

Rice Farmers' Perception and Determinants of Climate Change Adaptation Measures: A Case Study in Vietnam

Le Phuong Nam

Viet Nam National University of Agriculture (VNUA), Ha Noi, Viet Nam

Email: lephuongnam87@gmail.com

Nguyen Dang Que *

National Academy of Public Administration (NAPA), Ha Noi, Viet Nam

Email: dangquenapa@gmail.com

Nguyen Van Song

Viet Nam National University of Agriculture (VNUA), Ha Noi, Viet Nam

Email: nguyensonghua@gmail.com

Tran Thi Hoang Mai

Vinh University (VU), Vinh City, Vietnam

Email: hoangmaikt@gmail.com

Nguyen Thi Minh Phuong

Vinh University (VU), Vinh City, Vietnam

Email: minhphuongn78@yahoo.com

Nguyen Thi Xuan Huong

Viet Nam National University of Forestry (VNUF), Ha Noi, Viet Nam

Email: xuanhuongfuv@gmail.com

Nguyen Cong Tiep

Viet Nam National University of Agriculture (VNUA), Ha Noi, Viet Nam

Email: nctiep@vnua.edu.vn

Tran Ba Uan

Dien Bien Technical Economic College, Dien Bien, Vietnam

Email: bauandb@gmail.com

* **correspondence:** Nguyen Dang Que

Email: dangquenapa@gmail.com

The study used Mann Kendall's and Sen's slope tests to elicit rice farmers' perceptions of climate change due to extreme weather occurrences and compared them to hydro-meteorological data. According to the findings, temperatures increased by 0.4 degrees during the last 35 years. While rainfall has increased, the pattern has been difficult to discern. The test results corroborated farmers' perceptions of increased heat spells, but rainfall frequency and intensity vary and are difficult to anticipate. Three adaptation strategies are frequently employed in the Nong Cong district: adjusting the seasonal calendar to alter transplanting and harvesting timing; increasing fertiliser and pesticide application; and changing variety to short-time kinds. Due to the interdependence of adaption techniques, the study used a multivariate probit model. The regression findings indicated that several relevant variables influence the decision to apply adaption methods. Numerous policy ideas for enhancing adaptation to climate change can be derived from the results of this study. District governments must improve their capacity to forecast weekly weather and train how to adapt production to climate change.

Key words: Adaptation climate change measures, multivariate probit model, farmers' perception.

1. INTRODUCTION

The output of paddy of Viet Nam has been increased from 16.4 million tons in 1987 to 50.4 million tons in 2015, with average food per capita doubling from 275 kg/person (1985) to 550 kg/person (2015). Exports of agricultural, forestry and fishery products in 2017 reached USD 36.7 billion, an increase of 14.05% over 2016 (Nguyen Van Song et al., 2020). However, agriculture is vulnerable to climate change due to its reliance on natural circumstances. Warming has a detrimental effect on crops, particularly in low-latitude developing nations (Mendelsohn, 2009), threatening food security and increasing agricultural production costs (Wheeler & Braun, 2013). (Alboghady & El-Hendawy, 2016; Joshia, 2013; Kakumanu, Kuppanan, Ranganathan, Shalander, & Amare, 2016). This indicates that climate change and long-term economic objectives are inextricably linked (Huq, Reid, & Murray, 2006; Stern & Stern, 2007).

Farmers had little access to detailed meteorological and hydrological data; they perceived only changes in

temperature and precipitation. Simultaneously, farmers have observed the effects of climate change solely through extreme weather occurrences and have concluded that these changes have influenced agricultural production (Asare-Nuamah & Botchway, 2019; Debela, Mohammed, Bridle, Corkrey, & McNeil, 2015).

According to the Intergovernmental Panel on Climate Change (IPCC, 2007), identifying adaptation measures and coping with climate change's adverse repercussions enables the pursuit of good possibilities without a climate window (e.g., land use replanning, infrastructure construction). Additionally, adaptation mitigates the negative consequences of climate change and capitalises on opportunities created by changing weather and climate variables (Maddison, 2007; Ndamani & Watanabe, 2016; Uddin, Bokelmann, & Entsminger, 2014). Adaptation also boosts agricultural output and contributes to the sustainability of agricultural development (Roco, Bravo-Ureta, Engler, & Jara-Rojas, 2017).

According to the annual social-economic report (Committee, 2020), the Nong Cong district in Vietnam has a natural area of 28,700ha, of which over 14,000ha is agricultural land. Agriculture accounts for 25% of the district's total income. With an average rice yield of 6 tons/ha, it is one of Thanh Hoa province's largest rice-producing districts. In recent years, agricultural output employed up to 80% of the worker force. However, meteorological problems grow problematic when unpredictable rainfall and temperature patterns are present. As a result, extreme weather occurrences (symptoms of climate change) harm agricultural production in Nong Cong province. Due to insufficient awareness and other problems, a tiny number of farmers continue to adopt adaptation strategies.

The purpose of this study was to elicit farmers' perceptions of the signs and consequences of climate change. Farmers' views of the current situation were then compared to real meteorological data to determine the extent to which farmers observed and understood the current situation. Additionally, adaptation strategies in response to a changing climate were discovered and the factors determining their implementation.

2. LITERATURE REVIEW

Climate change has had extensive ecological and systemic consequences, changing global average temperatures precipitation rates, and generating an alarming rise in sea levels, among other things (Gamage, Pearson, & Hanna, 2017). These impacts are most noticeable in Southeast Asia's vulnerable countries, where climate change diminishes crop yields, farmer income, and food supplies (Reidsma, Ewert, Oude Lansink, & Leemans, 2008). Climate change endangers agriculture in developing countries and impairs farmers' lives (Jellason, Baines, Conway, & Ogbaga, 2019; Paudel et al., 2020; Rondhi, Fatikhul Khasan, Mori, & Kondo, 2019). Climate change contributes to extreme weather events such as heat waves, droughts, and floods. Due to inadequate infrastructure and rapid population increase (Banerjee, 2015), these consequences can harm agricultural productivity, soil quality, crop diseases, farmers' economies, and food security (Fahad & Wang, 2018; Iqbal et al., 2020; Liverpool-Tasie & Parkhi, 2021). Numerous adaptation techniques are applied, including crop diversification, pesticide and fertiliser adjustment, increased water conservation, diversification of farming activities, and smart farming at the family level (Fahad & Wang, 2018; Mustafa et al., 2017). (Abegunde, Sibanda, & Obi, 2020). However, adaption methods must be implemented following the magnitude of climate change consequences and farmers' opinions (Mustafa et al., 2017; Rondhi et al., 2019). While much research concentrates exclusively on analysing adaptation measures, the analysis of adaptive decision-making is also a critical topic to investigate (Etana, Snelder, van Wesenbeeck, & de Cock Buning, 2020). Perception, intention, and adaptation are all stages of this process (Mustafa et al., 2017).

Climate and weather change perceptions, particularly perceptions of rising temperatures and precipitation, are irregular in frequency and severity, making them more difficult to predict (Ayanlade, Radeny, & Morton, 2017; Hundera, Mpandeli, & Bantider, 2019; Raghase & Norris, 2015; Sahu & Mishra, 2013; Tesfaye & Seifu, 2016). According to the study, over 89% of farmers feel that the temperature is rising. More than 90% say that rainfall has changed significantly (Saguye, 2017). This finding is consistent with the study (Gbetibouo, 2009), which examined perceived changes in temperature and rainfall. However, only approximately 63% of families feel climate change and sustainable agricultural output are beneficial. Weather information is critical for understanding climate change perceptions. The more information on weather and climate, the more likely people will agree on the effects of climate change (Amadou, Villamor, Attua, & Traoré, 2015; Ochenje, Ritho, Guthiga, & Mbatia, 2016).

Farmers' perceptions are critical for adaptation in small-scale agriculture (Desquith & Renault, 2021); farmers employ a variety of adaptation strategies to mitigate the risks associated with the effects of climate change on agricultural production (Mustafa et al., 2017; Vo, Mizunoya, & Nguyen, 2021). We employed econometric models to analyse the influencing elements. Several studies have used the ordered probit model to assess farmers' awareness of the impact of climate change (Rondhi et al., 2019), the generalised ordered logit model to consider farmers' adoption of sustainable agricultural practices (Abegunde et al., 2020), and the binary logistic regression model to compare farmers' perceptions (Paudel et al., 2020). Additionally, studies (Jellason et al., 2019) and factor analysis (Iqbal et al., 2020) demonstrate the elements affecting perception transition from perception to adaptive intention. Heckman's probit model was also used to investigate the relationship between the two stages of perception and adaption (Aihounton, Yegbemey, & Yabi, 2013).

Adaptation solutions are critical for mitigating climate change's adverse consequences (Hassan & Nhemachena, 2008; Kabubo-Mariara & Karanja, 2007). Adaptation strategies are changes made to the production system to mitigate the losses caused by extreme weather events while pursuing other advantageous opportunities (Moser & Ekstrom, 2010). However, adaption techniques can be either short- or long-term and take on various shapes, either locally or globally. They may serve multiple purposes, including mitigating the detrimental consequences of climate change and advancing other socio-economic development objectives (Smit & Pilifosova, 2003).

Numerous research has been conducted on farmers' adaptability to climate change (Alam, Alam, & Mushtaq, 2016; Alauddin & Sarker, 2014). Farmers' adaptation techniques to climate change have been documented in previous research (Amare & Simane, 2017; Dasmani, Darfor, & Karakara, 2020; Gebu, Ichoku, & Phil-Eze,

2020). However, earlier research has documented the various adaption techniques but not their interaction (Tessema, Joerin, & Patt, 2019).

Socio-economic characteristics and agricultural production factors such as education, irrigation, extension access, farmer association membership, land tenure, and credit influence how farmers perceive and respond to climate change (Abegunde et al., 2020; Aihounton et al., 2013; Rondhi et al., 2019; Van Song, Cuong, Huyen, & Rañola, 2020). Additionally, risk aversion influences the choice of adaptation forms (Iqbal et al., 2020; Van Song et al., 2020), or the previous year's adaptation strategy influences the current adaptation strategy. Additionally, biophysical parameters influenced farmer perception (Paudel et al., 2020). Additional drivers include the number of farm labourers, income levels, community organising participation, and perceptions of the effectiveness of adaption techniques (Abegunde et al., 2020; Vo et al., 2021). Young farmers are more conscious of the negative repercussions of climate change, whereas more educated farmers can comprehend and adjust more effectively. However, households with higher incomes frequently exhibit less awareness, as they retain the financial potential to expand output (Chingala, Mapiye, Raffrenato, Hoffman, & Dzama, 2017). Additionally, property rights and subsidies influence farmers' perceptions and adaptation. However, perception cannot predict actual adaptation (Etana et al., 2020), as climate change adaptation measures depend on each Farmer's ability and the real effects of climate change (Mfere, 2021). Adaptation barriers have also been identified, including insecure land ownership and a scarcity of labour, credit, and information (Etana et al., 2020; Mfere, 2021).

Perception and adaption occur over an extended period and are constantly altered (Mustafa et al., 2017). As a result, methods were also presented to raise awareness, allowing for more adaptable decision-making (Jellason et al., 2019). Several solutions have been offered, including educating

women on the effects of climate change and expanding routes for agricultural extension services (Rondhi et al., 2019). Adaptation methods such as the use of drought- and pest-tolerant cultivars, as well as improved water management, are also promoted (Banerjee, 2015; Paudel et al., 2020). While others advise enhancing farmer training and expanding the operations of community organisations (Vo et al., 2021), providing farmers with access to agricultural inputs, information, and extension services, and implementing measures to stabilise output prices (Fahad & Wang, 2018; Iqbal et al., 2020). Climate change also affects the market supply of agricultural products. As a result, governments must also address other actors in the value chain to ensure price stability in the face of imminent climate change challenges (Liverpool-Tasie & Parkhi, 2021).

3. RESEARCH METHODS

3.1 Study Area

Figure 1 is a map showing the location of the study area, which is Nong Cong district in Thanh Hoa province, Vietnam. Specifically, in Figure 1, quadrant (a) is the map of Vietnam and the location of Thanh Hoa province. Quadrant (b) is Thanh Hoa province and location of Nong Cong district which is shown as the red point. Quadrant (c) is Nong Cong district, where this is the study area. Quadrant (d) is 2 communes of Nong Cong district (Thang Long and Thang Binh), these are the two representative communes that the study selected, to collect data on farmers' perception of climate change and adaptation measures in Nong Cong district. Nong Cong is a delta district of Thanh Hoa province, and the district centre is 28km southwest of Thanh Hoa city. The area's geographical coordinates are from 105°68' – 106°63' East longitude, from 21°48' – 21°70' North latitude. The district has 28 communes and one town. It has an area of 292.5 km², and the population in 2018 was 271,250. Moreover, over 70% of the population are working in the agricultural sector.

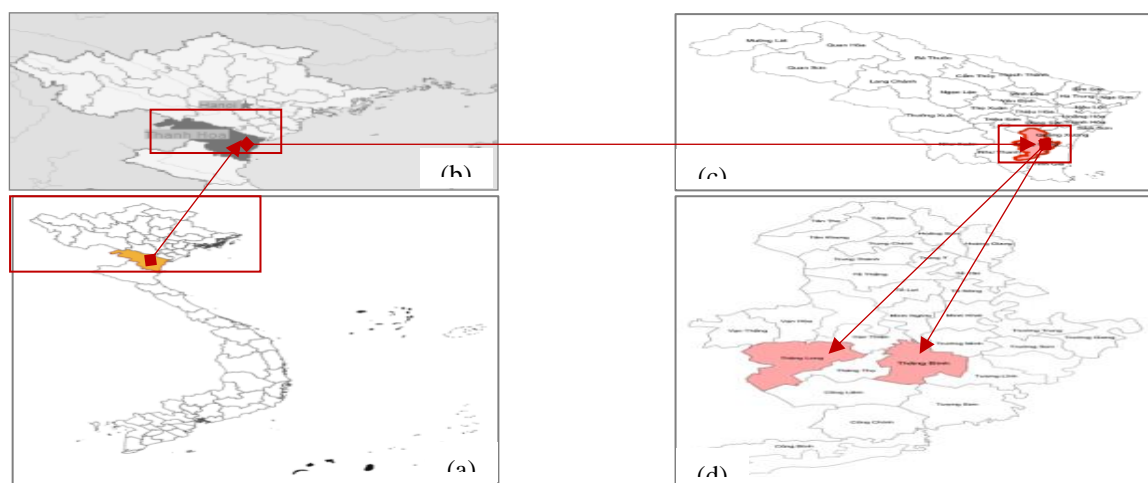


Figure 1: Map of the Study

The Nong Cong district has been severely impacted by extreme weather occurrences, incurring losses of \$0.304 million in 2017 and \$1.6 million in 2018 due to 1,000 hectares planted to rice and vegetables (Committee, 2020). However, the damage caused by climate change has a serious impact on the district, as over 80% of the district's population is reliant on agriculture. Additionally, previous research has demonstrated that climate change negatively impacts agriculture.

3.2 Data Collection

This study incorporated both primary and secondary sources of data. Several secondary data sources were consulted, including information on the research area's socio-economic situation and agricultural production. Additionally, information on the annual socio-economic status of the community and others pertinent to the research topic was acquired.

At the moment, the Nong Cong district lacks a hydro-meteorological station. As a result, hydro-meteorological data were gathered at the Nhu Xuan station (19038' North latitude - 105034' East longitude). Although the Nhu Xuan meteorological station is located outside the district of Nong Cong, it collects weather and meteorological data for Nong Cong. Temperature data collection includes monthly average temperatures and rainfall for the 35 years from 1985 to 2019.

Pre-testing of the questionnaire was conducted to ascertain the data to be collected and to find common adaption measures in Thang Long and Thang Binh communes. Enumerators were taught the study's aims and questionnaire before data collection. Finally, in January 2021, the survey was conducted. The survey was undertaken to elicit information about extreme events that occurred at the research locations, rice production throughout the Spring - Summer crop season (from January to May), and Summer-Autumn crop season (from June to August) (from May to September).

Primary data were collected by conducting in-depth interviews with farmer households using a pre-designed questionnaire. The study collected data from two communes in Nong Cong: Thang Long and Thang Binh. These are the two communes in the district with the most agricultural land, including rice production. Rice is a component of the agricultural production of the selected farming households. The number of respondents was equivalent to the total number of farming households in the two communes. The sample size for respondents was determined using a basic proportions approach (Yamane, 1967). The equation was used to calculate the representative sample size.

Sample size = $\frac{N}{1+N(e)^2}$. Where N is the population size, and e is the level of precision (sampling error).

Thang Long commune has approximately 2,100 farmer households (Division, 2020), while Thang Binh commune has about 1,400 farmer households (Division, 2020). As a

result, the total sample size was 189 agricultural families using the sampling procedure described above and a 10% sampling error. However, the study examined an additional 71 farming homes to ensure the data was valid. Additionally, farmers were picked under the direction of the village head and utilising the commune's registered farming households. Following that, primary data were gathered by a thorough home survey of 260 randomly selected farming households in the two communes.

Data on farmer characteristics, farm characteristics, and rice output were collected to mitigate the adverse effects of weather. Additionally, data on farmers' understanding of the effects of climate change on agricultural production and their adaption strategies were acquired.

3.3 Data Analysis

3.3.1 Mann Kendall Test for Consideration of Trend

The Mann Kendall (MK) is a nonparametric test that sorts (rank) data to test for the tendency (trend) (Kendall, 1948; M.G., 2008; Mann, 1945). This method tests the H_0 hypothesis of the lack of trend versus the H_a hypothesis that a trend is present, whether upward or downward; it depends on the sample size and time-series variation.

When this period's value is greater than the previous period, the MK test gets a value of +1. Otherwise, it takes a value of -1. Then, it takes the cumulative values for all of the periods.

The formula for the Mann Kendall test is expressed as follow:

$$T = \sum_{i=1}^{n-1} \sum_{j=i+1}^n A; \text{ With } A = (X_j - X_i)$$

Where: n is total of time point, i is the time point at *ith*, j is the time point at *jth*, and $j > i$

X_i is data value at time point *ith*

X_j is data value at time point *jth*

If $(X_j - X_i) > 0$ then A have value of +1

If $(X_j - X_i) < 0$ then A have value of -1

If $(X_j - X_i) = 0$ then A have value of 0

When the number of time points is greater than or equal to ten ($n \geq 10$), the MK test is then characterized by a normal distribution having a mean $E(T)$ equal to zero and variance equated (Ma, He, Xu, van Noordwijk, & Lu, 2014), as:

$$\begin{aligned} \text{Variance}(T) &= \delta_T^2 \\ &= \frac{n(n-1)(2n+5)}{18} \\ &\quad - \frac{\sum_{m=1}^w t_m(t_m-1)(2t_m+5)}{18} \end{aligned}$$

Where w is the number of the tied groups in the sample data (data point has same value will be bunched into one group), and t_m is the number of ties in the *mth* tied group.

For example, set of value (8, 9, 0, 9, 0, 9), so that $n = 6$, $w = 2$, $t_1 = 2$ for the value of 0, $t_1 = 3$ for the value of 3.

If $T > 0$, we have $D = \frac{T-1}{\sqrt{\text{Variance}(T)}}$

If $T = 0$, we have $D = 0$

If $T < 0$, we have $D = \frac{T+1}{\sqrt{\text{Variance}(T)}}$

When $D > 0$, it indicates the upward and downward trends of $D > 0$. Next, D value is compared to the standard normal distribution table (z -table) to compare the statistical significance. If the absolute value of D value is greater than the tabular z , then reject H_0 , which means there is a trend in the data (Ahmad, Tang, Wang, Wang, & Wagan, 2015).

3.3.2 Sen’s Slope Estimator for Consideration of Trend Magnitude

Sen’s slope is then calculated further to examine the magnitude of the trend (Sen, 1968). If Sen’s slope value is positive and statistically significant, there is an increasing trend.

The model $F(x)$ can be described as (Drápela & Drápelová, 2011):

$$F(x) = Ax+B$$

The slope, A , of between two data points can be expressed as:

$A_i = \frac{X_g - X_h}{g-h}$ for $g = 2, 3, \dots, m$ and $h = 1, 2, \dots, m-1$. We have (A_1, A_2, \dots, A_M) .

X_g is data year g , X_h is data year h ($g > h$)

If there is only one data point for a specific year, then M slope estimates ($M = \frac{m(m-1)}{2}$). Where m is the number of time points.

The M values of the slope are sorted from lowest to highest value ($A_{\text{lowest value}}, \dots, A_{\text{highest value}}$). Then, Sen’s slope is the median slope inside M values.

Sen’s slope value, A_{med} , is computed as:

$$A_{\text{med}} = \begin{cases} A_{\frac{M+1}{2}} & \text{if } M \text{ is odd} \\ \frac{1}{2}(A_{\frac{M}{2}} + A_{\frac{M}{2}+1}) & \text{if } M \text{ is even} \end{cases}$$

If Sen’s slope value is positive, it shows an increasing trend and a decreasing trend if it is negative. The A_{med} value of 0 implies no trend, which means that the data have a constant trend over time. Sen’s slope value, A_{med} is tested by a normal distribution with a two-sided test (Partal & Kahya, 2006).

3.3.3 Multivariate Probit Model for Factors Influence to Use Adaptation Measures

A random utility model describes a choice decision in which individual i has a set of m choices from which to choose (McFadden, 1978). When applied to adaptation decision, Farmer i will choose an adaptation strategy if its

expected benefits are positive. These benefits include increased farm performance and well-being of farmers, which are demonstrated by latent variables.

When considering an adaptation strategy (m th) to cope with climate change, farmers’ utility when adaptation strategy m is not implemented is u_0 and u_m when implemented. In agricultural production, Farmer i will choose an adaptation strategy m , when $u_{im} - u_{i0} > 0$, set $z_{im} = u_{im} - u_{i0}$, so $z_{im} = u_{im} - u_{i0} > 0$ or $z_{im} > 0$. This means farmers that implement adaptation strategy m when the net benefit, z_{im} is positive.

The net benefit (z_{im}) from strategy m , a latent variable, is determined by observable and unobservable factors. Latent variables are not directly observed but are derived from visible variables. Observed variables, including variable y_{im} and independent variables, determine the relationship between latent variables z_{im} and variable y_{im} . Latent variables are the expected benefits (increase productivity, increase profit) from adaptation strategies.

The general model for net benefit is:

$$z_{im} = x'_{im}\beta_m + \varepsilon_{im} (*)$$

where m is adaptation measures, $m=1, 2, \dots, M$

$i = 1, \dots, n$ are the farmers considered in the study

$\beta_m = (\beta_1, \dots, \beta_M)'$ is a matrix of coefficients, to be estimated;

x'_{im} is a vector of explanatory variables.

$$\varepsilon_{M \times 1} = \begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \vdots \\ \varepsilon_{iM} \end{pmatrix} \sim \text{MVN} (0, \Sigma)$$

$\varepsilon_{im} \sim \text{MVN}(0, \Sigma)$ as a multivariate normal distribution with a mean of zero and variance, Σ , is $M \times M$ correlation matrix.

$$\text{Correlation matrix}_{M \times M} \Sigma = \begin{pmatrix} 1 & \rho_{12} & \dots & \rho_{1M} \\ \rho_{21} & 1 & \dots & \rho_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m1} & \dots & \dots & 1 \end{pmatrix}$$

$$E(\varepsilon_m | x_1, \dots, x_M) = 0$$

$$\text{Var}(\varepsilon_m | x_1, \dots, x_M) = 1$$

$$\text{Cov}(\varepsilon_k \varepsilon_m | x_1, \dots, x_M) = \rho_{km}$$

The coefficient in the correlation matrix is denoted by ρ

The response variables in the multivariate probit model are usually binary. Let $y_{im} = (y_{i1}, y_{i2}, \dots, y_{iM})'$ ($1 \leq i \leq n$) denotes the collection of observed binary 0/1 responses on the i th farmer.

y_{im} has a value of 0 or 1, depending on the value of z_{im}

$$y_{im} = \begin{cases} 1 & \text{if } z_{im} = x'_{im}\beta_m + \varepsilon_{im} > 0 (**) \\ 0 & \text{otherwise} \end{cases}$$

This means that a farmer will use an adaptation strategy m , $y_{im} = 1$, if the expected net benefits from adaptation strategy m is positive (z_{im} greater than 0). Farmers will not choose an adaptation strategy when the expected benefits of the adaptation strategy are zero or negative.

$M = 1$ and 2 are probit and bivariate probit, respectively (or univariate and bivariate probit models). The advantage of using multivariable probit regression is that y_{im} will indicate the outcome selected from the M choices simultaneously.

The diagonal values of the correlation matrix are normalized to 1. In the correlation matrix, the off-diagonal values show the unobserved relation between the observations in adaptation strategies mth and jth (Guan, Ye, Shi, & Zou, 2019). The most popular simulation method for simulated maximum likelihood is the Geweke–Hajivassiliou–Keane (GHK), which estimates parameters

under the assumption of multivariate normal distribution (Nhemachena, Hassan, & Chakwizira, 2014). All estimations were calculated by STATA software, version 14.0 (StataCorp, 2015).

Multivariate probit model in this study:

$$Y_{\text{Adaptation}} = \beta_0 + \beta_1 \text{EDU} + \beta_2 \text{AGE} + \beta_3 \text{GENDER} + \beta_4 \text{FARMEXP} + \beta_5 \text{FARMSIZE} + \beta_6 \text{FARMINC} + \beta_7 \text{FARMLABOR} + \beta_8 \text{TRAINING} + \beta_9 \text{MEMBERSHIP} + \beta_{10} \text{AWINFO} + \beta_{11} \text{CREDIT} + \varepsilon$$

The variables for the multivariate probit are defined in **Error! Reference source not found.** below:

Table 1: Description of the Variables

VARIABLE LABEL	DESCRIPTION	MEASURE
Dependent variables		
$Y_{\text{Adaptation}}$	Adjustment for seasonal calendar	0 = if famer did not use this adaption measure 1 = if famer use this adaption measure
	Application of more fertilizers and pesticides	0 = if a farmer did not use this adaption measure 1 = if Farmer use this adaption measure
	Change of variety	0 = if famer did not use this adaption measure 1 = if famer use this adaption measure
Independent variables		
<i>Farmer's characteristics</i>		
EDU	Farmer's education	Years in school
AGE	Farmer's age	Year
GENDER	Farmer's gender	0=Female 1= Male
FARMEXP	Farming experience	Years of farming experience
<i>Farm's characteristics</i>		
FARM SIZE	Cultivated area	Sao (One "sao" is equal 500m ²)
FARMING	Agricultural income/year	VND million/year
FARM LABOR	Number of agricultural labour in farmer household	Number of agricultural labour
<i>Other factors</i>		
TRAINING	Participation in an agricultural training class	Agricultural training attendance
MEMBERSHIP	Membership in Farmer's association (social factor)	0 = if Farmer is not a member of any farmer's association 1= if Farmer is a member of any farmer's association.
AWINFO	Access the weather forecast information of 7 – 10 days.	0 = if Farmer has not accessed 7-10 days weather forecast. 1 = if Farmer has accessed weather forecast of 7-10days.
CREDIT	Access to credit	0 = if Farmer did not borrow money from any source 1 = if Farmer borrowed money from any source.

4. RESULTS AND DISCUSSION

4.1 General Characteristics of Respondents

4.1.1 Descriptive Statistics of Variables

Table 1 is the general information on the surveyed farmers. This study was conducted in two agricultural communes: Thang Long and Thang Binh in Nong Cong district. In these communes, there are two rice seasonal crops in these agricultural areas. According to the results of data analysis, farmers have an average of 10 schooling-years, average age of 48, production experience at 22 years, average rice area per household of 7.74sao (equivalent to 0.38 ha/household). The average income from agricultural production of the household is 93 VND million/year (about 4025 USD/year), the average number

of agricultural labor/households of 2.88 labors. Every year, each household attends an average of 2.23 training classes related to agriculture. The results also show that 82% of households in farmers' associations, 68% of farmers watch weather forecast information for 7-10 days, 75% of farmers have loans. According to the T-test results, characteristics of farmers are not different between the two communes, therefore the characteristics of farmer households are similar in these two communes. Thus, surveyed farmers from two communes are used as whole sample for study the perceptions and adaptation measures in Nong Cong district.

4.2 Sources of Weather Information

Figure 2 shows the source of weather information that farmers use to get information about weather forecasts. The results show that there is a difference between farmers using climate change adaptation measures (adapters) in rice production and farmers not using adaptation measures (non-adapters). Adapters gained access to weather information at a higher rate than non-adapters. Regarding weather-related information sources, 66% of adapters accessed weather information via loudspeakers, compared to 46% of non-adapters. For 40% of adapters, information was obtained through loudspeakers and talks with other farms. Additionally, the results indicated that daily weather information on television, loudspeakers, and conversations with other farmers were the most important sources of short-term weather information, as these are the most immediate and accessible. On the other hand, the training programmes provide long-term weather patterns. Conversations with their fellow farmers (52%) and their views and experiences with the weather were also used to determine their agricultural production activities. This shows that the farmers who monitor a lot of weather

information, they take adaptive measures, to reduce losses in rice production. Because weather forecast information has helped them to adjust from the time of rice planting, to adjust the time of fertilizer application and the time of harvest.

4.3 Sources of Information About Climate Change

Figure 3 shows the results of farmers' access to information on climate change. Farmers obtained knowledge on climate change from various sources. According to 48% of respondents, they became aware of climate change through their personal experiences and observations throughout time. Additionally, 62% of respondents obtained information on climate change from television shows. Agriculture education (35%) was also a critical source of information on climate change. Using data from these training sessions, farmers identified and evaluated the unfavourable effects of frequent extreme weather occurrences on their agricultural productivity. Finally, discussions with their fellow farmers (50%) allowed them to learn about and exchange thoughts about climate change.

Table 1: General Farm Household Characteristics in Nong Cong district

VARIABLES	WHOLE SAMPLE (N=260)		THANG LONG COMMUNE (N=154)		THANG BINH COMMUNE (N=106)		COMPARISON	
	Mean	SD	Mean	SD	Mean	SD	Diff.	t-test
EDU (years)	10.07	1.64	10.10	1.68	10.02	1.58	0.09	0.6821
AGE (years old)	48.10	6.06	48.11	5.72	48.09	6.56	0.02	0.9833
GENDER (Rate of male)	0.54	0.50	0.58	0.50	0.49	0.50	0.09	0.1660
FARMEXP (year)	22.35	6.06	22.21	5.74	22.55	6.51	-0.33	0.6641
FARMSIZE (Sao/Household)	7.74	2.05	7.81	2.16	7.64	1.88	0.16	0.5464
FARMINC (VND million/year)	93.35	1.60	95.22	2.23	90.62	2.19	4.60	0.1572
FARMLABOR (Labor)	2.88	0.78	2.88	0.78	2.88	0.78	0.00	0.9940
TRAINING (Class)	2.23	1.51	2.19	1.49	2.28	1.54	-0.09	0.6199
MEMBERSHIP (% respt)	0.82	0.39	0.82	0.39	0.81	0.39	0.01	0.8891
AWINFO (% respt)	0.68	0.47	0.71	0.45	0.62	0.49	0.09	0.1214
CREDIT (% respt)	0.75	0.43	0.73	0.44	0.77	0.42	-0.04	0.4681

Source: Field survey, 2021

Note: Diff. is the mean difference value between two communes. and ns is non-statistical significant. SD is the standard deviation

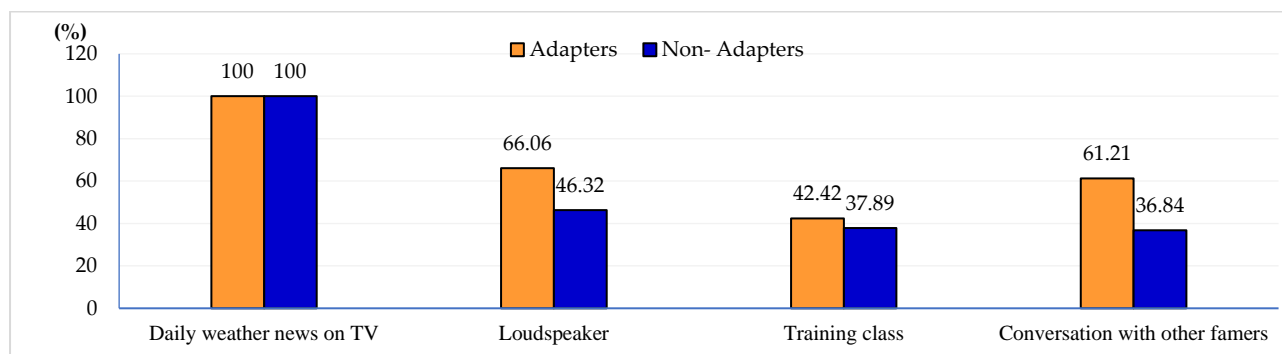


Figure 1: Sources of weather information

Additionally, it can be assumed that adapters obtain knowledge about climate change through television, observation, and interactions with other farmers. Adapters

made adjustments to their agricultural production based on this information. Training classes (41%) were also a significant source of climate change-related information for adapters.

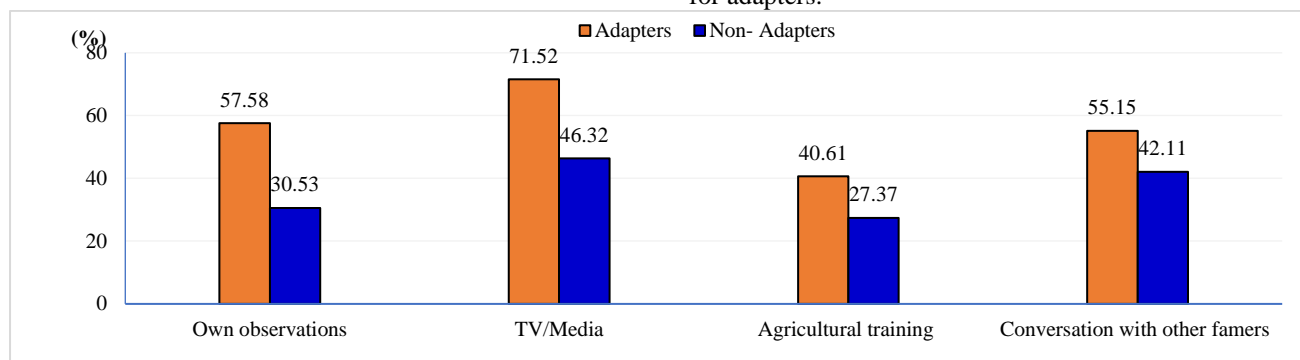


Figure 2: Sources of information about climate change

Even the adapter households themselves have accumulated more experience on climate change and have access to many sources of information to monitor climate changes, thereby adjusting in rice production. Because better understanding of climate change has led to the decision to use adaptation measures such as changing short-term rice varieties to limit weather risks, adjust quantity of fertilizers, pesticides or adjust the time of sowing and harvesting. The findings indicate that farmers have a variety of sources of information about climate change, although the majority of these sources are informal. As a result, developing and strengthening official climate change information channels is necessary, such as agricultural training via extension and village loudspeakers.

4.4 Farmers' Perceptions of Extreme Weather Events

4.4.1 Farmer's Perception on Temperature and Precipitation Change

Figure 4 shows the extreme weather phenomena related to temperature and farmers' awareness of these phenomena. The manifestations of climate change through temperature such as the temperature rises, the number of days/heat wave increased, Number of cold days/waves increased. As

results of comparison, adapters have a faster rate of temperature perception. Specifically, 84% of adapters stated that the temperature increases, compared to 44% of non-adapters. The percentage of adapters that perceive temperature change is much greater than that of non-adapters, the main reason indicated is that adapters access multiple sources of climate change information as discussed above, and direct influence of temperature on rice production output has helped farmers to recognize the manifestations of climate change through temperature changes. Similarly, in Figure 4 shows that 84% of adapters perceived a rise in extreme weather events, compared to 46% of non-adapters. It is 84% of adapters stated that extreme weather events are even more difficult to predict, a larger percentage than non-adapters (45%). Thus, being aware of weather variations enables adaptations to adjust agricultural output actions. Farmers are aware of fluctuations in temperature and the occurrence of extreme events such as many days with heat waves leading to drought, lack of irrigation water for rice, or prolonged cold spells, the rice may die and have to be replanted. With extreme weather events and difficult prediction, farmers respond by adjusting the amount of water in the field or adjusting the amount of fertilizer.

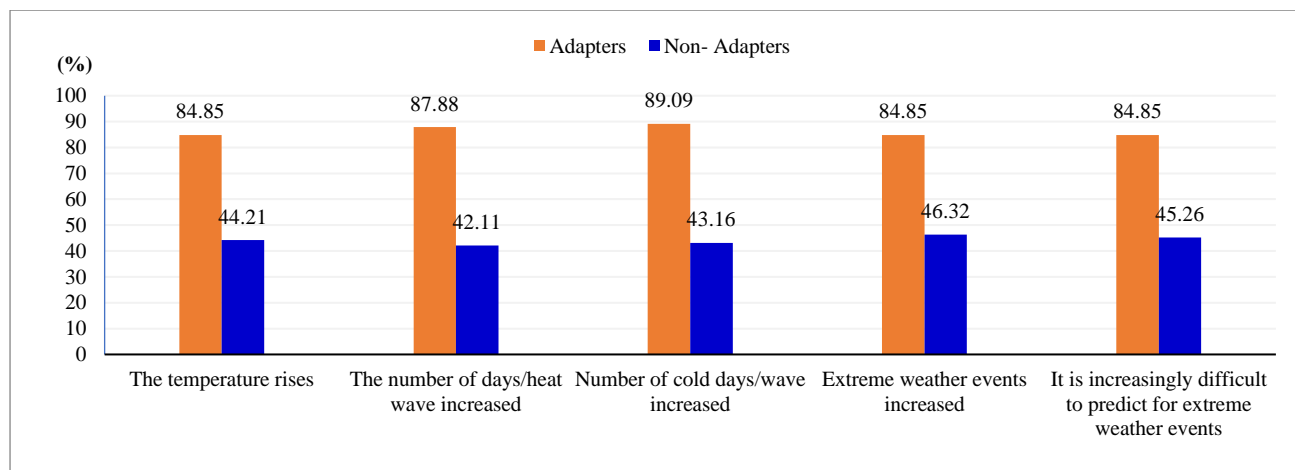


Figure 4: Farmers' perceptions of the changes in temperature in Nong Cong district, Thanh Hoa province, Vietnam, 2020

Figure 5 compares adapter and non-adapter perceptions of climate change through rainfall change and storm changes. The results show that 95% of farmers stated that storms in recent years ended late. When asked about their perspective of rainfall, 91% said that the frequency of rain varies from year to year, while 59% stated that rainfall has increased in recent years. Similarly, 91% stated that the intensity of the rain had risen, resulting in floods and inundation. This has resulted in agricultural productivity losses or damage. Additionally, most (90%) of adapters

claimed the rainy and stormy seasons arrived sooner than in the past. Over 90% reported that the severity and frequency of rain have also altered. Farmers were obliged to adapt their agricultural produce due to these developments. Reasons for the higher rates of adapter awareness of changes in rainfall and storms, on the grounds that adapters have more information about climate change and in adapter households that contain households have also experienced losses due to rain and storm events causing rice production.

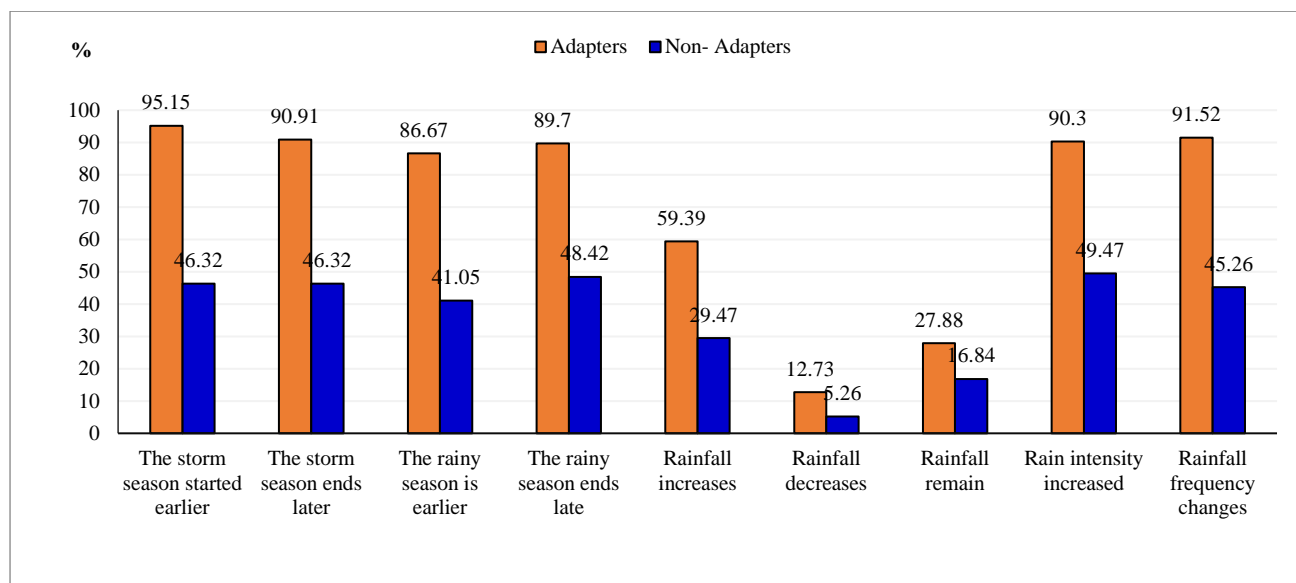


Figure 5: Perception about rainfall and storm changes between adapters and non-adapters, in Nong Cong, Thanh Hoa, Vietnam, 2020

4.5 Farmer's perception on effect of extreme weather events on crop production

According to Figure 6, 70% of adapters recognised climate change as the source of yield loss, while 69% claimed that

production costs increased due to extreme weather occurrences. Adapters implemented adaptation techniques before the crop season to reduce damage and maximise profit.

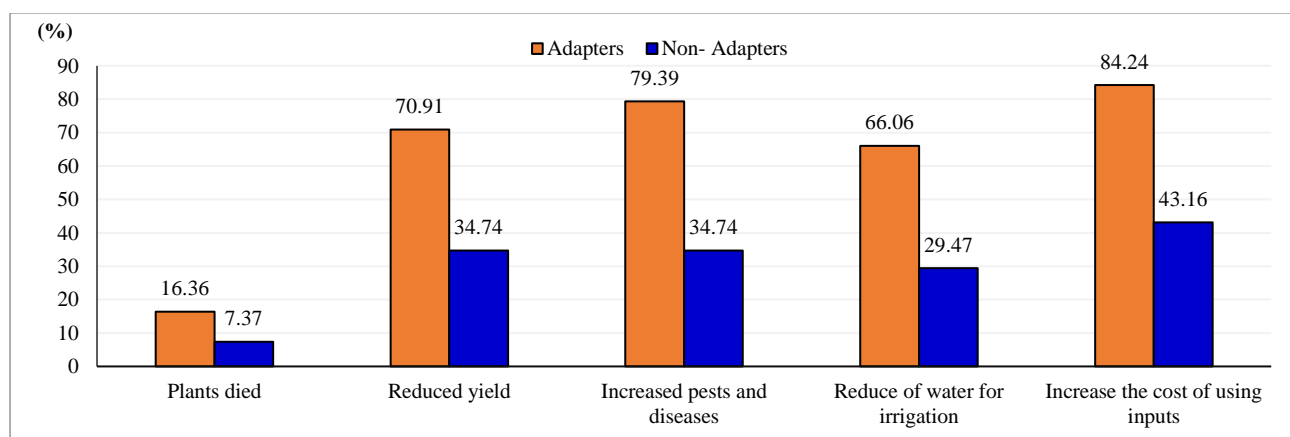


Figure 6: Perception on impacts of climate change to crop production between adapters and non-adapters in Nong Cong district, Thanh Hoa province, Vietnam, 2020

According to farmers, rising temperatures increased the prevalence of pests and diseases, consequently increasing the cost of production. Farmers must change their agricultural production in response to these perceptions.

To begin implementing adaptation strategies, farmers must first understand the implications of climate change, which they can combine with their years of practical experience. Farmers who recognise that climate change may

negatively influence output and profit are more likely to adjust to mitigate the damage caused by climate change consequences.

4.6 Farmer's Perception Compared to Meteorological Data

A Mann Kendall test was used to determine the presence of a trend in various meteorological data sets. The MK test yielded a positive and substantial result, implying an

increasing trend in Nong Cong's annual average temperature (Table 3). The Mann Kendall trend test result indicates that the yearly maximum average temperature tends to increase, confirming that the temperature is rising. However, the annual lowest temperature was not statistically significant, suggesting that it lacks a discernible pattern. The average precipitation result was positive and statistically significant, showing that the yearly rainfall average increased with time.

Table 3: Mann Kendall Trend Test of Annual Temperature and Precipitation

Indicators	Number of years	Kendall's tau	P-value
Average annual temperature	35	0.3227***	0.0067
Average annual temperature maximum/year	35	0.2840**	0.0169
Average annual temperature minimum/year	35	0.0017 ^{NS}	1.000
Average precipitation /year	35	0.2000*	0.0938

Note: NS means non-significant when p-value > 0.1,

***, ** and * means significant at the 1%, 5% and 10% probability levels, respectively.

Table 4 show result of using Sen's slope test to examine the change in temperature and rainfall over the past 35 years in Nong Cong district. For this reason, the Mann Kendall test only shows the trend in change, while the Sen Slope's test will confirm whether this trend is really changing or not. Thus, the study examined the magnitude of changes in the temperature trend in Nong Cong using Sen's slope analysis. The findings indicated that both the yearly average and maximum temperatures are increasing. However, there is no discernible trend in the average

annual lowest temperature. These findings corroborate farmers' observations and opinions that temperature has increased over time, hurting agricultural production and livelihood. As a result, farmer awareness is consistent with observed facts. On the other hand, Sen's slope value for the average annual rainfall was positive but not significant, indicating that rainfall fluctuations are unpredictable. Thus, in Nong Cong district, the average rainfall does not change over the years, however, rain intensity is unlike the years and difficult to predict, easily causing floods, inundation, and damage to production. rice production.

Table 2: Sen's Slop Test for Temperature and Precipitation

Indicators	Number of years	Sen's slope	P-value
Average annual temperature	35	0.3227**	0.0120
Average annual temperature maximum/year	35	0.2840***	0.0050
Average annual temperature minimum/year	35	0.0017 ^{NS}	0.9900
Average annual precipitation	35	0.2 ^{NS}	0.126

Note: NS means non-significant when p-value > 0.1,

***, ** and * means significant at the 1%, 5% and 10% probability levels, respectively.

4.7 Determinants of Climate Change Adaptation Measures

4.7.1 Adaptation Measures

Adjustment of the seasonal calendar: The district administration provides a calendar for farmers to sow seeds and transplant rice at the start of each crop. When seeding and transplanting rice under extreme weather conditions, there may be cold spells (Spring-Summer season) or heat waves (Summer-Autumn season). Farmers responded by delaying transplanting during the Spring-Summer rice-producing season to February to prevent cold periods. Additionally, they harvest early to avoid rain and flooding in late May. At the same time, farmers would transplant earlier in the Summer-Autumn season, typically in early June, to prevent the rain. Additionally, farmers harvest early, typically mid- to late September, to escape significant rain and storms.

Application of more fertilizers and pesticides after extreme weather events: Additionally, the study examined whether

farmers would increase their usage of fertilisers and pesticides in response to harsh weather occurrences. For instance, during the rice harvest's cold season, producers employed plastic for seedlings or increased manure, phosphate fertiliser, and pesticide application. At the same time, farmers tend to add green waste and spray insecticides during hot waves to prevent disease.

Change of variety. Another method considered in this study is variety substitution, most notably for short-term and resistant types. During the Spring-Summer season, the cropping time for short-term rice cultivars is 120-125 days. As a result, farmers can avoid the cold at the start of the season and the late rain. On the other side, during the Summer-Autumn season, short-term rice types are harvested between 95 and 102 days before the rainy or stormy season.

Table 5 shows the number of farmers using each adaptation measure, among those who have adapted, 146 adapter (88% of the farmers) changed the seasonal

calendar as an adaptation strategy. It was found that the adjustment of seasonal calendar ranked as the most important strategy. Meanwhile, 143 of the farmers (86% of the farmers) employed additional inputs such as fertilizer, pesticides, the use of anti-cold nylon for seedlings as an adaptation response. This was followed by the increased

application of fertilizers and pesticides after extreme weather events ranked. Finally, the change of varieties was the third important strategy employed by farmers. Moreover, 140 adapters (around 85% of the farmers) shifted to short-term, high tolerant varieties as these were more resilient to bad weather condition.

Table 3: Adaptation Measures of Farmers in Crop Production in Nong Cong District, Thanh Hoa Province, Vietnam, 2020

ADAPTATION MEASURES	WHOLE SAMPLE	
	Adapters	Non- Adapters
Adjustment for seasonal calendar	146	114
Application of more fertilizers and pesticides	143	117
Change of variety	140	120

Farmers were questioned about reasons other than climate change for implementing a certain adaptation approach. Additional causes are expansion, pest or disease control, and market shifts.

Table 6 is the result of the Wilcoxon Signed-Rank test, used to confirm the adaptation measures farmers use are driven by climate change. The Wilcoxon signed-rank test was used to assess the scores for each adaptation measure for each driver. Apart from climate change, farmers adjust for various reasons, including extension, disease and pest,

and market considerations such as demand and pricing. Farmers assigned a value to each cause in determining whether to employ an adaptation strategy. Scores are given on a three-point scale, with three equaling high, two equaling medium, and one equaling low. Following that, the rationale for employing each adaptation measure was compared. The Wilcoxon signed-rank test's null hypothesis is that there is no difference between climate change driver and other driver on farmers' decision to employ a given adaptation measure.

Table 4: Results of the Wilcoxon Signed-Rank Test

Farm adaptive strategies	Z value (H0: each adaptive strategy, the influence by Climate change is not different the influence by other driver)	Information from extension	
		Disease and Pest	Change of input cost
Adjustment for seasonal calendar	7.026***	5.912***	6.270***
Applying more fertilizers and pesticides because of extreme weather events	6.433***	0.177 ^{NS}	-5.214***
Change of variety	-0.442 ^{NS}	6.395***	5.458***

*** and ns: level of statistical significance 1% and not significance

Values in bold are where climate change is rated to have a higher influence than the other driver

The results indicated that climate change was the key driver for implementing this method for the seasonal calendar adjustment. As a result, farmers' seasonal calendars were altered primarily due to variations in weather and climatic circumstances.

Additionally, a significant and positive coefficient is obtained when the impact of climate change versus information of extension is compared to influence farmers' decision to use additional fertilisers and pesticides. This indicates that climatic change was a more significant reason in farmers increasing their fertiliser application than extension knowledge. The coefficient was not important for diseases and pests versus climate change. The coefficient was negative and significant in change of input costs and climate change. This entails farmers applying additional fertilisers and insecticides to mitigate the adverse effects of climate change and manage pests and illnesses and adjust to increasing input costs.

The choice of farmers to switch to short-term rice varieties was primarily motivated by the need to mitigate the risks associated with extreme weather events. As such, the change in rice variety resulted from climate change's effects. Similarly, variation in rice varieties may be

influenced by extension knowledge, as local officials may encourage planting a new type of rice. While climate change has a greater influence on farmers changing rice varieties than the other two driver. Diseases and pests, change of input cost, climate change has a greater influence on farmers changing rice varieties because the coefficients are statistically significant.

4.8 Factors Influencing Farmers' Decision to Use of Specific Adaptation Measure

This study was conducted in two agricultural communities: Thang Long and Thang Binh. There are two seasonal crops and one seasonal winter for growing vegetables in these agricultural areas. About 80% of the workforce are involved in agricultural production in these two communes. Based on the results (**Error! Reference source not found.**), farmers who adapted had more years of schooling, training courses, access to 7-10 days of weather forecast information, and a higher participation rate in farmers' associations than non-adapters. These imply that adapters are more knowledgeable and informed about climate change and the benefits of using adaptation measures.

Table 7: Socio-Economic Characteristics of The Study Participants by Adapters and Non-Adapters in Nong Cong District, Thanh Hoa Province, Vietnam, 2020

Variable	AVERAGE (N=260)	WHOLE SAMPLE (N=260)		THANG LONG (N=154)		THANG BINH (N=106)	
		Adapters (n=165)	Non-Adapters (n=95)	Adapters (n=97)	Non-Adapters (n=57)	Adapters (n=68)	Non-Adapters (n=38)
EDU (years)	10.07	10.45	9.41	10.56	9.33	10.31	9.53
AGE (years old)	48.10	47.76	48.69	48.07	48.18	47.32	49.47
GENDER (rate of male)	0.54	0.53	0.57	0.58	0.58	0.46	0.55
FARMEXP (year)	22.35	23.89	19.67	23.75	19.60	24.09	19.79
FARMSIZE (Sao/Household)	7.74	7.87	7.51	8.01	7.46	7.67	7.59
FARMINC (VND million/year)	93.35	95.85	89.00	96.92	92.33	94.31	84.01
FARMLABOR (Labor)	2.88	2.88	2.86	2.90	2.84	2.87	2.89
TRAINING (Class)	2.23	2.69	1.42	2.70	1.32	2.68	1.58
MEMBERSHIP (% respt)	81.54	90.91	65.26	91.75	64.91	89.71	65.79
AWINFO (% respt)	67.69	78.79	48.42	84.54	49.12	70.59	47.37
CREDIT (% respt)	75.00	80.61	65.26	80.41	61.40	80.88	71.05

Source: Field survey, 2021

Before assessing each variable, the study used the Variance Inflating Factors to check for potential multicollinearity (VIF). The mean VIF value was 2.3, ranging from 5.03 to 1.07. Because the VIF values were less than 10, this implies that the model's independent variables are not multicollinear.

Table 8 is the result of running the multivariable probit model, the model results are tested for each factor affecting the decision for each specific measure. Numerous elements have a substantial impact on farmers' adaption techniques selection. To begin, the educational attainment of farmers is strongly associated with their likelihood of increasing fertiliser and pesticide use and altering types. Farmers that are more educated have a better understanding of which fertiliser to use and when to improve the plant's health and ability to withstand adverse weather. Additionally, farmers with a better level of education have a greater understanding of variety. As a result, they are more knowledgeable about which cultivars provide the highest yields, generate the most profit, and resist adverse weather. Additionally, farming expertise has a crucial role in farmers' seasonal calendar adjustment decisions. The positive coefficient indicates that the probability of farmers altering their planting schedule increases with each additional year of agricultural experience. Farmers with more expertise understand how to utilise their findings to mitigate the effects of extreme weather events. This is a low-cost method based solely on historical data and present weather conditions. However, because the weather has become more unpredictable, farmers' prior experiences may be difficult to use. As a result, the human experience must be merged with current

meteorological data and agricultural production techniques to improve farmers' ability to cope with bad weather situations. Combining farmer experience and current information can mitigate the unfavourable effects of harsh weather and potentially boost agricultural productivity.

Farm wealth has a major impact on the likelihood that farmers will increase their use of fertilisers and pesticides in the aftermath of catastrophic weather events. More precisely, increased farm revenue increases the likelihood that farmers will use more fertilisers and pesticides. This makes sense, as farmers with a larger income have the financial means to invest more in inputs. By doing so, farmers reduce their exposure to possible losses caused by extreme weather occurrences and boost agricultural yields. This outcome corroborated prior research (Abid, Schilling, Scheffran, & Zulfiqar, 2016; Ahmed et al., 2015).

Participating in agricultural training programmes such as extension classes on production practices and crop varieties enhances farmers' likelihood of altering their seasonal calendars. Additionally, it has a positive and significant effect on the possibility of increasing fertiliser use and variety switching. Typically, training is supplied by extension workers or through workshops sponsored by fertiliser and seed firms. These classes provide technical information on agricultural production pertinent to farmers in the Nong Cong district. Farmers now have a solid foundation for selecting whether to apply adaption tactics due to the knowledge gained throughout this training programme. This finding is consistent with earlier research (Abid et al., 2016; Deressa, Hassan, Ringler, Alemu, & Yesuf, 2009; Hassan & Nhemachena, 2008). Access to seven-day weather forecasts has a considerable effect on

adapting tactics such as seasonal calendar adjustment and variety modification. When farmers have forecasted weather, they can be proactive in sowing and harvesting to prevent severe cold, heat waves, and other extreme weather events. The more precise the forecast data, the more advantageous it is for farmers. While the information is free and provides major benefits to farmers, it does not include detailed weather forecasts for the Nong Cong district. Another study confirmed this finding (Trinh, Rañola, Camacho, & Simelton, 2018).

Finally, farmer association participation raises the likelihood that farmers will increase their usage of

fertilisers and other inputs following catastrophic weather occurrences. Farmers who are members of an organisation pool their resources to purchase additional pumps in a drought. Additionally, they clear the canals before the rainy season or a storm. Additionally, farmer associations served as an excellent information channel via which members could exchange farming-related information, such as using organic fertilisers, insecticides, or chemical fertilisers following harsh weather occurrences. This finding is consistent with earlier research (Adger, 2003; Ngaruiya & Scheffran, 2016).

Table 5: Results of Multivariable Probit Model for Adaptation Strategies in Crop Production in Nong Cong District, Thanh Hoa, Vietnam, 2020

VARIABLES	ADJUSTMENT FOR SEASONAL CALENDAR		APPLICATION OF MORE FERTILIZERS AND PESTICIDES		CHANGE OF VARIETY	
	Coef.	SE	Coef.	SE	Coef.	SE
EDU	0.0272 ^{ns}	0.075	0.1570 ^{**}	0.073	0.1910 ^{**}	0.074
AGE	-0.0119 ^{ns}	0.017	-0.0126 ^{ns}	0.018	-0.0133 ^{ns}	0.018
GENDER	-0.0531 ^{ns}	0.176	0.0805 ^{ns}	0.177	0.1171 ^{ns}	0.178
FARMEXP	0.0375 [*]	0.021	-0.0016 ^{ns}	0.02	0.0097 ^{ns}	0.021
FARMSIZE	-0.0947 ^{ns}	0.091	-0.0719 ^{ns}	0.092	-0.0077 ^{ns}	0.093
FARMINC	0.0131 [*]	0.007	0.0150 ^{**}	0.007	0.0043 ^{ns}	0.007
FARMLABOR	-0.0179 ^{ns}	0.147	-0.1763 ^{ns}	0.148	-0.0685 ^{ns}	0.147
TRAINING	0.1717 ^{**}	0.087	0.2404 ^{***}	0.087	0.2148 ^{**}	0.087
MEMBERSHIP	0.3764 ^{ns}	0.29	0.5242 [*]	0.291	0.1439 ^{ns}	0.301
AWINFO	0.3392 [*]	0.206	0.0356 ^{ns}	0.216	0.3484 [*]	0.212
CREDIT	-0.1554 ^{ns}	0.236	0.0434 ^{ns}	0.233	0.1112 ^{ns}	0.238
CONST	-1.6469 ^{ns}	1.057	-2.1817 ^{**}	1.091	-2.5507 ^{**}	1.111
rho21	0.9071 ^{***}					
rho31	0.8598 ^{***}					
rho32	0.9549 ^{***}					
Log-likelihood	-295.74255					
Number of obs	260					
Wald chi2(33)	96.39					
Prob > chi2	0.0000					
Likelihood ratio test of rho21 = rho31 = rho32 = 0: chi2(3) = 272.196						
Prob > chi2 = 0.0000						
The marginal success probability for each equation	0.5455		0.5626		0.5371	
Joint probability(success): 0.4477						

Coef. is coefficient; SE is standard error; Non significant ns when p-value > 0.1,

***, ** and * means significant at the 1%, 5% and 10% probability levels, respectively.

Also in Table 8, the results showed the probability that farmers use the adaptation strategies – adjustment of the seasonal calendar, application of more fertilizers and pesticides, change of variety - are 55%, 56%, and 54%, respectively. The joint probability of using all adaptation strategies is 45%, while not applying all adaptation strategies is 35%.

5. CONCLUSIONS AND RECOMMENDATIONS

The purpose of this study was to determine how farmers view the effects of climate change. The findings indicate that farmers' perceptions of the extent and trend of temperature change are congruent with weather data. Additionally, farmers have varying strategies for adapting to climate change. However, the survey found that farmers employing adaptation methods remains low. Farmers' adaptation is constrained by a lack of complete and reliable meteorological data, the difficulty of forecasting extreme weather occurrences, which has resulted in farmers' refusal

to use adaptation measures, and the extra cost of utilising adaptation methods.

This study has several policy implications. First, the district government should expand its layers of awareness about climate change. Similarly, another viable programme is to develop agricultural production practices and climate change adaptation training in the commune. Finally, district authorities must improve their capacity to anticipate weekly and monthly weather in Nong Cong and implement early warning systems for various extreme weather events.

REFERENCES

- Abegunde, V. O., Sibanda, M., & Obi, A. (2020). Determinants of the Adoption of Climate-Smart Agricultural Practices by Small-Scale Farming Households in King Cetshwayo District Municipality, South Africa. *Sustainability*, 12(1), 195. doi:<https://doi.org/10.3390/su12010195>

- Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F. (2016). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of The Total Environment*, 547, 447-460. doi:<https://doi.org/10.1016/j.scitotenv.2015.11.125>
- Adger, W. N. (2003). Social Capital, Collective Action, and Adaptation to Climate Change. In M. Voss (Ed.), *Der Klimawandel: Sozialwissenschaftliche Perspektiven* (Vol. 79, pp. 327-345). Wiesbaden: VS Verlag für Sozialwissenschaften.
- Ahmad, I., Tang, D., Wang, T., Wang, M., & Wagan, B. (2015). Precipitation Trends over Time Using Mann-Kendall and Spearman's rho Tests in Swat River Basin, Pakistan. *Advances in Meteorology*, 2015, 1-15. doi:<https://www.doi.org/10.1155/2015/431860>
- Ahmed, A., Masud, M. M., Al-Amin, A. Q., Yahaya, S. R. B., Rahman, M., & Akhtar, R. (2015). Exploring factors influencing farmers' willingness to pay (WTP) for a planned adaptation programme to address climatic issues in agricultural sectors. *Environmental Science and Pollution Research*, 22(12), 9494-9504. doi:<https://doi.org/10.1007/s11356-015-4110-x>
- Aihounton, G. D., Yegbemey, R. N., & Yabi, J. A. (2013). *Modelisation Simultanée De La Perception Et De L'Adaptation Au Changement Climatique: Cas Des Producteurs De Maïs Du Nord-Bénin*. Paper presented at the 2013 Fourth International Conference, September 22-25, 2013, Hammamet, Tunisia.
- Alam, G. M. M., Alam, K., & Mushtaq, S. (2016). Influence of institutional access and social capital on adaptation decision: Empirical evidence from hazard-prone rural households in Bangladesh. *Ecological Economics*, 130, 243-251. doi:<https://doi.org/10.1016/j.ecolecon.2016.07.012>
- Alauddin, M., & Sarker, M. A. R. (2014). Climate change and farm-level adaptation decisions and strategies in drought-prone and groundwater-depleted areas of Bangladesh: an empirical investigation. *Ecological Economics*, 106, 204-213. doi:<https://doi.org/10.1016/j.ecolecon.2014.07.025>
- Alboghady, M., & El-Hendawy, S. E. (2016). Economic impacts of climate change and variability on agricultural production in the Middle East and North Africa region. *International Journal of Climate Change Strategies and Management*, 8(3), 463-472. doi:<https://doi.org/10.1108/IJCCSM-07-2015-0100>
- Amadou, M., Villamor, G., Attua, E., & Traoré, S. (2015). Comparing farmers' perception of climate change and variability with historical climate data in the Upper East Region of Ghana. *Ghana Journal of Geography*, 7(1), 47-74. Retrieved from <https://www.ajol.info/index.php/gjg/article/view/126290>
- Amare, A., & Simane, B. (2017). Determinants of smallholder farmers' decision to adopt adaptation options to climate change and variability in the Muger Sub basin of the Upper Blue Nile basin of Ethiopia. *Agriculture & Food Security*, 6(1), 64. doi:<https://doi.org/10.1186/s40066-017-0144-2>
- Asare-Nuamah, P., & Botchway, E. (2019). Comparing smallholder farmers' climate change perception with climate data: the case of Adansi North District of Ghana. *Heliyon*, 5(12), e03065. doi:<https://doi.org/10.1016/j.heliyon.2019.e03065>
- Ayanlade, A., Radeny, M., & Morton, J. F. (2017). Comparing smallholder farmers' perception of climate change with meteorological data: A case study from southwestern Nigeria. *Weather and Climate Extremes*, 15, 24-33. doi:<https://doi.org/10.1016/j.wace.2016.12.001>
- Banerjee, R. R. (2015). Farmers' perception of climate change, impact and adaptation strategies: a case study of four villages in the semi-arid regions of India. *Natural Hazards*, 75(3), 2829-2845. doi:<https://doi.org/10.1007/s11069-014-1466-z>
- Chingala, G., Mapiye, C., Raffrenato, E., Hoffman, L., & Dzama, K. (2017). Determinants of smallholder farmers' perceptions of impact of climate change on beef production in Malawi. *Climatic Change*, 142(1), 129-141. doi:<https://doi.org/10.1007/s10584-017-1924-1>
- Committee, N. C. d. P. s. (2020). Report on the results of socio-economic development, defense - security tasks at Nong Cong district in 2019.
- Dasmani, I., Darfor, K. N., & Karakara, A. A.-W. (2020). Farmers' choice of adaptation strategies towards weather variability: Empirical evidence from the three agro-ecological zones in Ghana. *Cogent Social Sciences*, 6(1), 1751531. doi:<https://doi.org/10.1080/23311886.2020.1751531>
- Debela, N., Mohammed, C., Bridle, K., Corkrey, R., & McNeil, D. (2015). Perception of climate change and its impact by smallholders in pastoral/agropastoral systems of Borana, South Ethiopia. *SpringerPlus*, 4(1), 236. doi:<https://doi.org/10.1186/s40064-015-1012-9>
- Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19(2), 248-255. doi:<https://doi.org/10.1016/j.gloenvcha.2009.01.002>
- Desquith, L. E., & Renault, O. (2021). Gestion du risque climatique: les déterminants des stratégies d'adaptation des agriculteurs en Afrique Subsaharienne. *EconomiX Working Papers*(2021-17). doi:<https://ideas.repec.org/p/drm/wpaper/2021-17.html>

- Division, T. B. S. (2020). Statistical Yearbook 2019.
- Drápela, K., & Drápelová, I. (2011). *Application of Mann-Kendall test and the Sen's slope estimates for trend detection in deposition data from Bílý Ku í (Beskydy Mts., the Czech Republic) 1997-2010*.
- Etana, D., Snelder, D. J. R. M., van Wesenbeeck, C. F. A., & de Cock Buning, T. (2020). Dynamics of Smallholder Farmers' Livelihood Adaptation Decision-Making in Central Ethiopia. *Sustainability*, 12(11), 4526. doi:<https://doi.org/10.3390/su12114526>
- Fahad, S., & Wang, J. (2018). Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. *Land Use Policy*, 79, 301-309. doi:<https://doi.org/10.1016/j.landusepol.2018.08.018>
- Gamage, A. U., Pearson, D., & Hanna, F. (2017). A review of climate change in South East Asian Countries and human health: Impacts, vulnerability, adaptation, and mitigation. *South East Asia Journal of Public Health*, 6(2), 3-10. doi:<https://doi.org/10.3329/seajph.v6i2.31829>
- Gbetibouo, G. A. (2009). Understanding farmers perceptions and adaptations to climate change and variability: The case of the Limpopo Basin farmers South Africa. *IFPRI Discussion Paper*, 849. Retrieved from <https://cgspace.cgiar.org/handle/10568/21662>
- Gebru, G. W., Ichoku, H. E., & Phil-Eze, P. O. (2020). Determinants of smallholder farmers' adoption of adaptation strategies to climate change in Eastern Tigray National Regional State of Ethiopia. *Heliyon*, 6(7), e04356. doi:<https://doi.org/10.1016/j.heliyon.2020.e04356>
- Guan, X., Ye, X., Shi, C., & Zou, Y. (2019). A Multivariate Modeling Analysis of Commuters' Non-Work Activity Allocations in Xiaoshan District of Hangzhou, China. *Sustainability*, 11(20). doi:<https://www.doi.org/10.3390/su11205768>
- Hassan, R. M., & Nhemachena, C. (2008). Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, 2(1), 569-69. doi:<https://www.doi.org/10.22004/ag.econ.56969>
- Hundera, H., Mpandeli, S., & Bantider, A. (2019). Smallholder farmers' awareness and perceptions of climate change in Adama district, central rift valley of Ethiopia. *Weather and Climate Extremes*, 26, 100230. doi:<https://doi.org/10.1016/j.wace.2019.100230>
- Huq, S., Reid, H., & Murray, L. A. (2006). *Climate change and development links* (Vol. 123): IIED London.
- IPCC. (2007). Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (P. [Core Writing Team, RK and Reisinger, A.
- Iqbal, M. A., Abbas, A., Naqvi, S. A. A., Rizwan, M., Samie, A., & Ahmed, U. I. (2020). Drivers of Farm Households' Perceived Risk Sources and Factors Affecting Uptake of Mitigation Strategies in Punjab Pakistan: Implications for Sustainable Agriculture. *Sustainability*, 12(23), 9895. doi:<https://doi.org/10.3390/su12239895>
- Jellason, N. P., Baines, R. N., Conway, J. S., & Ogbaga, C. C. (2019). Climate Change Perceptions and Attitudes to Smallholder Adaptation in Northwestern Nigerian Drylands. *Social Sciences*, 8(2), 31. doi:<https://doi.org/10.3390/socsci8020031>
- Joshia, K., & Chaturvedib, P. (2013). Impact of climate change on agriculture. *Octa Journal of Environmental Research*, 1(1).
- Kabubo-Mariara, J., & Karanja, F. K. (2007). The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach. *Global and Planetary Change*, 57(3), 319-330. doi:<https://doi.org/10.1016/j.gloplacha.2007.01.002>
- Kakumanu, K. R., Kuppanan, P., Ranganathan, C. R., Shalander, K., & Amare, H. (2016). Assessment of risk premium in farm technology adoption as a climate change adaptation strategy in the dryland systems of India. *International Journal of Climate Change Strategies and Management*, 8(5), 689-717. doi:<https://doi.org/10.1108/IJCCSM-10-2015-0149>
- Kendall, M. G. (1948). Rank correlation methods. Retrieved from <https://psycnet.apa.org/record/1948-15040-000>
- Liverpool-Tasie, L. S. O., & Parkhi, C. M. (2021). Climate Risk and Technology Adoption in the Midstream of Crop Value Chains: Evidence from Nigerian Maize Traders. *Journal of Agricultural Economics*, 72(1), 158-179. doi:<https://doi.org/10.1111/1477-9552.12394>
- M.G., K. (2008). Kendall Rank Correlation Coefficient. In *The Concise Encyclopedia of Statistics* (pp. 278-281). New York, NY: Springer New York.
- Ma, X., He, Y., Xu, J., van Noordwijk, M., & Lu, X. (2014). Spatial and temporal variation in rainfall erosivity in a Himalayan watershed. *CATENA*, 121, 248-259. doi:<https://doi.org/10.1016/j.catena.2014.05.017>
- Maddison, D. (2007). *The perception of and adaptation to climate change in Africa* (Vol. 4308): World Bank Publications.
- Mann, H. B. (1945). Nonparametric Tests Against Trend. *Econometrica*, 13, 245.
- McFadden, D. (1978). Modelling the choice of residential location.
- Mendelsohn, R. (2009). The Impact of Climate Change on Agriculture in Developing Countries. *Journal of Natural Resources Policy Research*, 1(1), 5-19. doi:<https://doi.org/10.1080/naturesopolirese.1.1.0005>

- Mfere, W. U. A. (2021). *Econometric Analysis of the Perception and Adaptation to Climate Change Risks Among Farmers in Congo-Brazzaville*: AERC.
- Moser, S. C., & Ekstrom, J. A. (2010). A framework to diagnose barriers to climate change adaptation. *Proceedings of the national academy of sciences*, 107(51), 22026-22031. doi:<https://doi.org/10.1073/pnas.1007887107>
- Mustafa, G., Latif, I. A., Ashfaq, M., Bashir, M. K., Shamsudin, M. N., & Wan Daud, W. M. N. (2017). Adaptation process to climate change in agriculture-an empirical study. *International Journal of Food and Agricultural Economics (IJFAEC)*, 5(4), 81-98. doi:<https://www.doi.org/10.22004/ag.econ.266464>
- Ndamani, F., & Watanabe, T. (2016). Determinants of farmers' adaptation to climate change: A micro level analysis in Ghana. *Scientia Agricola*, 73(3), 201-208. doi:<https://doi.org/10.1590/0103-9016-2015-0163>
- Ngaruiya, G. W., & Scheffran, J. (2016). Actors and networks in resource conflict resolution under climate change in rural Kenya. *Earth Syst. Dynam.*, 7(2), 441-452. doi:<https://doi.org/10.5194/esd-7-441-2016>
- Nhemachena, C., Hassan, R. M., & Chakwizira, J. (2014). *Analysis of determinants of farm-level adaptation measures to climate change in Southern Africa*.
- Nguyen, V.S. et al., 2020. Vietnamese Agriculture before and after Opening Economy. *Modern Economy*. Vol.11.No4. doi: <https://www.doi.org/10.4236/me.2020.114067>.
- Ochenje, I., Ritho, C., Guthiga, P., & Mbatia, O. (2016). *Assessment of farmers' perception to the effects of climate change on water resources at farm level: the case of Kakamega county, Kenya*. Retrieved from
- Partal, T., & Kahya, E. (2006). Trend Analysis in Turkish Precipitation Data. *Hydrological Processes*, 20, 2011-2026. doi:<https://www.doi.org/10.1002/hyp.5993>
- Paudel, B., Zhang, Y., Yan, J., Rai, R., Li, L., Wu, X., . . . Khanal, N. R. (2020). Farmers' understanding of climate change in Nepal Himalayas: important determinants and implications for developing adaptation strategies. *Climatic Change*, 158(3), 485-502. doi:<https://doi.org/10.1007/s10584-019-02607-2>
- Rakgase, M. A., & Norris, D. (2015). Determinants of livestock farmers' perception of future droughts and adoption of mitigating plans. *International Journal of Climate Change Strategies and Management*, 7(2), 191-205. doi:<https://doi.org/10.1108/IJCCSM-01-2014-0011>
- Reidsma, P., Ewert, F., Oude Lansink, A., & Leemans, R. (2008). Vulnerability and adaptation of European farmers: a multi-level analysis of yield and income responses to climate variability. *Regional Environmental Change*, 9(1), 25. doi:<https://doi.org/10.1007/s10113-008-0059-3>
- Roco, L., Bravo-Ureta, B., Engler, A., & Jara-Rojas, R. (2017). The Impact of Climatic Change Adaptation on Agricultural Productivity in Central Chile: A Stochastic Production Frontier Approach. *Sustainability*, 9(9), 1648. doi:<https://doi.org/10.3390/su9091648>
- Rondhi, M., Fatikhul Khasan, A., Mori, Y., & Kondo, T. (2019). Assessing the Role of the Perceived Impact of Climate Change on National Adaptation Policy: The Case of Rice Farming in Indonesia. *Land*, 8(5), 81. doi:<https://doi.org/10.3390/land8050081>
- Saguye, T. S. (2017). Assessment of Farmers' Perception of Climate Change and Variability and It's Implication for Implementation of Climate-Smart Agricultural Practices: The Case of Geze Gofa District, Southern Ethiopia. *Assessment*, 30, 1-15. doi:<https://www.doi.org/10.4172/2167-0587.1000191>
- Sahu, N. C., & Mishra, D. (2013). Analysis of Perception and Adaptability Strategies of the Farmers to Climate Change in Odisha, India. *APCBEE Procedia*, 5, 123-127. doi:<https://doi.org/10.1016/j.apcbee.2013.05.022>
- Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall's Tau. *Journal of the American Statistical Association*, 63(324), 1379-1389. doi:<https://www.doi.org/10.1080/01621459.1968.10480934>
- Smit, B., & Pilifosova, O. (2003). Adaptation to climate change in the context of sustainable development and equity. *Sustainable Development*, 8(9), 9.
- StataCorp. (2015). *Stata Statistical Software: Release 14*. College Station, TX: StataCorp LP.
- Stern, N., & Stern, N. H. (2007). *The economics of climate change: the Stern review*: cambridge University press.
- Tesfaye, W., & Seifu, L. (2016). Climate change perception and choice of adaptation strategies. *International Journal of Climate Change Strategies and Management*, 8(2), 253-270. doi:<https://doi.org/10.1108/IJCCSM-01-2014-0017>
- Tessema, Y. A., Joerin, J., & Patt, A. (2019). Climate change as a motivating factor for farm-adjustments: Rethinking the link. *Climate Risk Management*, 23, 136-145. doi:<https://doi.org/10.1016/j.crm.2018.09.003>
- Trinh, T. Q., Rañola, R. F., Camacho, L. D., & 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. doi:<https://doi.org/10.1016/j.landusepol.2017.10.023>
- Uddin, M. N., Bokelmann, W., & Entsminger, J. S. (2014). Factors Affecting Farmers' Adaptation Strategies

- to Environmental Degradation and Climate Change Effects: A Farm Level Study in Bangladesh. *Climate*, 2(4), 223-241. doi:<https://doi.org/10.3390/cli2040223>
- Van Song, N., Cuong, H. N., Huyen, V. N., & Rañola, R. F. (2020). The determinants of sustainable land management adoption under risks in upland area of Vietnam. *Sustainable Futures*, 2, 100015. doi:<https://doi.org/10.1016/j.sftr.2020.100015>
- Vo, H. H., Mizunoya, T., & Nguyen, C. D. (2021). Determinants of farmers' adaptation decisions to climate change in the central coastal region of Vietnam. *Asia-Pacific Journal of Regional Science*, 5(2), 327-349. doi:<https://doi.org/10.1007/s41685-020-00181-5>
- Wheeler, T., & Braun, J. v. (2013). Climate Change Impacts on Global Food Security. *Science*, 341(6145), 508-513. doi:<https://doi.org/10.1126/science.1239402>
- Yamane, T. (1967). *Statistics, An Introductory Analysis* (2nd ed.). New York:: Harper and Row.