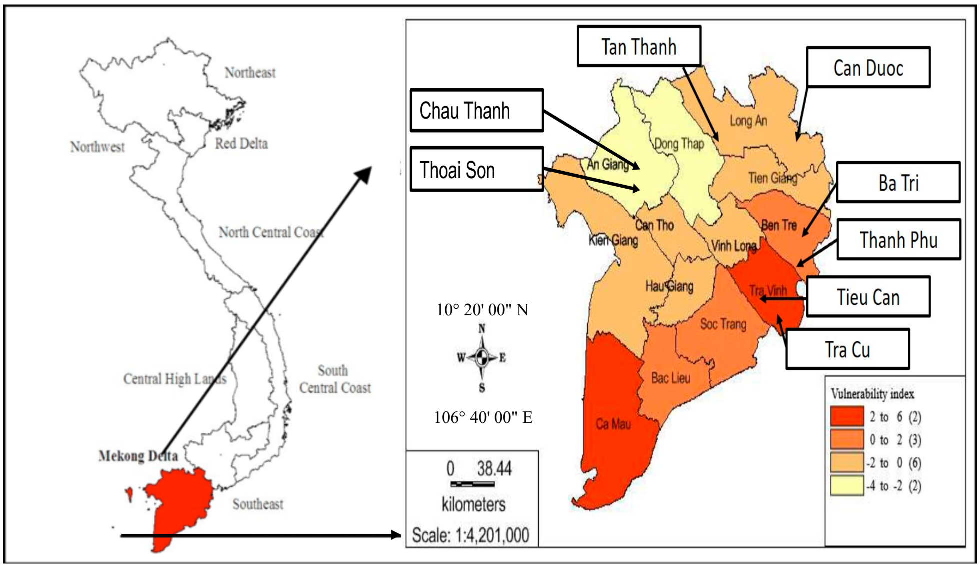

Figure 1. Map of Vietnam and the Mekong Delta Study Area

3. Results

The result of the survey showed that 212 cases (60.57%) had adopted climate-smart agriculture, while 138 cases (39.43%) had not. Considering the adopters, 96 cases (27.4%) adopted weather-risk management, 60 cases (17.10%) adopted soil and water management, and 56 cases (16.0%) adopted yield management. Men headed about 93.10% of the small-holder farm households, both climate-smart agriculture adopters and non-adopters. Other characteristics of the adopters and non-adopters in the sample are presented in Table 3 and Table 4.

Table 3. Farmer's Characteristics (All Cases)

Variable	Min	Max	Mean	*SD*
Gender	0.00	1.00	0.93	0.25
Age	20.00	63.00	39.61	11.11
Education level	0.00	16.00	8.64	4.26
Farmland size	0.50	11.00	4.35	2.22
Social capital	1.00	6.00	3.31	0.89
Access to extension	2.00	5.00	2.75	1.04
Perceived climate change	0.00	1.00	0.50	0.50
Farmland tenure	0.00	1.00	0.80	0.40
Market constraint	1.00	13.00	4.30	1.86

Results off-tests and chi-square tests in Table 4 indicate that a male farmer who is head of household, with a higher education level, a larger farm, access to extension, access to markets, higher social capital, access to credit, perceived climate change, and secured farmland is more likely to adopt climate-smart agricultural practices than other farmers.

The estimation results of the multinomial logit model in Table 5 show the logistic coefficient for each independent variable for each alternative category of the dependent variable. The chi-square results show that the likelihood ratio statistics are highly significant ($p < .0001$), suggesting the model has a reliable explanatory power for behaviour to adopt climate-smart agricultural technologies among farmers. The distribution in Table 5 reveals that the value of Pseudo McFadden R^2 was at 0.394, Cox and Snell R^2 was at 0.646, and Nagalkerke R^2 was at 0.696, suggesting that 39.40%, 64.60%, and 69.60% of the variability is explained by this set of variables used in the model, respectively.

Table 5 presents the estimated marginal effects, p-levels, and the estimated coefficients of the multinomial logit model. The results show that most of the relevant explanatory variables in the model are statistically significant at 10% or higher, and the signs on most variables are as expected. The chi-square results show that likelihood ratio statistics are highly significant ($p < .001$), suggesting the model has a reliable explanatory power for adoption behaviour of climate-smart agriculture among rice farmers in the case of the Mekong Delta, Vietnam.

The marginal effects are presented in Table 5 by variable category. As is shown in this table, the most critical determinants of climate-smart agricultural technology adoption include perceived climate change impact, education level, farmland size, access to credit, social capital, access to extension, secure farmland tenure, and constraint to market.

Table 4. Comparisons of Explanatory Variables Means among Groups

	Non-adopters	Weather-risk management	Soil and Water management	Yield management	p_value
Gender	0.81	0.97	0.99	0.97	0.043
Age	41.01	40.40	39.54	40.16	0.474
Education level	5.33	10.00	10.19	11.47	***
Farmland size	2.07	4.08	4.44	5.82	***
Access to credit	0.44	0.56	0.66	0.91	***
Social capital	0.22	0.22	0.84	0.90	***
Extension access	0.54	0.87	2.90	2.95	***
Perceived climate change risk	0.45	0.74	0.77	0.91	***
Farmland tenure status	0.64	0.84	0.89	0.97	***
Market constraint	5.12	4.45	4.33	3.58	***

Note. ***$p < 0.001$

Table 5. Parameter Estimates and Marginal Effects of Explanatory Variables from the Multinomial Logit Adoption Model

Variables	Weather-risk management		Soil and Water management		Yield management	
	Estimated coefficients	Marginal effects	Estimated coefficients	Marginal effects	Estimated coefficients	Marginal effects
Gender	−0.480 (0.710)	0.150	15.731 (0.071)	0.144	−0.984 (1.299)	−0.053
Age	0.023 (0.016)	0.005	0.009 (0.022)	−0.0004	0.026 (0.023)	0.0006
Education level	0.297*** (0.053)	0.048	0.316*** (0.069)	0.006	0.442*** (0.078)	0.012
Farmland size	0.305*** (0.118)	0.055	0.267** (0.142)	0.003	0.353** (0.148)	0.008
Financial access	0.294 (0.400)	0.014	1.020* (0.555)	0.040	1.777*** (0.713)	0.075
Social capital	0.079 (0.250)	0.027	0.694*** (0.294)	0.034	0.734*** (0.316)	0.033
Extension service access	0.107 (0.231)	0.008	0.539** (0.264)	0.025	0.519* (0.282)	0.021
Perceived climate change	2.207*** (0.404)	0.197	3.839*** (0.586)	0.133	4.090*** (0.661)	0.140
Land tenure status	0.150 (0.462)	0.026	1.324* (0.714)	0.050	1.183 (0.126)	0.041
Market access	−0.066 (0.105)	0.006	−0.234 (0.148)	−0.009	−0.465*** (0.163)	−0.021
Constraint to market	−5.342 (1.373)	–	−27.017 (1.926)	–	−13.130 (2.430)	-
Number of obs = 350; LR chi^2 (30) = 363.64; Prob > chi2 = 0.000; Log likelihood = 558.47; Pseudo Cox and Snell R^2 = 0.646; Pseudo Nagelkerke R^2 = 0.696; Pseudo McFadden R^2 = 0.394.						

Note. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; standard errors are in parentheses; reference category: non-adoption

4. Discussion

Small farmers play a crucial role in increasing production to ensure food security, but they are faced with many barriers such as market access, knowledge, skills and technology innovations, new value chains, and lack of many other opportunities. Overcoming these difficulties to develop sustainable agriculture requires dedication and effort. All stakeholders must participate, including the government, businesses, farmers, scientists, and banks, and the role of farmers is crucial. Therefore, an understanding of the factors that restrict farmers from adopting climate-smart agriculture has become a significant question for stakeholders. This understanding may aid in the design and implementation of interventions to overcome barriers. Subsequently, a critical issue that requires attention at the policy, research, and practical levels is the successful adoption and diffusion of climate-smart agricultural technology innovations. This study aligns with other research results that are cited in the literature review of this study.

The education level of the household head was found to be positively and significantly correlated with weather-risk management, soil and water management, and yield management at $p < 0.01$. A one-unit increase in the education level of farmers increased the probability of adoption of weather-risk management by 4.8%, soil and water management by 0.6%, and yield management by 1.2%, respectively, relative to the base category (nonadopting). Previous studies have also shown that farmers with better formal education may be more likely to adopt climate-smart agricultural technologies than others (Addisu et al., 2016; Asrat & Simane, 2018; Fadina & Barjolle, 2018; Gebrehiwot & Van Der Veen, 2013). The availability and quality of labour make it difficult for farmers to proactively cope with and reduce losses due to extreme weather events, especially when there is unseasonal rain in the Mekong Delta. Farmers often make use of family labour in rice cultivation. The main household labour force has tended to decrease while the rural labour force is also becoming scarce because migrants are seeking jobs in urban areas. Therefore, less labour-intensive or mechanised methods of agricultural production in some stages—especially in harvesting—is an urgent requirement for farmers to be able to adopt climate-smart agricultural technologies.

Farm size appears to be positively and significantly correlated with weather-risk management, soil and water management, and yield management at $p < 0.01$ and $p < 0.05$, respectively, relative to the base category. A 1,000 square meter per household unit increase would increase the probability of adopting weather-risk management, soil and water management, and yield management by 5.5%, 0.3%, and 0.8%, respectively, for households with a small farmland size. The relationship between climate-smart agricultural technology application and the amount of farmland is due to financial constraints. Farmers with large production scales are more financially capable; therefore, they have a higher probability of being able to afford climate-smart agricultural technology in production (Atinkut & Mebrat, 2016; Fadina & Barjolle, 2018). In the Mekong Delta, agricultural land is limited, more than 50% of fields have an area of less than 0.5 ha, which makes it difficult for farmers to cope with unexpected weather impacts. Although a financial support policy for agricultural development at the household level has been issued, it is difficult to access this financial resource due to procedures and timing of bankers, and demand difference of farmers with financial products provided. It is difficult to obtain loans from commercial banks in time to meet the needs of farmers because they not only need capital for rice cultivation but also for other economic and livelihood needs. As a result, most farmers buy deferred payments that come due at the end of each rice harvest, and they pay more than twice as much as they would pay the bank.

Access to credit showed a positive and significant correlation with soil and water management and yield management at $p < 0.10$ and $p < 0.05$, respectively, relative to the base category. A farmer, who has available credit is more likely to adopt climate-smart agricultural technologies by 4% and 7.5%, respectively, higher compared to those who do not have access to credit. Inability to access credit might discourage households from adopting technology if the application faces legal constraints or involves additional investment. This may prevent small farmers from adopting climate-smart agricultural technologies (Addisu et al., 2016; Asrat & Simane, 2018; Gebrehiwot & Van Der Veen, 2013; Tessema et al., 2013).

Social capital is positively and significantly correlated with the household decision to adopt soil and water management and yield management at $p < 0.01$. A one-relative/trader increase in farmer's trust can increase the probability of using these two adoption measures by 3.4% and 3.3%, respectively, relative to the base category. The effect of social capital and social networks on farm households on the choice of applying climate-smart agriculture has been assessed in many studies (Bandiera & Rasul, 2006; Isham, 2002; Kassie et al., 2013; Wollni et al., 2010). Farmers' social capital can affect the application of technological advances in many ways, such as information exchange, market access, labour exchange, and capital access, as well as coping with risks in production and the market. In the context of the Mekong Delta, the collective actions by farmers include knowledge sharing, mass sowing, dyke protection, water management, and meeting market requirements.

Contacts with the extension service have a positive and significant correlation with the likelihood of choosing of soil and water management and yield management by $p < 0.05$ and $p < 0.10$, respectively, relative to the base category. A one-unit increase in the number of extensions contact sources is likely to increase the probability of the farmer adopting the two measures by 2.5% and 2.1%, respectively, over those households who do not use extension services. Agricultural extension is the official source of information for farmers in agrarian production. Official information about markets, scientific advances or technical solutions can minimise risks, uncertainties, and asymmetric information. Extension thereby plays a crucial role in increasing the choice of application of technological advances in general and climate-smart agriculture measures in particular (Jansen, Pender, Damon, Wielemaker, & Schipper, 2006).

Households' perception of the impact of climate change was found to be positively and significantly correlated with the choice of weather-risk management, soil and water management, and yield management at $p < 0.01$. A farmer who perceives the impact of climate change on production is more likely to adopt climate-smart agricultural technologies by 19.7%, 13.3%, and 14.0% more, respectively, compared to those who do not perceive the effects of climate change. The impact of environmental stresses and climate change on the probability and extent of the application of climate-smart agricultural practices might depend on the costs and characteristics of the techniques applied. The government's role is to assist farmers in having a substantial impact on the probability and application of climate-smart agricultural practices (Kassie et al., 2013; Nyanga, Johnsen, & Aune, 2011).

Farmland tenure has a positive and significant correlation with the likelihood of choosing soil and water management at $p < 0.1$, relative to the referenced category. Having a land ownership certification can increase the probability of adopting soil and water management by 5.0% over those households that lease farmland. Carolan (2005), Nkonya, Schroeder, and Norman (1997), and Polson and Spencer (1991) concluded that farmers who cultivate on leased land tend to be less likely to apply technological advances than farmers who own property.

Constraint to markets is negatively and significantly correlated with the household's decision to pursue yield management at $p < 0.01$. A one-kilometre increase in the distance to the agricultural input/output market can decrease the probability of using yield management measures by 2.1%. Input markets allow farmers to acquire the inputs they need, such as different seed varieties, fertilisers and irrigation technologies. Access to output markets provides farmers with positive incentives to produce cash crops that can help improve their resource base and hence their ability to respond to changes in climate. Farmer's accessibility to input and output markets effect on the transaction costs and then effect on the likelihood of climate-smart agriculture adoption (Dimara & Skuras, 2003; Neill & Lee, 2001; Pretty, Toulmin, & Williams, 2011).

This study has certain limitations. First, the study has considered only farmers' adoption of climate-smart agriculture measures as the dependent variable in the research model. Other alternative variables such as farmer perception, or/and extent in the adoption of climate-smart agricultural technologies and the efficiency of climate-smart agriculture have not been considered in this study. Secondly, the data sets were collected only in the Mekong Delta area by surveying rice farmers; therefore, the model might not fit other regions of the country at large. Future studies should concentrate on other areas and different types of agricultural cooperative models.

5. Conclusion

Climate change adaptation practices play a crucial role in improving technical efficiency, economic benefits, and food security. Farmers play a significant role in the agricultural sector's supply chain, and their adoption behaviour concerning climate-smart agriculture will determine the sustainability of agricultural development for the economy, the environment, and society. Therefore, an understanding of factors that restrict farmers in the adoption of climate-smart agriculture may become a significant question for all stakeholders. A vital issue requiring attention at the policy, research, and practice levels is the successful adoption and diffusion of climate-smart agricultural technological innovations. Based on survey data of 350 rice farmers in the Mekong Delta, this study analysed the factors that determine the probability of adoption of climate-smart agriculture among Vietnamese rice farmers using a multinomial logit model. The estimation results indicate that the likelihood of climate-smart agricultural technology adoption is affected by perceived climate change, a higher education level, larger farm size, access to credit, strong social capital, access to extension, secure farmland tenure, and lower constraints to market entry.

The education level of the household was found to be positively and significantly correlated with weather-risk management, soil and water management, and yield management. Providing more training about climate change to farmers through the extension service system can build resilience and increase knowledge of climate-smart agricultural technologies and climate change.

Farmland size appears to be positively and significantly correlated with weather-risk management, soil and water management, and yield management. Farmland tenure has a positive and significant correlation with the likelihood of choosing soil and water management. Implementation of the 2013 Vietnamese Land Law, taxation policies and agricultural, forestry, and fishery extension activities should be directed toward restructuring the agricultural sector to increase productivity through transitions to higher-value products and strengthened value chains for farmers' products.

Access to credit showed a positive and significant correlation with soil and water management and yield management. Public investment in terms of quantity, level, and effectiveness of climate-smart agricultural practice projects in rural areas needs more attention, and there is a need to pay attention to specific characteristics of each locality and region to make investment solutions effective.

Social capital is positively and significantly correlated with the household decision to adopt soil and water management and yield management. The quality of social capital can be improved through investing in effective operations of the local organisations such as the farmer's association, agricultural cooperatives, farmer collaboration groups, and large-field and production-trade linkage models. Collective action is treated as a significant adaptation decision regarding the management of agricultural and other resources in support of the community co-adapting to climate change.

Extension contact sources have a positive and significant correlation with the likelihood of choosing soil and water management and yield management. Agricultural extension staffs can improve the effectiveness of agricultural extension activities and strengthen and foster knowledge about agricultural development policies.

Household perceptions of the impact of climate change were found to be positively and significantly correlated with the choice of weather-risk management, soil and water management and yield management. A focus on marketing and disseminating awareness and information about climate change in the community can promote participation in resource management. Farmers' sense of usefulness can be increased through disseminating information about the economic, social, and environmental effects of climate-smart agricultural practices in mass media.

Constraints to market access are negatively and significantly correlated with the household's decision to pursue yield management. Building necessary infrastructure for production, such as in-field lanes, irrigation canals, roads, and electrical systems, will have a massive impact on the entire community.

References

Abrha, M. G. (2015). Local climate trends and farmers' perceptions in Southern Tigray, Northern Ethiopia. *International Journal of Environment and Sustainability*, *4*(3), 11–28. doi: 10.24102/ijes.v4i3.563

Addisu, S., Fissha, G., Gediff, B., & Asmelash, Y. (2016). Perception and adaptation models of climate change by the rural people of lake Tana Sub-Basin, Ethiopia. *Environmental Systems Research*, *5*(1), 7. doi: 10.1186/s40068-016-0059-0

Asrat, P., & Simane, B. (2018). Farmers' perception of climate change and adaptation strategies in the Dabus watershed, North-West Ethiopia. *Ecological Processes*, *7*(1), 7. doi: 10.1186/s13717-018-0118-8

Atinkut, B., & Mebrat, A. (2016). Determinants of farmers choice of adaptation to climate variability in Dera woreda, south Gondar zone, Ethiopia. *Environmental Systems Research*, *5*(1), 6. doi: 10.1186/s40068-015-0046-x

Ayal, D. Y., & Leal Filho, W. (2017). Farmers' perceptions of climate variability and its adverse impacts on crop and livestock production in Ethiopia. *Journal of Arid Environments*, *140*, 20–28. doi: 10.1016/j.jaridenv.2017.01.007

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in northern Mozambique. *Economic Journal*, *116*(514), 869–902. doi: 10.1111/j.1468-0297.2006.01115.x

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*, *9*. London: MIT Press.

Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys*, *21*(1), 174–205. doi: 10.1108/IJCCSM-01-2019-0003

Carolan, M. S. (2005). Barriers to the adoption of sustainable agriculture on rented land: An examination of contesting social fields. *Rural Sociology*, *70*(3), 387–413. doi: 10.1526/0036011054831233

Chi, T. T. N., Anh, T. T. T., Tuyen, T. Q., Palis, F. G., Singleton, G. R., & Toan, N. V. (2013). Implementation of "one Must and Five Reductions" in rice production in An Giang province. *Omonrice*, *19*, 237–249.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95–S120. doi: 10.1086/228943

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile Basin of Ethiopia. *Journal of*

Agricultural Science, *149*(1), 23–31. doi: 10.1017/S0021859610000687

Dimara, E., & Skuras, D. (2003). Adoption of agricultural innovations as a two-stage partial observability process. *Agricultural Economics*, *28*(3), 187–196. doi: 10.1111/j.1574-0862.2003.tb00137.x

Dung, L. T., Ho, D. P., Hiep, N. T. K., & Hoi, P. T. (2018). The determinants of rice farmers' adoption of sustainable agricultural technologies in the Mekong Delta, Vietnam. *Applied Economics Journal*, *25*(2), 55–69. Retrieved from https://so01.tci-thaijo.org/index.php/AEJ/article/view/179746

Fadina, A. M. R. & Barjolle, D. (2018). Farmers' adaptation strategies to climate change and their implications in the Zou Department of South Benin. *Environments*, *5*(1), 15. doi: 10.3390/environments5010015

Food and Agricultural Organization of the United Nations. (2013). *Climate-Smart Agriculture-Sourcebook*. Rome: Food and Agriculture Organization.

Food and Agriculture Organization of the United Nations. (2010). *Climate-smart agriculture: Policies, practices, and financing for food security, adaptation and mitigation*. Rome: Food and Agriculture Organization.

Fukuyama, F. (1995). Social capital and the global economy. *Foreign Affairs*, *74*(5), 89–103. doi: 10.2307/20047302

Gebrehiwot, T., & Van Der Veen, A. (2013). Farm-level adaptation to climate change: The case of farmer's in the Ethiopian highlands. *Environmental Management*, *52*(1), 29–44. doi: 10.1007/s00267-013-0039-3

General Statistics Office of Vietnam. (2019). *Statistical yearbook of 2018*. Ha Noi, Vietnam: Statistics Publishing.

Hasan, M. K., Desiere, S., D'Haese, M., & Kumar, L. (2018). Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. *Food Security*, *10*(4), 1073–1088. doi: 10.1007/s12571-018-0824-1

Heong, K. L., Escalada, M. M., & Mai, V. (1994). An analysis of insecticide use in rice: Case studies in the Philippines and Vietnam. *International Journal of Pest Management*, *40*(2), 173–178. doi: 10.1080/09670879409371878

Ho, T., & Shimada, K. (2019). Technical efficiency of rice farming in the Vietnamese Mekong Delta: A stochastic frontier approach. *Ritsumeikan Econ. Rev.*, *67*, 130–144. doi: 10.3390/agriculture9050099

Huan, N. H., Mai, V., Escalada, M. M., & Heong, K. L. (1999). Changes in rice farmers' pest management in the Mekong Delta, Vietnam. *Crop Protection*, *18*(9), 557–563. doi: 10.1016/S0261-2194(99)00059-9

Isgin, T., Bilgic, A., Forster, D. L., & Batte, M. T. (2008). Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. *Computers and Electronics in Agriculture*, *62*(2), 231–242. doi: 10.1016/j.compag.2008.01.004

Isham, J. (2002). The effect of social capital on fertiliser adoption: Evidence from rural Tanzania. *Journal of African Economics*, *11*(1), 39–60. doi: 10.1093/jae/11.1.39

Jansen, H. G. P., Pender, J., Damon, A., Wielemaker, W., & Schipper, R. (2006). Policies for sustainable development in the hillside areas of Honduras: A quantitative livelihoods approach. *Agricultural Economics*, *34*(2), 141–153. doi: 10.1111/j.1574-0864.2006.00114.x

Jost, C., Kyazze, F., Naab, J., Neelormi, S., Kinyangi, J., Zougmore, R., ... & Nelson, S. (2016). Understanding gender dimensions of agriculture and climate change in small-holder farming communities. *Climate and Development*, *8*(2), 133–144. doi: 10.1080/17565529.2015.1050978

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in small-holder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change*, *80*(3), 525–540. doi: 10.1016/j.techfore.2012.08.007

Khatri-Chhetri, A., Aggarwal, P. K., Joshi, P. K., & Vyas, S. (2017). Farmers' prioritisation of climate-smart agriculture (CSA) technologies. *Agricultural Systems*, *151*, 184–191. doi:10.1016/j.agsy.2016.10.005

Khatri-Chhetri, A., Aryal, J. P., Sapkota, T. B., & Khurana, R. (2016). Economic benefits of climate-smart agricultural practices to small-holder farmers in the Indo-Gangetic Plains of India. *Current Science*, *110*(7), 1251–1256.

Lampayan, R. M., Rejesus, R. M., Singleton, G. R., & Bouman, B. A. M. (2015). Adoption and economics of alternate wetting and drying water management for irrigated lowland rice. *Field Crops Research*, *170*, 95–108. doi: 10.1016/j.fcr.2014.10.013

Le Dang, H., Li, E., Nuberg, I., & Bruwer, J. (2014). Farmers' perceived risks of climate change and influencing factors: A study in the Mekong Delta, Vietnam. *Environmental Management*, *54*(2), 331–345. doi:10.1007/s00267-014-0299-6

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Hottle, R. (2014). Climate-smart agriculture for food security. *Nature Climate Change*, *4*(12), 1068–1072. doi: 10.1038/nclimate2437

Maertens, A., & Barrett, C. B. (2013). Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics*, *95*(2), 353–359. doi:10.1093/ajae/aas049

Maguza-Tembo, F., Mangison, J., Edris, A. K., & Kenamu, E. (2017). Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi: An ordered probit analysis. *Journal of Development and Agricultural Economics*, *9*(1), 1–7. doi: 10.5897/jdae2016.0753

Marenya, P. P., & Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among small-holder farmers in western Kenya. *Food Policy*, *32*(4), 515–536. doi: 10.1016/j.foodpol.2006.10.002

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics*. New York: Academic Press.

Mersha, A. A., & Van Laerhoven, F. (2016). A gender approach to understanding the differentiated impact of barriers to adaptation: Responses to climate change in rural Ethiopia. *Regional Environmental Change*, *16*(6), 1701–1713. doi: 10.1007/s10113-015-0921-z

Neill, S. P., & Lee, D. R. (2001). Explaining the adoption and disadoption of sustainable agriculture: The case of cover crops in northern Honduras. *Economic Development and Cultural Change*, *49*(4), 793–820. doi: 10.1086/452525

Nkonya, E., Schroeder, T., & Norman, D. (1997). Factors affecting adoption of improved maise seed and fertiliser in northern Tanzania. *Journal of Agricultural Economics*, *48*(1–3), 1–12. doi: 10.1111/j.1477-9552.1997.tb01126.x

Nyanga, P. H., Johnsen, F. H., Aune, J. B., & Kalinda, T. H. (2011). Small-holder farmers' perceptions of climate change and conservation agriculture: Evidence from Zambia. *Journal of Sustainable Development*, *4*(4), 73–85. doi: 10.5539/jsd.v4n4p73

Polson, R. A., & Spencer, D. S. C. (1991). The technology adoption process in subsistence agriculture: The case of cassava in southwestern Nigeria. *Agricultural Systems*, *36*(1), 65–78. doi: 10.1016/0308-521X(91)90108-M

Pretty, J., Toulmin, C., & Williams, S. (2011). Sustainable intensification in African agriculture. *International Journal of Agricultural Sustainability*, *9*(1), 5–24. doi: 10.3763/ijas.2010.0583

Schattman, R. E., Conner, D., & Méndez, V. E. (2016). Farmer perceptions of climate change risk and associated on-farm management strategies in Vermont, Northeastern United States. *Elementa: Science of the Anthropocene*, *4*, 1–14. doi: 10.12952/journal.elementa.000131

Schwab, J. A. (2002). *Multinomial logistic regression: Basic relationships and complete problems*. Austin, TX: University of Texas.

Tabachnick, B. G., Fidell, L. S., & Osterlind, S. J. (2001). *Using multivariate statistics*. Boston: Allyn & Bacon.

Taneja, G., Pal, B. D., Joshi, P. K., Aggarwal, P. K., & Tyagi, N. K. (2019). Farmers' preferences for climate-smart agriculture-an assessment in the Indo-gangetic plain. In *Climate smart agriculture in South Asia*,91–111. Singapore: Springer.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597-623. doi: 10.1111/1477-9552.12011

Tessema, Y. A., Aweke, C. S., & Endris, G. S. (2013). Understanding the process of adaptation to climate change by small-holder farmers: The case of east Hararghe Zone, Ethiopia. *Agricultural and Food Economics*, *1*(1), 13. doi: 10.1186/2193-7532-1-13.

Tuan, L. A., Hoanh, C. T., Miller, F. A., & Sinh, B. T. (2007). Flood and salinity management in the Mekong Delta, Vietnam. In T. T. Be, B. T. Sinh & F. Miller (Eds.), *Challenges to sustainable development in the Mekong Delta: Regional and national policy issues and research needs: Literature analysis* (pp. 15–68). Bangkok: The Sustainable Mekong Research Network.

Van Mai, T., & Lovell, J. (2015). Impact of climate change, adaptation and potential mitigation to Vietnam agriculture. In W. Y. Chen, T. Suzuki & M. Lackner (Eds.), *Handbook of Climate Change Mitigation and Adaptation*. New York: Springer.

Wassie, A., & Pauline, N. (2018). Evaluating small-holder farmers' preferences for climate smart agricultural practices in Tehuledere District, northeastern Ethiopia. *Singapore Journal of Tropical Geography*, *39*(2), 300-316. doi:10.1111/sjtg.12240

Wollni, M., Lee, D. R., & Thies, J. E. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics*, *41*(3-4), 373-384. doi:10.1111/j.1574-0862.2010.00445.x

World Bank. (2016). *Viet Nam Development Report 2016: Transforming Vietnamese agriculture: Gaining more for less*. Washington, DC: World Bank.

World Bank. (2010). *Economics of adaptation to climate change in Viet Nam*. Washington, DC: World Bank.

Received date: 11 November 2019
Revised date: 13 February 2020
Accepted date: 03 March 2020