Graduate School of Economics, Hitotsubashi University

Discussion Paper No.2020-06

Ambiguity Aversion and Individual Adaptation to Climate Change: Evidence from a Farmer Survey in Northeastern Thailand

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August 2020

Abstract

Understanding the triggers of individual adaptation behavior is critical for empowering those who are highly vulnerable to climate change. This study explores the effect of ambiguity aversion on adaptation behaviors in the context of climate change. We conduct a field survey on 230 rice farmers in northeastern Thailand to examine the association between the elicited ambiguity aversion and the implementation of climate change adaptation. We find that ambiguity aversion does not encourage farmers' adaptation behaviors and can even discourage the uptake of adaptation strategies. The role of ambiguity aversion varies depending on the characteristics of the adaptation strategy: Ambiguity-averse farmers are less likely to adopt adaptation strategies that entail shifts from the status quo. A deliberate approach is needed to understand farmers' adaptation behaviors outside the laboratory setting and to reduce ambiguity in the results concerning adaptation to increasing climate risk.

Keywords: ambiguity aversion, climate change adaptation, Thailand, weather index insurance
JEL classification: O13, Q12, Q54

This research work was carried out with financial support by JSPS KAKENHI, grant number 17K18343. We are grateful for the helpful comments from the conference participants at 23th SEEPS Annual Conference 2018.

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1. Introduction

Economies heavily dependent on the agricultural sector are greatly affected by climate change and the increasing number of extreme weather events (Nelson *et al*., 2009). Individual behavior in response to climate change is a form of decision-making under uncertainty (Grothmann and Patt, 2005). Most studies deal with climate change uncertainty as a typical kind of risk (Lemoine and Rudik, 2017; Weyant, 2017), but others consider climate change as a problem of "ambiguity" as well.[1] Climate change poses ambiguity because individuals tend to lack precise knowledge about the probability distribution of extreme climate events. This is due to the variability in estimations and continuous revisions of knowledge, as well as the irreversible effects of climate change, which invalidates any scientific consensus (Eismont and Welsch, 1996; Eichberger and Guerdjikova, 2012; Millner *et al*., 2013; Heal and Millner, 2014; Heal and Millner, 2018). Ellsberg (1961) reveals that people typically prefer known risks over an ambiguous process, or the unknown probability of an undesirable situation; this is generally referred to as "ambiguity aversion."

Does individual preference for ambiguity affect climate change adaptation behaviors? As it is recognized that ambiguity aversion affects individual behaviors in general (Slovic and Tversky, 1974; Fox and Tversky, 1995), ambiguity attitudes in the face of a changing climate may influence decisions regarding adaptation (Malik and Smith, 2012). Although climate change adaptation will often require technology adoption by individuals and households (Eichberger and Guerdjikova, 2012; Zilberman *et al.,* 2012), there is some empirical evidence for the impact of ambiguity aversion on the adoption of new agricultural technology, which shows mixed results. Some studies show that ambiguity aversion decreases the adoption of technology (Warnick *et al*., 2011; Ross *et al.,* 2012). By contrast, Barham *et al.* (2014), who conducted a field experiment with U.S. grain farmers, reveals that ambiguity aversion speeds up their adoption of GM maize and soybeans. Ward and Singh (2015) conducted a similar experiment in rural India but found no significant impact of ambiguity aversion on individuals' adoption of drought-tolerant rice.

Technology adoption as climate change adaptation can involve uncertainties in terms of multiple dimensions. Eichberger and Guerdjikova (2012) argue that, although farmers choose the best technology available to tackle climate change, such new technologies are ambiguous because of a lack of information on the adaptation process. The decision-making process in climate change adaptation seems more complex than that of the conventional technology adoption. Those making climate change adaptation decisions also consider the uncertainty concerning technology efficacy and performance, a factor that may countervail the uncertainty about future climate change (Bernedo and Ferraro, 2017; Malik and Smith, 2012). For instance, farmers who are ambiguity averse may be unwilling to undertake an adaptation strategy due to

[1] Ambiguity is defined as a situation in which the probability distribution is unknown (Machina and Siniscalchi, 2014) and is usually used in the same sense as "Knightian uncertainty," under which agents are provided no basis on which to measure their objective probability (Knight, 1921). For more discussion on the concept of ambiguity, see Camerer and Weber (1992), Dequech (2000), and Izhakian (2020).

their aversion to the ambiguity about the expected performance of that technology in the face of climate change. As a result, ambiguity-averse farmers may remain status-quo rather than adopt an unfamiliar strategy (Ortoleva, 2010).

Another complex issue is how to measure attitudes to risk and ambiguity. Few studies on the behavioral influence of ambiguity design their empirical setting to elicit ambiguity in a specific context; they use a general context instead. However, Naranjo *et al.* (2018) show that general surveys of risk attitudes that lack a specific context fail to capture actual behavior. Alpizar *et al*. (2011) provide the only exception, by empirically assessing ambiguity aversion in the context of climate change. They conduct a framed field experiment with farmers in Costa Rica in which farmers are asked to decide whether to adapt to climate change, on the assumption that their answers reflect their actual behaviors. The findings show that the farmers are more likely to adapt in the experiment where the risk of a disaster is unknown than they are in a similar situation where the risk is known. Alpizar *et al*. (2011) indicate that ambiguity associated with negative climate impacts induces farmers to adapt. In reality, however, farmers also consider another kind of ambiguity in performing adaptation strategies for climate change, and it remains unknown whether ambiguity aversion in the context of climate change affects farmers' actual adaptation behaviors.

This study is the first to empirically examine farmers' ambiguity preferences in the face of climate change, as well as to explore the relationship between ambiguity concerning climate change and individual adaptation behaviors in response to it. A survey was conducted as a case study involving 230 rice farmers in northeastern Thailand, where agriculture accounts for a significant proportion of the labor force. Following Alpizar *et al.* (2011), we identify farmers who are averse to ambiguity regarding climate change. We then investigate whether they undertake adaptation strategies. We consider seven potential adaptation strategies at the study site: changes in crop calendar, growing other crops, irrigation facilities, farm ponds, alternative jobs, change in rice varieties, and weather index-based insurance.

Our work contributes to the literature on the factors affecting individuals' climate change adaptation by identifying the relationship between climate change ambiguity and behaviors in the field. Although there is a growing literature on the determinants of climate change adaptation (Di Falco and Veronesi, 2013; Alauddin and Sarker, 2014; Da Cunha *et al.*, 2015; Bunclark *et al.*, 2018; Khanal *et al.*, 2018), no empirical study (except for Alpizar *et al*. [2011]) has examined the effect of ambiguity as a factor affecting individual adaptation decision. While some studies investigate the effect of risk aversion on farmers' adaptation behaviors in developing countries (Jianjun *et al.*, 2015; Dassanayake *et al.*, 2018), no comparable attempt has been made regarding ambiguity aversion. We focus on aversion to climate change ambiguity, which is distinct from technology ambiguity. We aim to contribute to the literature on climate change adaptation by investigating how farmers' attitudes to climate change ambiguity affects their decision to adapt to a changing climate. Alpizar *et al*. (2011) elicit farmers' attitudes to ambiguity regarding climate change in a framed setting but find that they have no effects on their adaptation behaviors. Therefore, this study is the first to examine the association between elicited aversion to climate change ambiguity and farmers' adaptation.

Furthermore, this study builds on the literature on the factors affecting the take-up of index-based insurance (Giné *et al.*, 2008; Cole *et al.*, 2013; Hill *et al.*, 2013; Elabed and Carter, 2015; Cole *et al.*, 2017), a type of innovative crop insurance that has been used as an adaptation strategy in developing countries[2]. While Bryan (2019) provides empirical evidence that ambiguity aversion undermines the facilitative effect of index-based insurance on the adoption of new agricultural technologies, this study focuses on the specific association between ambiguity aversion and the adoption of index-based insurance.

The results of our analysis show that our elicited ambiguity aversion shows no significant association with most of the listed adaptation strategies and, more interestingly, has a significantly negative association with changing rice varieties and shifting the crop calendar. In addition, this study finds that ambiguity aversion in the climate change setting has a positive association with demand for index-based insurance.

In summary, our study provides empirical evidence that ambiguity associated with climate change is not a driver of farmers' adaptation and can even be a hindrance to some adaptation strategies. Our findings also indicate that the role of climate change ambiguity varies depending on the adaptation strategies' characteristics; in particular, ambiguity-averse farmers are less likely to adopt adaptation strategies that require them to change their current practices and follow unfamiliar ones.

The remainder of this paper is organized as follows. In section 2, we describe the study sites and the survey design. Section 3 presents econometric models that examine the determinants of climate change adaptation strategies, including the ambiguity aversion elicited in the survey. In section 4, we present the study's econometric model and report the results of the estimation models. Section 5 outlines the study's conclusions and limitations, and discusses avenues for further research.

2. Study Sites and Survey Instruments

2-1. Study Sites

Northeastern Thailand (called *Isaan* in Thai), composed of 20 provinces, is one of the largest rice production areas in the country. Up to 75% of its land is devoted to rice fields (Babel *et al*., 2011), and agriculture is a major sector of its economy. Pornamnuaylap *et al*. (2014) find that the overall daily temperatures in northeastern Thailand increased between 1983 and 2012. Since rice growing in the region relies mainly on rain-fed farming, frequent and intense droughts negatively affect production (Babel *et al*., 2011). Farmers are exposed to irregular rainfall distribution, such as a deficiency of rainfall, delayed rainy seasons, and early cessation of rainfall (Wattanakij *et al*., 2006; Polthanee and Promkhambut, 2014). Floods present another threat to rice farmers in northeastern Thailand. In flood-prone areas, floods occurring before the rice harvest can damage rice plants (Chinvanno, 2011).

We carried out the survey in Khon Kaen province, the fifth largest province in northeastern Thailand, which has 26 districts and 198 sub-districts. Figure 1 describes the locations of the study sites. The rice production system in Khon Kaen is mixed. Farmers living near the Ubol Ratana Dam employ irrigation facilities, while rain-fed cropping remains the most common system in the rest of the province.

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[2] Many researchers in the field of development economics have examined how demand for index-based insurance increases (Giné *et al.*, 2008; Cole *et al.*, 2013; Mobarak and Rosenzweig, 2013; Cai, 2016).

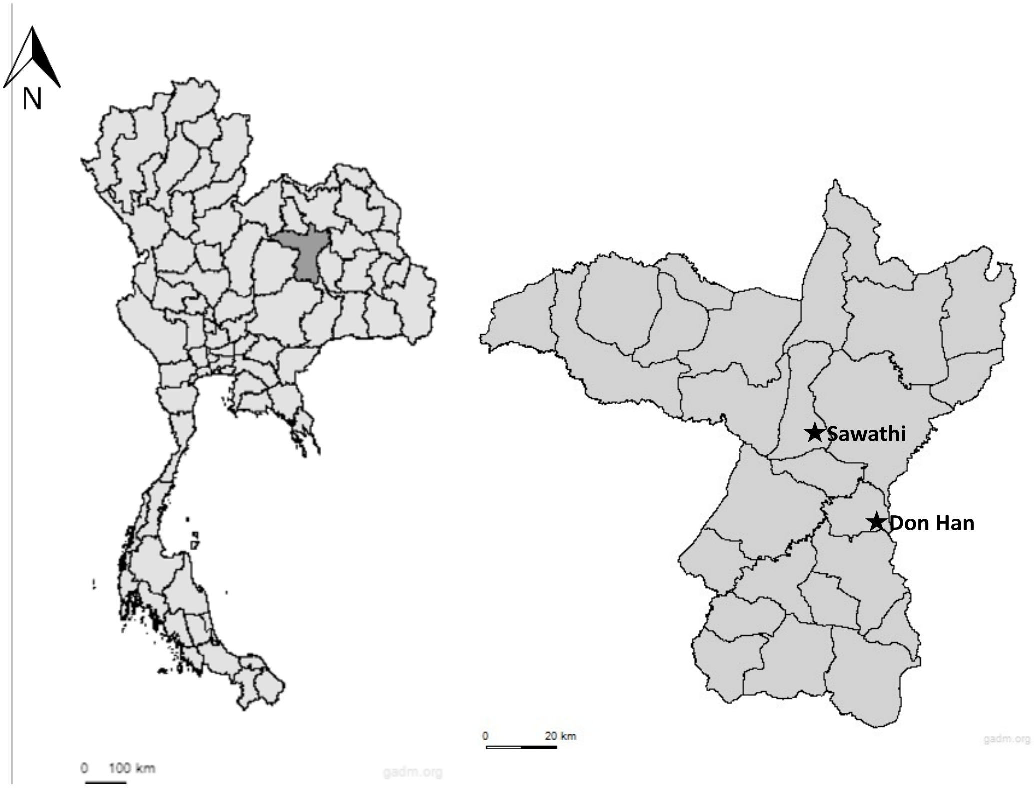

Figure 1. Khon Kaen Province in Northeastern Thailand (*Isaan*)
Source: Global Administrative Areas (https://gadm.org/)

2-2. Sampling

A field survey was conducted in September and October 2017 involving 240 rice farmers in two small villages in Khon Kaen. One village, located in the Don-Han sub-district, was affected primarily by serious flooding. The other village was in a drought-prone area in Sawathi District. Stratified random sampling was conducted based on the strata of these two districts. In the sampling process, we randomly selected farming households using contact information from the Bank for Agricultural and Agricultural Cooperatives, which provides rice farmers with index-based insurance.[3] In both study areas, 110 farmers were included in the list. The selected samples were contacted via telephone regarding possible survey participation. Since some potential samples refused to cooperate and some had inactive phone numbers, an additional collection procedure was implemented. The chiefs of the two districts made an announcement about the field study just before it started, saying that we would be conducting a survey to learn about rice farmers' perceptions of the changing environment and that villagers could earn some money by participating. We also screened out non-rice farmers. On the day, 240 farmers (including 71 insured farmers) from four villages in the two sub-districts asked to participate. After all the missing information was cleaned, 230 observations remained for analysis.

[3] In 2010, Japanese insurance company SOMPO Japan launched index-based insurance for rice farmers in northeastern Thailand to deal with losses caused by serious drought at the micro level (Chantarat *et al*., 2015).

2-3. Survey Design and Procedure

The field study consisted of two surveys. One of the survey instruments was designed to examine farmers' risk and ambiguity preferences associated with climate change. It largely followed Alpizar *et al*.'s (2011) experiment procedures, but consisted only of a survey without monetary reward for the respondents. The other instrument was a questionnaire survey used to investigate the villagers' adaptation strategies as well as subjective risk perceptions and demographic attributes. The analysis uses the combined results from these surveys.

We held a morning session and an evening session, each of which had a capacity of 30 seats. Participants were asked to draw a colored ball (green, red, or blue) from a box and were randomly assigned to three groups according to the color of the ball that they picked. Since farmers were supposed to return the picked ball to the box, the number of subjects varied by group. After finishing the group allocation, the surveyors explained the purpose of our survey and the overall process, including the time required to complete the session. The survey team consisted of nine surveyors, including a team leader and a group leader. The team leader supervised all groups, while the three group leaders took care of their own group.[4]

2-4. Risk Aversion and Ambiguity Aversion

To make ambiguity aversion regarding climate change explicit, we first used a survey design based on that of the framed field experiment used in Alpizar *et al*. (2011), with slight modifications. Farmers' risk aversion and ambiguity aversion were measured by asking them to make a lottery choice between "adapt" or "not adapt" with several risk probabilities as well as in an ambiguous situation. Alpizar *et al*. (2011) employed a framed experimental design that contextualized farmers' choices in terms of climate change, specifically in terms of extreme weather events that could have affected their land. Likewise, the farmers in our study were told to consider the risk of droughts and its negative impact on their rice production because one of our interests is the uptake of the insurance product, which is designed to cover crop losses due to severe drought.

The game had four sessions, and the farmers received four choice sheets with different risk probabilities of extreme drought: 10%, 20%, 30%,[5] and unknown (could be 10%, 20%, or

[4] Eight surveyors were allocated to each group to assist the subjects in completing the questionnaire. Group leaders proceeded with the survey according to the script. They briefly explained the sections before the subjects answered each section. In other words, all subjects started and finished each section at the same time. Farmers were allowed to leave the session for specific reasons such as a lack of time. At the beginning of the survey, we asked the subjects to provide informed consent while making clear that we would use their survey responses in our analysis.

[5] These risk levels were chosen based on the historical dataset. This dataset comprised 0.05° × 0.05° grid data on daily precipitation in Thailand from the Data Integration and Analysis System, which was constructed using data from the Thai Meteorological Department covering 1979 to 2011. We extracted the data on our study sites with latitudes and longitudes and added daily rainfall data from 2012 to 2017 obtained from the Thai Meteorological Department. We then plotted the maximum daily precipitation in the cropping season (July to September) of each year on logarithmic-normal probability paper. The risk levels were determined according to the insurance contract of SOMPO's index-based insurance, the index

30%). First, the farmers were told to assume that they possessed 500 baht as an initial endowment before the cropping season. They were then asked to choose whether to invest in adaptation strategies in the framed experiment. Farmers who decided to "adapt" needed to pay 200 baht as the investment cost and would certainly receive the remaining 300 baht as their net profit after the cropping season. Those who chose "not adapt" were to bet on their profit in the next cropping season. Farmers were told that their profit would be only 50 baht in the case of drought but that they would gain 500 baht if nothing happened. The survey with a total of four rounds is summarized in Table 1. Considering the order effect, different probabilities were randomly shown in each group in the first three sessions, and the risk level became "unknown' in the final session for all groups. The choice sheets provided visual aids to help the respondents understand the probability of damage to their rice production, indicating the risk (see Appendix. 1). Based on the results of the risk survey, we created variables representing the risk and ambiguity preferences. First, risk aversion is determined as an ordinal variable, based on the shifting point into "not adapt" using scales ranging from 1 to 4. In the first three sessions, farmers were told to choose "adapt" or "not adapt" at 10%, 20%, and 30%. For instance, the scale of risk aversion for participants who answered "adapt" at any known risk level is 4, while that of those who chose "not adapt" at the 10% risk level is 3. Likewise, farmers who chose "not adapt" at the 20% risk level but did not at 30% have a risk aversion of 2. Those who answered "not adapt," even at a 30% risk level, have a risk aversion of 1.

Then, we created a dummy variable for ambiguity aversion by using the risk-aversion level and respondents' answers in the last session with an unknown setting. Alpizar *et al.* (2011) classify ambiguity-averse individuals as those who choose "not adapt" when the risk level is almost equivalent to the expected risk of ambiguity situation but choose "adapt" when the risk is unknown. According to the expected utility theory, farmers are supposed to choose "not adapt" in the face of an unknown risk when they accept a comparable or higher risk level.[6] In this study, we assume that farmers who did not adapt at a 20% or higher risk level would choose "not adapt" in an unknown setting where the expected risk was 20%, when the unknown risk could be 10%, 20%, or 30%. However, some farmers chose "adapt" for the unknown risk even though they did not do so at a greater risk level. We call these farmers "ambiguity-averse." Hence, the ambiguity aversion variable was composed in the following two steps. First, we extracted the farmers who chose "not adapt," even at the 20% or higher risk level (i.e., with a scaled risk aversion of 1 or 2). Second, among these, those who checked "adapt" in the unknown risk situation were defined as "ambiguity-averse" farmers. Consequently, we generated a variable equal to 1 when they were ambiguity averse and 0 otherwise.

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of which is based on cumulative daily rainfall. For example, when cumulative daily rainfall reaches 100 mm (early drought) in July or 320 mm (drought) and 220 mm (severe drought) in August and September, farmers are assumed to receive an insurance payout. The probabilities that rainfall will exceed these criteria (the probability precipitation) can be identified using plotted logarithmic-normal probability paper. 0.0303 USD = 1 baht (September 2017).

[6] In considering ambiguity-averse individuals, Alpizar *et al.* (2011) excludes farmers who did not adapt even at the highest risk level but shifted their choice with unknown risks, assuming that they were inconsistent respondents. However, we extend this interpretation of ambiguity aversion and consider farmers who chose "adapt" in the ambiguous setting but chose "not adapt" at an equivalent and higher risk level as ambiguity-averse.

2-5. Climate Change Adaptation Strategies

We then conducted a questionnaire-based survey to identify the farmers' adaptation strategies. Drawing from the preliminary interviews and studies that list the common adaptation strategies in Khon Kaen (Babel *et al*., 2011; Kawasaki and Herath, 2011; Polthanee and Promkhambut, 2014), our questionnaire considered seven adaptation strategies: (1) changing the crop calendar, (2) growing other crops that consume less water than rice (e.g., cassava, sugarcane), (3) introducing irrigation facilities, (4) introducing farm ponds, (5) engaging in nonagricultural employment, (6) changing rice varieties, and (7) purchasing index-based insurance.

How to investigate farmers' adaptation practices requires careful consideration. The literature lacks a consensus definition of "adaptation strategies" (Lobell, 2014), but some studies first ask about farmers' preference for climate risks and then use questions to investigate whether they take measures to adapt to these risks (Di Falco and Veronesi, 2013; Dassanayake, 2018). Others consider commonly used farming practices that reduce climate risks (e.g., water harvesting, diversification of crops, use of chemical fertilizers) as adaptation strategies (Da Cunha *et al*., 2015; Bunclark *et al*., 2018; Huang e*t al*., 2018; McCord *et al*., 2018). Hassan and Nhemachena (2008) distinguish between "perceived adaptation" (i.e., the measures and practices farmers select to cope with climate shock) and "actual adaptation" (i.e. those actually carried out in a surveyed year). Huang *et al*. (2015) distinguished between farmers' responses to climate change and their daily farming practices by comparing practices in normal years with those in recent years during extreme weather events. Our survey thus examined "actual adaptation" practices in order to determine farmers' behavior by asking them "Have you used the following farming practices in the past five years?" and then showing them the list of seven strategies.

2-6. Subjective Risk Perception

We asked farmers a set of questions about their perceptions of past and future climate change. First, we investigated how frequently the farmers experienced droughts and floods (FRQ) and to what extent each event damaged their crop production over the past five to 10 years (DMG). Consequently, we obtained variables representing the perceived frequency and perceived damage of droughts and floods, where SRP = FRQ × DMG, ranging from 1 to 10. Then, we asked the same questions about the next one to five years. Farmers were told to evaluate their opinions using five-point Likert scales, which are typically employed to capture individual risk perception (Niles and Mueller, 2016; Alam *et al*., 2017; Hitayezu *et al*., 2017).Consequently, we obtained variables representing past and future perceptions of each drought risk and flood risk. In addition, we asked the farmers about their perceptions of the degree of the drought threat in the next cropping season at the individual and community levels, thus creating two more risk perception variables ranging from 1 to 5.

3. Econometric Model

To test whether ambiguity aversion influences adaptation strategies, we employ a multivariate probit model, which estimates the multiple correlated binary choices jointly. We assume that farmers usually select a combination of adaptation strategies, and thus select the model that allows a farmer to choose more than two alternatives.

We specify binary outcome equations for each adaptation strategy, where the dependent variable is equal to 1 if the farmer undertakes an adaptation practice. Consider the decision of farmer i (i = 1, 2…...N) to adopt adaptation strategies. Let $\mathcal{U}_j$ represent the benefit of undertaking adaptation strategy j, where j denotes the choice among the seven adaptation strategies (j = 1, 2…...7). The farmer decides to undertake adaptation strategy j if $A^*_{ij} = \mathcal{U}_j{}^* - \mathcal{U}_0 > 0$. The net benefit A^*_{ij} for the farmer is a latent variable A^*_{ij}, determined as follows:

$$A^*_{ij} = \alpha_j + \beta_j Ambiguity_{ij} + \gamma_j Risk_{ij} + \delta_j X_{ij} + \rho_j Z_{ij} + \varepsilon_{ij}$$

$$\text{with } A_{ij} = \begin{cases} 1 \text{ if } A^*_{ij} > 0 \\ 0 \text{ otherwise} \end{cases}$$

where A_{ij} is the observed individual decision variable. The estimation models contain the risk-aversion (measured by a five-point Likert scale) and ambiguity-aversion dummies. We controlled for the subjective risk perception to eliminate bias in the extent to which concern about climate change risk was subjective. The estimation models also contain the demographic variables used to control for exogenous factors influencing farmers' adaptation decisions, including a regional dummy (coded 1 for a farmer based in Don Han and 0 for one based in Sawathi). A further control variable representing inconsistent farmers' answers in the survey (1 if the farmer provided an inconsistent answer and 0 otherwise) was added to the model. A detailed description of the study's variables is provided in Table A2.

$Ambiguity$ is a dummy variable that equals one if a farmer is ambiguity-averse, while $Risk$ represents risk aversion. X_{ij} is a vector that represents the demographic variables affecting adaptation decisions through the coefficients δ_j, including gender, farming expense, land size, income, and household rice consumption. In the multivariate probit model, where a choice among several adaptation strategies is possible, the error terms ε_{ij} are assumed to follow multivariate normal distribution. The vector Z_{ij} indicates the risk perception about droughts and floods, which also affects farmers' adaptation decisions, while ρ_j is its parameter. We estimate the parameter of the ambiguity dummy and the remaining explanatory variables on each adaptation strategy.

4. Results

4-1. Ambiguity Aversion

We first examine whether unknown risk induces more adaptation than the corresponding situation with known risk. Table 2 reports the results of the survey on risk and ambiguity. The survey indicates that nearly half of the respondents showed the highest level of risk aversion (128 out of 240) and that they are most likely to choose “adapt” in an unknown risk setting as well (110 out of 128). At other risk levels, however, we observe only slight differences in the proportions of each choice, “adapt” or “not adapt,” when risk is unknown. For the group of farmers who did not adapt at low risk levels, nearly half of those who adapted at a 20% risk level (five out of 12) and at a 30% risk level (28 out of 54) are ambiguity-averse. This result does not strongly confirm Cárcamo and Cramon-Taubadel (2016) and Alpizar *et al*. (2011), who reported that farmers are likely to be ambiguity-averse through field experiments in rural Chile and Costa Rica, respectively.

Table 2
Number of Farmers Not Adapting and Adapting When Risk is Unknown

Choice when risk is known			Choice when risk is unknown.	
Sets of farmers	Risk-aversion level	Number	Does not adapt	Adapts
Adapts when risk is 10%	4	128	18	110
Adapts when risk is 20%, but not when risk is 10%	3	46	21	25
Adapts when risk is 30%, but not when risk is 20%	2	12	7	5
Does not adapt even when risk is 30%	1	54	26	28

4-2. Summary Statistics

Table 3 reports the summary statistics of the variables used in our regression analyses. For comparison purposes, we report the results for the regional subsample groups as well. The result shows that the risk aversion means are almost identical between the two subdistricts. Meanwhile, the group of farmers from Sawathi district, the drought-prone area, shows a mean ambiguity-aversion value higher than that of the other group.

Concerning subjective risk preferences for droughts and floods, a remarkable regional gap is observed in future perception, while only a slight difference is observed in past perception. Farmers in the drought-prone area show a perception of future droughts greater than that of the other subsample. Similarly, farmers from Don-Han district, the flood-prone area, are more likely to perceive a flood risk than are the others. A similar tendency can be observed regarding both the individual- and community-level risk perceptions of flood-related risks. Contrariwise, there is no remarkable regional difference in drought perceptions at the individual and community levels, although farmers in drought-prone areas have slightly higher perceptions. Farmers show a high risk perception about rice production at both the individual and community levels regardless of where they live.

The results also reveal regional differences in respondents' demographic attributes, including gender, land size, and farming expense. Farmers in Sawathi tend to expense slightly more for their farming and to own more land, while their average annual income is slightly lower than that of farmers in the Don-Han district.

Table 3

Descriptive Statistics of Explanatory Variables

Variable	Total Sample		Don-Han		Sawathi	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variable						
Adaptation strategy						
Change in the crop calendar	0.339	0.471	0.342	0.476	0.312	0.468
Other crop varieties	0.504	0.501	0.208	0.408	0.800	0.402
Irrigation	0.325	0.469	0.550	0.500	0.100	0.301
Ponds/water reservoirs	0.754	0.431	0.633	0.484	0.875	0.332
Off-farm employment	0.688	0.464	0.625	0.486	0.750	0.435
Changing rice varieties	0.554	0.498	0.392	0.490	0.720	0.453
Index-based insurance	0.296	0.457	0.258	0.440	0.333	0.463
Independent variable						
Risk aversion	2.958	1.129	2.983	1.243	2.93	1.200
Ambiguity aversion (dummy)	0.158	0.37	0.142	0.350	0.175	0.382
Inconsistent answer	0.204	0.40	0.200	0.402	0.208	0.408
Risk perception of droughts						
SRP of droughts in the past	8.704	5.307	8.500	6.117	8.908	4.366
SRP of droughts in the future	7.883	5.727	7.567	6.011	8.200	5.435
Individual perceived risk of droughts	4.313	0.980	4.125	1.081	4.500	0.830
Community perceived risk of droughts	4.279	0.994	4.092	1.116	4.467	0.755
Risk perception of floods						
SRP of floods in the past	6.300	6.873	6.442	4.039	6.156	8.861
SRP of floods in the future	5.658	5.958	6.550	4.620	4.767	6.953
Individual perceived risk of floods	4.071	1.442	4.550	1.060	3.592	1.564
Community perceived risk of floods	4.042	1.449	4.550	0.969	3.533	1.660
Demographic factors						
Gender (Dummy for female)	0.617	0.487	0.667	0.473	0.567	0.498
Expense of farming (6-point scale)	3.058	1.602	2.792	1.506	3.325	1.656
Land size (6-point scale)	5.204	1.210	4.878	1.298	5.526	1.026
Income (baht)	76,432	73,071	76,679	69,099	76,186	77,129
Household consumption (6-point scale)	5.587	0.962	5.465	1.074	5.707	0.824
Don-Han (regional dummy)	0.500	0.501	-	-	-	-

Note: Sample size is 230.

4-3. Adaptation Behaviors and Factors

We then examine how the elicited ambiguity aversion in the context of climate change affects farmers' adaptation behaviors. Table 4 reports the parameter estimates of the factors determining the adoption of climate change adaptation. Ambiguity aversion has a statistically significant effect on several adaptation strategies. It has a negative correlation with changing rice varieties, which indicates that ambiguity-averse farmers tend to shift to new rice varieties; indeed, ambiguity aversion decreases the probability of undertaking this activity. We also find a weakly negative correlation between ambiguity aversion and changing the crop calendar, indicating that ambiguity-averse farmers are less likely to change the crop calendar than those who are not; by contrast, ambiguity aversion increases the adoption of index-based insurance. We find no statistically significant relationships for the remaining strategies.

On the other hand, risk aversion shows no significant relationships. Previous studies have tried to investigate the effect of risk aversion on adaptation decisions, but few have found significant correlations. For example, Dassanayake *et al*. (2018) examines six adaptation strategies but finds that only natural resource harvesting shows a statistically significant correlation with risk aversion. Barham *et al*. (2014) also find only a small impact of risk aversion on shifting crop varieties.

The results also show that subjective risk perceptions about droughts in the past significantly affects the adoption of a new crop calendar and irrigation. The positive coefficient shows that farmers who perceived a risk of drought in the past five to 10 years are more likely to undertake these strategies, implying that farmers with past experience tend to adapt to droughts. Contrariwise, perceptions of future droughts is negatively related to farmers' decision to undertake these two strategies. Concerns about damage to the community also serve as an accelerator of several adaptation strategies concerning both droughts and floods.

Gender affects strategy choice. Male farmers implement more adjusting crop calendars, introducing other types of crops, and changing rice varieties. Land size is positively related to farm ponds and negatively related to nonagricultural employment. Richer farmers are more likely to purchase index-based insurance, which is to be expected given that the evidence tends to show a positive association between income and the take-up of index-based insurance (Cole *et al.*, 2012).

We also find significant regional differences in farmers' adaptation strategies. Changing rice varieties and investing in irrigation systems are undertaken much more frequently by farmers in the Don-Han district (i.e., the flood-prone area). This district is located relatively near the Ubol Ratana Dam, meaning that farmers can easily access water resources for irrigation purposes. Farmers in Sawathi (i.e., the drought-prone area) use other forms of adaptation, such as shifting from rice to other crop varieties, changing rice varieties, and purchasing index-based insurance.

To quantify the impact of each explanatory variable in the model, we estimate the marginal effects based on univariate probit analysis, assuming that alternative adaptation strategies are independent of each other. Detailed results on the marginal effects are reported in Table A1. This additional analysis generates results consistent with the multivariate probit model estimations. It shows that ambiguity-averse farmers are 25 percent points and 17 percent points less likely to undertake shifting rice varieties and changing crop calendars respectively, while they are 19 percent points more likely to purchase index-based insurance.

Table 4
Parameter Estimates of Multivariate Probit Analysis of Factors Affecting Climate Change Adaptation Strategies

Variable	(1) Calendar	(2) Other Crops	(3) Irrigation	(4) Farm Pond	(5) Off farm	(6) Rice Change	(7) Insurance
Risk aversion	0.0504	0.0423	-0.00995	0.227*	-0.126	-0.0455	-0.0292
	(0.135)	(0.143)	(0.127)	(0.126)	(0.132)	(0.137)	(0.126)
Ambiguity aversion	-0.539*	-0.484	0.248	-0.376	-0.333	-0.785**	0.633**
	(0.318)	(0.349)	(0.334)	(0.327)	(0.313)	(0.360)	(0.323)
Inconsistent answer	0.744**	0.404	-0.124	0.168	-0.695*	-0.191	-0.180
	(0.352)	(0.402)	(0.383)	(0.349)	(0.363)	(0.390)	(0.367)
SRP drought past	0.0579***	-0.0145	0.0563***	0.0121	-0.00701	0.0252	-0.0299
	(0.0212)	(0.0212)	(0.0196)	(0.0221)	(0.0200)	(0.0209)	(0.0204)
SRP drought future	-0.0561***	-0.00442	-0.0429**	-0.0287	0.0296	-0.0296	0.0142
	(0.0204)	(0.0201)	(0.0191)	(0.0201)	(0.0187)	(0.0181)	(0.0178)
Individual drought	-0.264**	-0.0693	0.0768	0.0528	-0.135	0.0448	-0.000867
	(0.109)	(0.108)	(0.111)	(0.125)	(0.113)	(0.109)	(0.113)
Community drought	0.406***	0.0819	-0.158	-0.0722	0.307***	-0.198*	-0.121
	(0.141)	(0.115)	(0.112)	(0.120)	(0.107)	(0.112)	(0.105)
SRP flood past	-0.0202	-0.00115	-0.0217	-0.0145	-0.00924	-0.00815	-0.0416***
	(0.0167)	(0.0177)	(0.0159)	(0.0184)	(0.0161)	(0.0148)	(0.0160)
SRP flood future	-0.0446**	-0.0195	-0.0166	0.0178	0.00222	0.00102	0.0130
	(0.0210)	(0.0204)	(0.0197)	(0.0201)	(0.0203)	(0.0180)	(0.0189)
Individual flood	-0.0548	0.0186	-0.177	-0.107	-0.0501	0.290**	0.104
	(0.123)	(0.150)	(0.138)	(0.167)	(0.132)	(0.127)	(0.125)
Community flood	-0.0664	-0.0863	0.191	0.345**	0.103	-0.0649	0.248**
	(0.117)	(0.144)	(0.133)	(0.162)	(0.131)	(0.124)	(0.123)

Table 4
Parameter Estimates of Multivariate Probit Analysis of Factors Affecting Climate Change Adaptation Strategies (Continued)

Variable	(1) Calendar	(2) Other Crops	(3) Irrigation	(4) Farm Pond	(5) Off farm	(6) Rice Change	(7) Insurance
Gender	-0.407**	-0.678***	-0.221	-0.102	-0.0662	-0.366**	0.0241
	(0.192)	(0.206)	(0.204)	(0.220)	(0.189)	(0.186)	(0.192)
Expense of farming	0.182***	0.0124	-0.0330	0.0573	-0.00835	0.00403	-0.114*
	(0.0600)	(0.0628)	(0.0613)	(0.0695)	(0.0573)	(0.0599)	(0.0603)
Land size	0.0827	0.157	0.0676	0.184**	-0.332***	0.0780	0.0754
	(0.0898)	(0.0983)	(0.0934)	(0.0814)	(0.0968)	(0.0829)	(0.0892)
Income	3.58e-07	7.15e-08	1.49e-07	1.82e-06	3.22e-07	1.20e-06	2.69e-06**
	(1.31e-06)	(1.22e-06)	(1.40e-06)	(1.40e-06)	(1.19e-06)	(1.44e-06)	(1.28e-06)
Household consumption	0.0339	-0.119	-0.0359	-0.172*	0.146	0.0483	0.144
	(0.115)	(0.118)	(0.113)	(0.0981)	(0.0993)	(0.0994)	(0.115)
Don-Han	0.560**	-1.656***	1.569***	-1.274***	-0.554**	-1.234***	-0.564***
	(0.221)	(0.229)	(0.258)	(0.254)	(0.221)	(0.218)	(0.218)
Constant	-1.730	1.362	-0.916	-0.110	1.236	0.328	-1.935*
	(1.218)	(1.065)	(1.108)	(1.045)	(1.030)	(1.029)	(1.028)

Multivariate probit (MSL, # draws = 5); N = 230; Wald chi2 (119) = 812.87

Log pseudo likelihood = -787.83176; Prob > chi2 = 0.0000; Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61 = rho71 = rho32 = rho42 = rho52 = rho62 = rho72 = rho43 = rho53 = rho63 = rho73 = rho54 = rho64 = rho74 = rho65 = rho75 = rho76 = 0;

chi2(21) = 35.4339 Prob > chi2 = 0.0253

Note: Coefficients are reported. Numbers in parentheses are robust standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

5. Conclusion

This study empirically examined whether ambiguity aversion is a factor determining individuals' adaptation behaviors. Taking risk preferences as exogenously given, we used regression models including ambiguity aversion in the context of climate change to illustrate the determinants of the seven adaptation strategies commonly adopted by the farmers in our study sites. Ambiguity aversion was elicited through a survey, following Alpizar *et al.* (2011).

The results show that the role of climate change ambiguity in adaptation decisions varies depending on the characteristics of the adaptation strategy involved. Our findings show that ambiguity aversion related to climate change is not significantly associated with most of the adaptation strategies examined in this study, whereas there is a negative association with changing the crop calendar and shifting to new rice varieties. These results suggest that, contrary to the conclusion of Alpizar *et al*. (2011), ambiguity aversion does not encourage farmers' adaptation behaviors in a practical setting, and even discourages the uptake of some adaptation strategies. This result may occur because farmers consider the ambiguity about the effectiveness of possible adaptations in the climate change setting. This may be different from the ambiguity arising from unfamiliarity with technology performance, which has commonly been discussed in the literature on technology adoption (e.g., Barham *et al*., 2014; Ward and Singh, 2015). Even though new technologies may be known to reduce potential climate impacts, farmers face uncertainty about their effectiveness in the local context because it is difficult to predict future regional weather conditions and their impacts on local agriculture (Eichberger and Guerdjikova, 2012). Given a changing climate, probabilities associated with possible outcomes and the set of outcomes as such may be ambiguous, making farmers' evaluation of possible adaptations difficult (Malik and Smith, 2012).

The results also indicate that the adaptation strategies involving a shift from current practices to new ones are less likely to be undertaken by the ambiguity-averse. In other words, ambiguity-averse farmers are less likely to adopt adaptation strategies that entail a shift from the status quo. According to Bewley (2002), an agent in an ambiguous situation typically retains the status quo unless an alternative decision is preferred. Because the presence of ambiguity regarding the future climate might confuse farmers, they will be cautious about adopting new strategies and will prefer to continue their familiar current practices. Those who are averse to climate change risk do not necessarily adopt specific adaptation strategies; this should be carefully considered in policymaking processes.

Furthermore, ambiguity aversion related to climate change and the purchase of index-based insurance are positively related. This result implies that ambiguity-averse farmers are more likely to purchase insurance to protect their assets from severe drought. This result seems to be consistent with the theoretical view of Alary *et al*. (2013) that ambiguity aversion tends to increase the incentive to insure. It could be hypothesized from our results that ambiguity stemming from concerns about the future climate could offset ambiguity about the effectiveness of the insurance product. Future research should seek to identify which ambiguity has a greater influence on individuals' take-up decisions. The answer may depend on the extent to which this insurance scheme is understood by farmers.

Our study has several methodological limitations. The first concerns the variable we used to represent ambiguity aversion. Our dummy variable divides ambiguity aversion into only two types: ambiguity averse and non-ambiguity averse. This variable therefore provides only simple observations. To make the analysis more sophisticated, future research needs to create a continuous variable to evaluate the extent of ambiguity aversion[7]. Furthermore, we could not incentivize farmers to complete the survey using a monetary reward. According to Naranjo *et al*. (2018), an unincentivized approach may not have direct consequences for respondents. Future research should thus aim to overcome these limitations to capture farmers' actual behaviors.

Nevertheless, our findings help explain farmers' behaviors by showing the effect of ambiguity aversion associated with the future climate. The study suggests that exploring the characteristics of adaptation strategies further and considering the effect on them of ambiguity might be important for policymakers seeking to facilitate adaptation among farmers. Given that some farmers perceive ambiguity about future climate change, policymakers should not adopt a uniform approach to all adaptation strategies. In particular, adaptation strategies that require farmers to abandon their current practices should be promoted in a way that reduces ambiguity regarding the expected outcomes of these strategies.

Furthermore, our findings imply that policymakers should put more effort into reducing ambiguity in the performance of adaptation rather than merely increasing the perceived certainty about climate change risk. Providing information on the possible outcomes of adaptation would offer farmers evaluation standards, and this would be feasible through an agricultural extension program. Future research must also focus on creating concrete program designs and establishing methodologies for mitigating ambiguity related to adaptation in response to climate change.

[7] In generating a continuous variable to measure the extent of ambiguity aversion, see Barham *et al.* (2014) and Ward and Singh (2015).

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Table A1

Marginal Effects of the Probit Analysis of the Factors Affecting Climate Change Adaptation Strategies

Variable	(1) Calendar	(2) Other Crops	(3) Irrigation	(4) Farm Pond	(5) Off farm	(6) Rice Change	(7) Insurance
Risk aversion	0.0133	0.0102	0.000624	0.0550	-0.0428	-0.0167	-0.00745
	(0.0387)	(0.0345)	(0.0360)	(0.0338)	(0.0410)	(0.0405)	(0.0371)
Ambiguity aversion	-0.173*	-0.117	0.0788	-0.0893	-0.122	-0.246**	0.191**
	(0.101)	(0.0899)	(0.0892)	(0.0795)	(0.0996)	(0.0976)	(0.0925)
Inconsistent answer	0.226**	0.0989	-0.0237	0.0457	-0.204*	-0.0669	-0.0556
	(0.112)	(0.101)	(0.102)	(0.0922)	(0.113)	(0.112)	(0.102)
SRP drought past	0.0176***	-0.00398	0.0139**	0.00351	-0.00110	0.00782	-0.00906
	(0.00584)	(0.00583)	(0.00576)	(0.00557)	(0.00627)	(0.00634)	(0.00648)
SRP drought future	-0.0164***	-0.000979	-0.0109**	-0.00679	0.00896	-0.00879	0.00362
	(0.00530)	(0.00497)	(0.00509)	(0.00492)	(0.00561)	(0.00557)	(0.00571)
Individual drought	-0.0809**	-0.0152	0.0188	0.0167	-0.0409	0.0135	0.000993
	(0.0327)	(0.0300)	(0.0317)	(0.0294)	(0.0359)	(0.0342)	(0.0332)
Community drought	0.117***	0.0201	-0.0414	-0.0158	0.0855**	-0.0631*	-0.0321
	(0.0373)	(0.0315)	(0.0303)	(0.0303)	(0.0339)	(0.0343)	(0.0345)
SRP flood past	-0.00480	-0.000621	-0.00503	-0.00443	-0.00459	-0.00271	-0.0118**
	(0.00512)	(0.00455)	(0.00583)	(0.00511)	(0.00512)	(0.00546)	(0.00535)
SRP flood future	-0.0129**	-0.00425	-0.00493	0.00382	0.00185	0.000351	0.00484
	(0.00604)	(0.00537)	(0.00643)	(0.00580)	(0.00594)	(0.00642)	(0.00607)

Table A1

Marginal Effects of the Probit Analysis of the Factors Affecting Climate Change Adaptation Strategies (Continued)

Variable	(1) Calendar	(2) Other Crops	(3) Irrigation	(4) Farm Pond	(5) Off farm	(6) Rice Change	(7) Insurance
Individual flood	-0.0184	0.00356	-0.0432	-0.0374	-0.00689	0.0883**	0.0247
	(0.0411)	(0.0336)	(0.0392)	(0.0395)	(0.0396)	(0.0413)	(0.0418)
Community flood	-0.0164	-0.0219	0.0472	0.0921**	0.0296	-0.0175	0.0766*
	(0.0407)	(0.0332)	(0.0401)	(0.0387)	(0.0391)	(0.0410)	(0.0407)
Gender	-0.116**	-0.167***	-0.0570	-0.0265	-0.0131	-0.113*	0.00956
	(0.0562)	(0.0503)	(0.0556)	(0.0531)	(0.0606)	(0.0599)	(0.0584)
Expense of farming	0.0531***	0.00361	-0.00707	0.0165	-0.00169	0.000185	-0.0345*
	(0.0168)	(0.0165)	(0.0179)	(0.0170)	(0.0186)	(0.0185)	(0.0187)
Land size	0.0224	0.0386*	0.0200	0.0448**	-0.0986***	0.0253	0.0238
	(0.0262)	(0.0217)	(0.0234)	(0.0206)	(0.0286)	(0.0258)	(0.0262)
Income	9.08e-08	3.37e-08	6.36e-08	4.39e-07	4.02e-08	3.96e-07	8.10e-07**
	(3.85e-07)	(4.14e-07)	(3.92e-07)	(4.08e-07)	(4.24e-07)	(3.92e-07)	(3.67e-07)
Household consumption	0.00591	-0.0307	-0.00690	-0.0403	0.0469	0.0165	0.0401
	(0.0325)	(0.0257)	(0.0288)	(0.0294)	(0.0328)	(0.0309)	(0.0330)
Don-Han	0.158**	-0.411***	0.422***	-0.299***	-0.183***	-0.389***	-0.172***
	(0.0653)	(0.0382)	(0.0492)	(0.0615)	(0.0668)	(0.0563)	(0.0639)
Log Likelihood	-118.5	-102.9	-109.2	-98.2	-127.8	-127.5	-121.4

Note: Sample size is 230. Average marginal effects are reported. Average marginal effects imply the change in the dependent variable (uptake of each adaptation strategy) for a change in independent variable. For instance, column 1 shows that being categorized as ambiguity averse decreases change in crop calendar by 17 percentage points. Numbers in parentheses are standard errors. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively.

Table A2.

Variable definitions

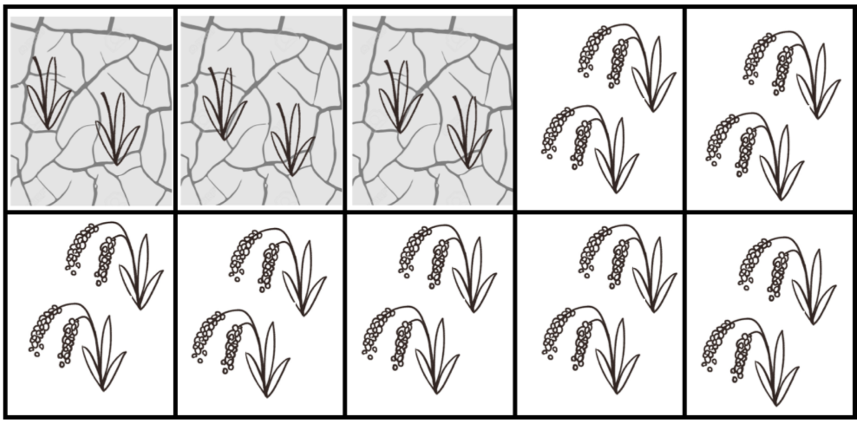
Variable Name	Description
Risk and Ambiguity Preference	
Risk Aversion	The level of risk aversion of the respondent (ranges from 1 to 4)
Ambiguity Aversion	Dummy variable coded as 1 if a respondent is ambiguity averse, and 0 otherwise
Irrational	Irrational choice in the risk experiment
Risk Perception of Drought	
SRP drought past	Subjective Risk Perception of Drought in the past 5 – 10 years (ranges from 1 to 10)
SRP drought future	Subjective Risk Perception of Drought in the next 1 – 5 years (ranges from 1 to 10)
Individual risk drought	Perceived Negative impact of Drought on own Rice Production in the next cropping season (ranges from 1 to 5)
Community risk drought	Perceived Negative impact of Drought on Community in the next cropping season (ranges from 1 to 5)
Risk Perception of Flood	
SRP flood past	Subjective Risk Perception of Flood in the past 5 – 10 years (ranges from 1 to 10)
SPR flood future	Subjective Risk Perception of Flood in the next 1 – 5 years (ranges from 1 to 10)
Individual risk flood	Perceived Negative impact of Flood on own Rice Production in the next cropping season (ranges from 1 to 5)
Community risk flood	Perceived Negative impact of Flood on Community in the next cropping season (ranges from 1 to 5)
Demographic factors	
Gender	Gender Dummy (1=Female, 0=Male)
Expense farm	Annual expenditure in the last year for rice farming per rai (4 points scale)
Land size	Land ownership (6 points scale)
Income	Total annual income (BAHT)
Household consumption	Annual household consumption of cropped rice
Don-Han	Regional dummy (1= Don-Han, 0=Sawathi)

Appendix. 1 Example Choice Sheet for Group Blue

CHOICE SHEET 1

for Group Blue

Your risk of losing is **30** out of each 100



Please circle your choice

Adapt	Not Adapt	
The cost is 300 BAHT then your net profit would be (500 BAHT - 200 BAHT)	Your gain depends on the risk	
	In 30 out of each 100 cases	In 70 out of each 100 cases
	DROUGHT!	SAFE
300 BAHT	50BAHT	500BAHT