



Measuring farmers' preferences for weather index insurance in the Ayeyarwady Delta, Myanmar: a discrete choice experiment approach

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Abstract

This study examines farmers' preferences for weather index insurance (WII) in the Ayeyarwady Delta, Myanmar, using discrete choice experiments. It employs data taken from a survey of 317 rice farmers in the district of Labutta in the Ayeyarwady Region, which was conducted in March 2019. After being informed about WII and the trigger conditions, farmers were asked to answer discrete choice questions on WII packages. The hypothetical WII packages consisted of three attributes: the types of disaster that the insurance covers, the insurance coverage rate, and the annual insurance premium rate. A random parameter logit model analysis of the responses reveals that farmers prefer the WII packages covering cyclones, floods, and droughts to that for salt damage. The probabilities of selecting 64 hypothetical WII packages calculated from the estimates indicate that more than 50% of farmers can be expected to purchase seven WII packages for cyclones, floods, and droughts.

Keywords Discrete choice experiments · Random parameter logit · Stated preference · Weather index insurance · Myanmar · Ayeyarwady delta

Introduction

Global climate change may have significant negative impacts on farm management. In this regard, crop insurance could mitigate the raised weather-related risk, as farmers who purchase insurance will receive a payout from their provider if their yields decrease due to any natural disaster specified in the insurance contract. However, various issues arise when establishing crop insurance markets in developing countries (Mahul and Stutley 2010; Miranda and Farrin 2012; Jensen and Barrett 2017). For example, when deciding upon

the payout for each farmer, the provider must investigate the damage caused by the disaster and estimate the extent of crop loss. In developing countries, this task could take longer and cost more because of poor infrastructure (i.e., high transaction cost). Additionally, farmers who have purchased crop insurance may reduce their efforts to increase yields, as the insurance company cannot effectively monitor farmers' laziness and their low yields become compensated by insurance payouts (i.e., moral hazard). If the insurance payout depends on the extent of crop damage, high transaction cost and moral hazard will increase the price of insurance and hence the crop insurance market will not be established without government subsidies.

The weather index insurance (WII) is thought to reduce inherent inefficiencies in crop insurance within developing countries (Collier et al. 2009). First, WII can reduce transaction cost because farmers who purchase WII in advance will receive an insurance payout regardless of the extent of their crop loss whenever the weather in their area meets predefined, measurable trigger conditions (e.g., monthly rainfall throughout a dry season being less than 50 mm). Companies can observe the weather in rural areas from remote locations using meteorological equipment. Second, WII can avoid moral hazard because farmers cannot control

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trigger conditions. Consequently, although the preparation of WII systems is costly, programs (or feasibility tests) have been operating in a number of developing countries, including Mexico, India, Ethiopia, and Thailand (see Barnett and Mahul 2007; Greatrex et al. 2015). To design a WII system for a given area, various conditions such as availability of weather information regarding the trigger, potential demand for WII, and local suppliers of WII must be assessed, and infrastructure, organizations, and other requirements for fulfilling these conditions are enhanced or constructed if necessary (International Fund for Agricultural Development 2011; World Bank 2011). Among these conditions, considering trigger conditions such as weather event and trigger level is vital. Trigger conditions for WII systems in practical use are set on the basis of rainfalls. This is because rainfall is good for the trigger conditions for WII: rainfall can be relatively and easily measured; an expected probability of meeting a trigger condition can be calculated well for a rainfall-based WII; and a relationship between the index (i.e., rainfall) and the extent of crop loss is understandable for both an insurance provider and farmers. The Government of Myanmar has recently been considering the introduction of WII. At present, a WII for the central arid region of Myanmar has been developed (SOMPO Holdings 2019) that uses rainfall as a trigger condition, while other areas, such as the Ayeyarwady Delta, remain without WII services. This is despite the fact that the Ayeyarwady Delta is a major producing area for rice (Ministry of Agriculture and Irrigation 2015) that is exposed to climate change effects because of its proximity to the sea and low elevation. However, designing a WII system with the trigger condition based on a cyclone or storm surge caused by climate change is a challenging task: unlike information regarding rainfall, climate change information is limited. Developing a suitable index for WII based on climate change is a natural scientific issue, whereas considering whether farmers demand such a WII is an economic issue.

To contribute toward an examination of the demand-side conditions of a feasible WII service for rice farmers in the Ayeyarwady Delta, this study measures farmers' preferences regarding the characteristics of a potential WII system using discrete choice experiments (DCEs), and then predicts farmers' probabilities of selecting various WII packages.¹ The DCE approach (Louviere et al. 2000) is a stated preference method, in which peoples' preferences for goods and services (or their characteristics) are measured through the statistical analysis of responses to hypothetical discrete choice questions. Stated preference methods, including contingent

valuation (CV) (Carson 2012), have been popular in agro-environmental valuation studies (e.g., Aizaki et al. 2006; Chiueh and Chen 2008; Maruyama and Takimoto 2008; Chen et al. 2018; Oishi et al. 2019); furthermore, they have also been applied in other fields, such as in the analysis of farmers' decisions regarding the introduction of new technologies (e.g., Cooper 1997; Kunimitsu 2009; Hong et al. 2017; Zuo et al. 2020; McGurk et al. 2020). DCEs are particularly appropriate for analyzing the decision-making of farmers because many conditions that could affect decisions can be considered. For example, Rigby et al. (2010) analyze horticultural producers' preferences for irrigation water contract conditions, such as the amount of guaranteed water and the probability of additional water, and Lutta et al. (2020) examine pastoralists' preferences for grazing management conditions, such as water availability and forage production (see, e.g., Bennett and Birol 2010 for more applications). Therefore, the DCE approach is suitable for our research. In fact, DCEs and CVs have been used to measure farmers' preferences or demands for WII in developing countries, including Bangladesh (Akter et al. 2016, 2017), Ethiopia (McIntosh et al. 2013; Castellani et al. 2014; Tadesse et al. 2017), Ghana (Adjabui et al. 2019), India (Ward and Makhija 2018), and Kenya (Sibiko et al. 2018).² Previous studies have focused on a drought-based WII system for rice production in an area of India (Ward and Makhija 2018) and an inundation- and (hail or wind) storm-based WII system for maize production in a coastal area of Bangladesh (Akter et al. 2016, 2017); however, farmers' preferences for these WII systems may not be suitable for the Ayeyarwady Delta area of Myanmar, where natural disasters such as saltwater and cyclone have affected farming. To the best of our knowledge, the only previous study that focused on farmers in the Ayeyarwady Delta area of Myanmar was conducted by Gu (2018), which reports the results of preliminary DCE questions gathered as part of the baseline survey for the project. The WII system designed in this study could help with the consideration of a WII system in other countries that are similar to those of the Ayeyarwady Delta area of Myanmar. For the entire project's details, refer to the editorial of the special issue.

¹ Other papers in the special issue may examine relationships between socio-economic conditions of farmers and their evaluation of WII.

² Among these studies, McIntosh et al. (2013) and Adjabui et al. (2019) use CV, while Castellani et al. (2014), Akter et al. (2016, 2017), Tadesse et al. (2017), Sibiko et al. (2018), and Ward and Makhija (2018) use DCEs. Stated preference methods have also been applied in various non-agricultural insurance studies. For example, Wakamatsu et al. (2019) measure preferences for micro health insurance, while Geweke (2012) conducts a DCE analysis of automobile insurance. See Jaspersen (2016) for more applications.

Methods and data

Outline of the survey

The survey was designed following the results of the preliminary DCE questions for WII (Gu 2018), the supplementary survey conducted the year before our survey, and experience drawn from another WII research project applying an experimental approach to farmers in Zambia (Miura and Sakurai 2012). The survey was conducted by (1) using visual aids to explain to farmers the concept of insurance and the characteristics of WII, including trigger conditions assumed for our study, (2) providing options in DCE questions using words and visual aids, and (3) asking warm-up questions to improve the farmers' understanding of WII. Survey materials, including questions and explanations, were developed in English and then translated into Burmese. The survey method is explained below.

Labutta District in the Ayeyarwady Region was chosen as our study site because it is one of the districts that are regularly affected by saline water intrusion in the region and the district was most heavily damaged by Cyclone Nargis in 2008 (Food and Agriculture Organization of the United Nations 2009). We selected a total of ten village tracts (hereafter we simply call them villages) that are facing the Thet Ke Thaung River, a branch of the Ayeyarwady River, and are contiguously located from the mouth of the Yway River. In each village, 32 rice-producing farm households were randomly chosen from the register of land-owning households provided by the village administration. As a result, we had a total of 320 sample households.³

The DCE for WII was conducted with the sample households in March 2019. Our enumeration team visited one or two villages per day. In each village, respondents from sample households were gathered at a location such as a temple, a village meeting place, or a village leader's house. They were then divided into four or five groups of five to eight farmers, and group sessions were conducted. A session consisted of four steps: (1) explaining insurance and WII with the aid of a poster; (2) asking warm-up questions; (3) explaining hypothetical WII arrangements, including the trigger conditions; and (4) asking questions about the hypothetical WII packages. The first step was undertaken by the leader of the enumerator team, and the remaining three steps were conducted person-to-person: an enumerator faced a farmer. After completing interviews in the 10 villages, we obtained 317 valid responses out of 320, as three farmers were absent.

The design of hypothetical WII services

The hypothetical WII packages in the DCE questions are as follows. An insurance company will sell various types of WII packages for rice farming in the next crop season, with packages specifying three characteristics: the types of disaster that the insurance covers, including cyclone, flood, drought, and salt damage; the insurance coverage rate, which is defined by the share of the expected normal rice yield, set at four levels of 100%, 80%, 60%, and 40%; and the annual insurance premium rate, which is also defined by the share of the expected normal rice yield and set at four levels of 1/100, 4/100, 8/100, and 12/100. Different combinations of these three characteristics produce different WII packages. Furthermore, we assume that insurance money will be paid when each disaster type fulfills the following trigger conditions: for cyclone-based WII, the issuance of a cyclone warning by the Government of Myanmar and the sea level at Haing Gyi Kyun exceeding four meters; for flood-based WII, the water level of the Thet Ke Thaung exceeding 3.5 m or the monthly rainfall in Labutta exceeding 1000 mm in August; for drought-based WII, the rainfall in Labutta being below 400 mm over August; and for salt damage-based WII, the salinity level of Thet Ke Thaung exceeding one part per thousand. These trigger conditions were decided through discussions with research project team members, including researchers in the fields of economics, remote sensing, and soil and water sciences.

After explaining the characteristics of the hypothetical WII packages, the respondents were asked to answer DCE questions in a binary choice format. Respondents were asked to classify 16 WII profiles, which were presented on paper cards (Fig. 1), into two groups: ones they would like to purchase and ones they would not. The 16 profiles were created using an orthogonal array with four four-level factors. The efficiency-based design approach has become popular in applied DCE studies (e.g., Scarpa and Rose 2008; Rose and Bliemer 2009), alongside the orthogonal array-based design approach (e.g., Franzén et al. 2016; Perni and Martínez-Paz. 2017; Just et al. 2018; Kikushima et al. 2018; Rakatama et al. 2018; Wu et al. 2020). Although the efficiency-based approach usually enables the generation of statistically highly efficient choice sets, it may also generate inefficient choice sets if preconditions are mis-specified (Walker et al. 2018). This means that the efficiency-based approach has no absolute advantage over other design approaches. While this binary choice format may be rare in some research fields, it has been applied: for example, Louviere and Islam (2008) use binary DCEs, in which profiles are designed with an orthogonal array. Aizaki et al. (2014) review three types of binary choice format in DCEs (see also Rao 2014). The format aided the ability of respondents to answer questions: with each profile presented on a physical card, the

³ Please refer to the editorial for details on the sample villages and farm households.

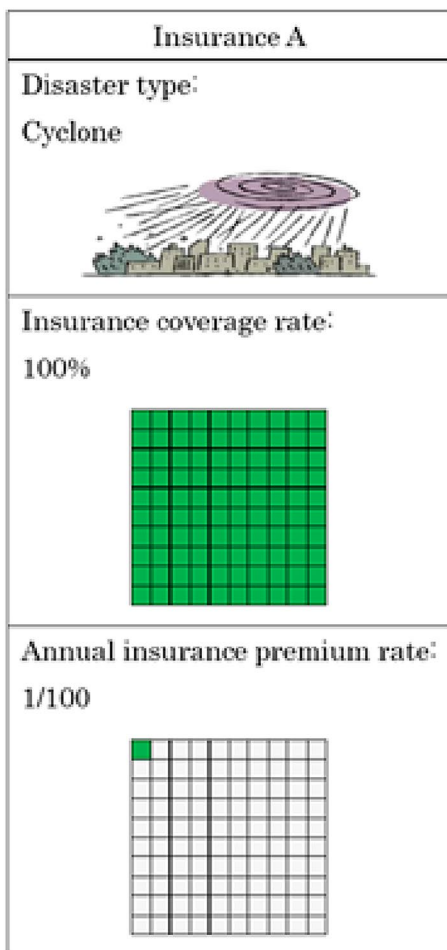


Fig. 1 An example profile for discrete choice experiment questions

respondents could easily compare profiles and make decisions by trial and error while considering the entire profiles.

After dividing the profiles into two groups, the respondents were also asked to rank the profiles they would like to purchase according to their preference, with the intention of providing more information about farmer preferences for WII packages. However, this also imposed the psychological burdens of ranking profiles on the respondents. Comparing the results from the binary analysis of the responses and those from the ranking analysis is a further issue to be discussed.

The survey also asked respondents to answer DCE questions in a multinomial choice format before the binary choice format questions (see the "Appendix" for more details), but these results are not used in this paper. This is because the value of the goodness of fit measure (i.e., the adjusted McFadden's R^2) for a conditional logit model analysis of the responses in multinomial choice format is 0.062 (see Table 5),

which is less than that of the binary logit model analysis of responses in the binary choice format (see Table 2) under the same utility function (see the next subsection for details on our models). Even when a random parameter logit model is used to analyze the responses to binary and multinomial DCE questions, the binary DCE model is superior to the multinomial DCE model (see Tables 2 and 5). These two formats are used because the pre-test conducted the year before the survey highlighted that some respondents were having difficulty answering DCE questions in a multinomial choice format. As a result, we adopted an easier format of DCE questioning. However, since we had no advance knowledge of which format would be more appropriate for the study, conducting both was a necessary exercise even though we faced the risk of causing the respondents greater psychological stress by asking more questions.

Specification of empirical discrete choice models

Responses to DCE questions can be analyzed using discrete choice models, which are based on the random utility theory (Train 2009). The theory assumes that individuals (e.g., farmers in this study) select an alternative in a choice set according to their utility of the alternatives included in the set. The utility of alternative i for farmer n (U_{in}) consists of a systematic component (V_{in}) and a stochastic component (ε_{in}), as follows:

$$U_{in} = V_{in} + \varepsilon_{in} \quad (1)$$

$$V_{in} = x'_{in}\beta \quad (2)$$

where x is a vector of independent variables and β is a vector of the coefficients.

Various discrete choice models can be derived from the utility function, following assumptions regarding the systematic and stochastic components. The fundamental model is a binary logit (BL) model, where the stochastic components are independently and identically distributed type I extreme value. Following the BL model, the probability of farmer n selecting alternative i as one they would like to purchase is expressed as follows:

$$P_n(i) = \frac{e^{V_{in}}}{e^{V_{in}} + 1} \quad (3)$$

where the systematic component of the utility for alternative i that farmer n would not like to purchase is normalized to 0. The above model assumes that coefficients are the same for all farmers (i.e., we assume homogenous preferences). Although our objective is to examine farmers' preferences for WII packages, farmers' characteristics

that affect their behavior are not included within the scope of the study. However, the homogeneity assumption may affect the accuracy of the analysis. Furthermore, the extent of heterogeneity in preference for WII is important for considering the potential demand for a WII package. A farmer's subjective probability of suffering from a disaster is likely to affect their preference for the disaster covered by the WII package. Therefore, a distribution of estimated coefficients for the disasters covered by WII packages allows for the indirect presumption of how widely and to what extent the disasters could affect farmers in a given area. Therefore, we also apply a random parameter logit (RPL) model (see, e.g., Hensher and Greene 2003; Train 2009), which assumes that coefficients for independent variables can differ among individuals.

The systematic component of the utility of a hypothetical WII (profile) i for farmer n is assumed to be given as follows:

$$V_{in} = \beta_0 + \beta_1 \text{CYCLONE}_{in} + \beta_2 \text{FLOOD}_{in} + \beta_3 \text{DROUGHT}_{in} + \beta_4 \text{COVERAGE}_{in} + \beta_5 \text{PREMIUM}_{in} \quad (4)$$

where CYCLONE_i is an effect-coded variable taking the value of 1 if package i is designed for cyclones, -1 for salt damage, and 0 otherwise; FLOOD_i is an effect-coded variable taking the value of 1 if package i is designed for floods, -1 for salt damage, and 0 otherwise; DROUGHT_i is an effect-coded variable taking the value of 1 if package i is designed for droughts, -1 for salt damage, and 0 otherwise; COVERAGE_i is the insurance coverage rate of package i (with a range from 0.4 to 1.0 according to the definition of the coverage attribute); PREMIUM_i is an annual insurance premium rate of package i (with a range from 0.01 to 0.12 according to the definition of the premium attribute); β_0 is a constant; and β_s are coefficients to be estimated. The dummy coding scheme, where the coefficient (utility weight) for the base level of a qualitative attribute is set to zero, enables us to easily interpret the coefficients for the remaining levels of the attribute. However, the dummy coding results in the coefficient for the base level being confounded with a constant in the utility function. An advantage of using the effect coding scheme is that a unique coefficient for the base level (i.e., salt damage in our models) can be calculated, and thus, the coefficients can be compared among all levels of an attribute (e.g., Hollin et al. 2015). In the model specification mentioned above, the coefficient corresponding to the salt damage is the negative sum of the coefficients for the remaining three effect-coded variables: $-(\beta_1 + \beta_2 + \beta_3)$ (see Beck and Gyrd-Hansen 2005 and Hensher et al. 2015 for details on the dummy and effect coding schemes). This feature of the effect coding scheme functions well, especially for the RPL model. This is because the RPL model allows us to calculate individual-specific coefficients (Train 2009),

and thus, we can view heterogeneity in preferences for the four disasters covered by WII in the sample.

For the RPL model, we assume that coefficients for the three disaster type attribute variables (β_1 , β_2 , and β_3) follow normal distributions with mean β_{j0} and standard deviation σ_j , respectively (where $j = 1, 2, 3$):

$$\beta_{jn} = \beta_{j0} + \sigma_j \eta_{jn}, \quad (5)$$

where η_{jn} follows a standard normal distribution. Furthermore, we assume that the coefficient for COVERAGE (β_4) varies according to a lognormal distribution with the parameters β_{40} and σ_4 and that for PREMIUM (β_5) varies according to a negative lognormal distribution with the parameters β_{50} and σ_5 (Train 2009; Holmes et al. 2017):

$$\beta_{4n} = \exp(\beta_{40} + \sigma_4 \eta_{4n}), \quad (6)$$

$$\beta_{5n} = -\exp(\beta_{50} + \sigma_5 \eta_{5n}) \quad (7)$$

The lognormal distribution assumption requires that the coefficient for coverage rate (β_{4n}) is positive for all farmers, while the negative lognormal distribution assumption (i.e., the exponential function is multiplied by -1 in Eq. (7)) holds the coefficient for the premium rate (β_{5n}) negative for all farmers. These assumptions are reasonable because rational farmers prefer higher coverage rates that payout higher amounts and, *ceteris paribus*, they also prefer low premium rates that decrease their payments for insurance packages. Note that the RPL model estimates β_{j0} and σ_j , while individual-specific coefficients β_{jn} are calculated from the estimates.

Software for the design and analysis

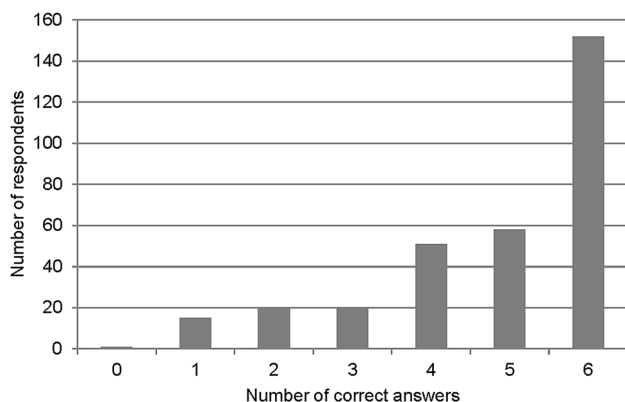
For our study, we used R (R Core Team 2020) and its add-in packages. The support.CEs (Aizaki 2012, 2016; Aizaki et al. 2014) and DoE.base (Grömping 2018) packages were used for designing choice sets and preparing the dataset for the study. The apollo (Hess and Palma 2019, 2020) package was used for the model estimations and the post-estimation calculations, such as predicting choice probabilities of WII packages. A maximum likelihood estimation procedure is used to fit the BL model, while a simulated maximum likelihood estimation procedure with 500 Halton draws is used to fit the RPL model.

Results and discussion

Table 1 shows the number of farmers who correctly understand the principles of insurance and WII. As a warm-up question, farmers were asked to select correct descriptions

Table 1 Percentages of respondents selecting correct statements

Statement	% Correct
Insurance is a way of helping one another when a problem occurs	88
Insurance companies pay the people who have purchased an insurance package and who face a predefined problem	78
People who need protection from a specific problem pay an insurance premium to an insurance company in advance	81
Farmers who need weather index insurance for a specific natural disaster pay an insurance premium to an insurance company before sowing crops	79
Farmers who have purchased the weather index insurance will receive insurance money regardless of the extent of crop loss if a predefined natural disaster affects the village they live in	75
Farmers who have not purchased the weather index insurance will not receive insurance money, even if they live in the village where the predefined natural disaster has struck and, consequently, damaged their crops	79

**Fig. 2** Respondents' understanding of insurance and WII

from six statements regarding both insurance and WII. Approximately 80% of farmers correctly categorized the statements, suggesting that farmers developed a good understanding of WII through our explanation in the first step of the survey session. Unfortunately, the extent of overall understanding was lower, as approximately 50% of respondents answered every question correctly while approximately 20% of respondents scored 50% or less (Fig. 2).⁴ All farmers were informed of the correct answers after the questioning.

Table 2 indicates the BL and RPL model estimation results. A goodness of fit measure (adjusted McFadden's R^2) reveals that the RPL model is superior to the BL model. Accordingly, we focus only on the RPL estimates. The P values show that all the parameters are significantly different from zero, at 5% or less. Although the mean for the annual insurance premium rate variable (PREMIUM) (β_{50}) has a positive value, this means that WII packages with

lower premium rates are preferred because the coefficient (β_{5n}) is assumed to follow a negative lognormal distribution (see Eq. (7)). The positive mean for the insurance coverage rate variable (COVERAGE) reveals that WII packages with higher coverage rates are preferred. The significantly positive standard deviations for PREMIUM and COVERAGE suggest that the coefficients of the two variables differ among farmers. The positive mean for three effect-coded disaster type variables (CYCLONE, FLOOD, and DROUGHT) show that cyclone-, flood-, and drought-based WII packages are preferred to salt damage-based ones, on average. The standard deviations for the three effect-coded variables are significantly positive, such that the preference orders of the four disaster types may differ among farmers. To display the heterogeneity of farmer preferences in disaster types, kernel density estimates (Hensher and Greene 2003) for the four disaster types are drawn from the RPL model results (Fig. 3). The variation in the preference for flood and drought is relatively small, whereas the variation for salt damage is relatively large. Furthermore, some farmers displayed a positive value for salt damage, meaning that they prefer a WII package for salt damage than for one or more of the remaining WII packages for cyclones, floods, and droughts, since the estimate for salt damage could be defined as a negative summation of those for the three effect-coded disaster type variables. Relatively large preference heterogeneity for salt damage suggests that the extent of salt damage varies among farmers: some farmers may incur no salt damage while others may incur large salt damage even under the same weather conditions, due to the differences in the location of their farmlands (e.g., distance from the mouth of the river).

To determine the share of farmers that prefer each disaster type, preference order of the four disaster types by farmer is estimated using individual farmers' estimates (Train 2009) for the three effect-coded disaster type variables (Table 3). Holding other conditions constant, 112 farmers (35% of the total) ranked the drought as their first preference, while 85

⁴ Respondents' characteristics such as their previous exposure to information regarding WII or their education levels may affect their correct response rates.

Table 2 Binary logit and random parameter logit model estimates

Variable	Binary logit (BL)			Random parameter logit (RPL)		
	Estimate	S.E. ¹	P value	Estimate ²	S.E. ¹	P value
Parameter (BL)/fixed parameter (RPL)						
Constant	-1.1338	0.1191	0.000	-1.4654	0.1995	0.000
Parameter (BL)/mean (RPL)						
CYCLONE	0.1540	0.0762	0.043	0.3693	0.1581	0.019
FLOOD	0.1547	0.0656	0.018	0.4589	0.1303	0.000
DROUGHT	0.2392	0.0712	0.001	0.5242	0.1409	0.000
COVERAGE	1.4119	0.1438	0.000	0.8442	0.1183	0.000
PREMIUM	-15.6042	1.1953	0.000	3.5984	0.0930	0.000
Standard deviation (RPL)						
CYCLONE				1.7631	0.2220	0.000
FLOOD				1.1736	0.2212	0.000
DROUGHT				1.4955	0.1902	0.000
COVERAGE				0.7448	0.0886	0.000
PREMIUM				1.4239	0.1683	0.000
Summary statistics						
Number of respondents			317			317
Number of observations			5072			5072
Log-likelihood value at 0			-3515.6			-3515.6
Log-likelihood value at convergence			-2717.6			-2238.3
Adjusted McFadden's R ²			0.225			0.360

¹S.E. stands for a robust standard error. ²Means and standard deviations for COVERAGE and those for PREMIUM refer to those of the underlying normal distribution, respectively (see the subsection “Specification of empirical discrete choice models.”)

Fig. 3 Kernel density estimates for effect-coded variables of cyclone, flood, drought, and salt damage

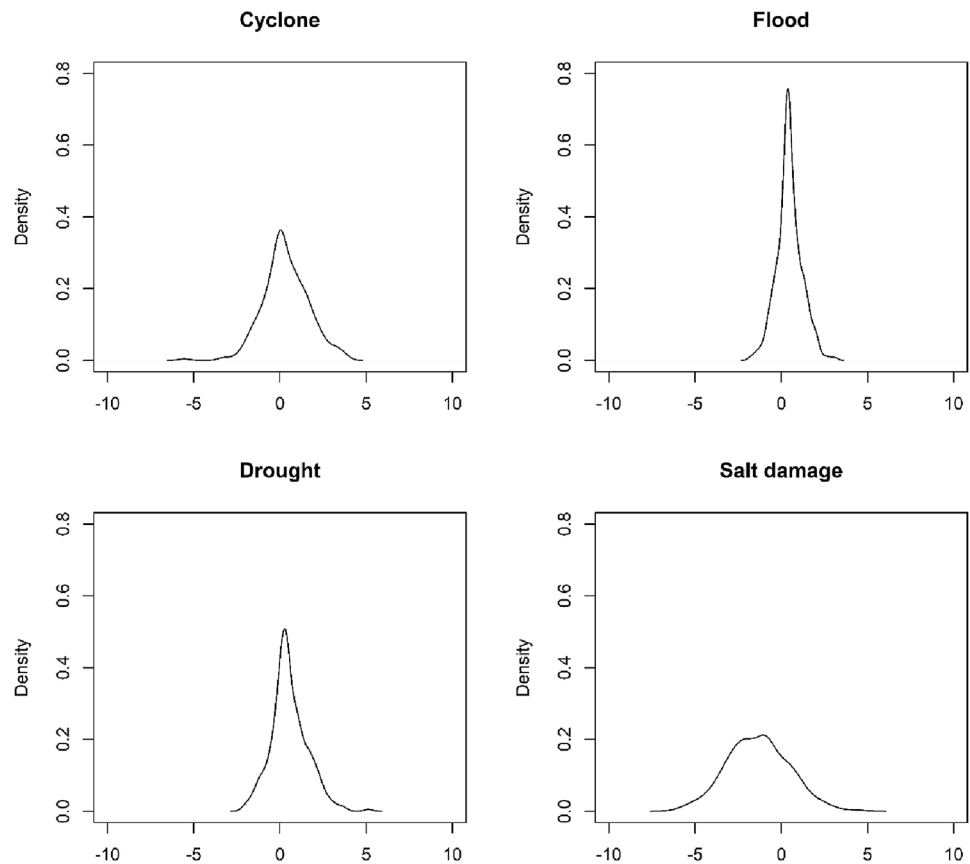


Table 3 Estimated preference order aggregation of four disaster types

	Cyclone	Flood	Drought	Salt damage
First preference	85 (27)	76 (24)	112 (35)	44 (14)
Second preference	51 (16)	146 (46)	96 (30)	24 (8)
Third preference	123 (39)	77 (24)	92 (29)	25 (8)
Fourth preference	58 (18)	18 (6)	17 (5)	224 (71)
Total	317 (100)	317 (100)	317 (100)	317 (100)

Unit: Numbers of respondents and percentages in parentheses

(27%), 76 (24%), and 44 (14%) farmers ranked the cyclone, flood, and salt damage as their first preference, respectively. On the other hand, 224 farmers (71%) ranked salt damage as their least preferred condition, while 58 (18%), 18 (6%), and 17 (5%) farmers ranked the cyclone, flood, and drought as their least preferred.

Table 4 shows the predictions of farmers’ demands for the 64 WII packages (made up of the combination of the four disaster types, the four coverage rates, and the four premium rates) calculated from the estimates. Each cell denotes the mean probability of 317 farmers selecting a particular WII package. For example, the probability that the farmers would purchase a cyclone-based WII package with a coverage rate of 40% and a premium rate of 1% is 0.404, meaning that 40.4% of farmers can be expected to purchase this WII package if only this package was made available. The calculated choice probabilities reveal that the seven WII packages with simulated probabilities of 0.5 or more are cyclone-, flood-, and drought-based, while there are no such packages for salt damage. Farmers’ median willingness-to-pay (WTP) values for the former seven packages can be calculated. The median WTP for a WII package is defined as the value of a premium rate for the WII package at which the probability of selecting it as a prospective purchase is exactly equal to 0.5. Accordingly, the median WTP values for cyclone-based WII packages with coverage rates of 80% and 100% are 1.6% and 2.6%, respectively. For flood-based WII packages with coverage rates of 80% and 100%, the median WTP values are 1.8% and 2.8%, respectively. For drought-based WII packages with coverage rates of 60%, 80%,

and 100%, the median WTP values are 1.0%, 1.9%, and 2.9%, respectively.

Concluding remarks

This study examines farmers’ preferences for WII among rice farmers in the Ayeyarwady Delta area of Myanmar using DCEs. The results indicate that heterogeneity in preference for salt damage is larger than those for cyclone, floods, and droughts and that more farmers prefer WII packages to cover themselves against cyclones, floods, and droughts than those to hedge against salt damage. This suggests that salt damage occurs as a local-specific disaster (i.e., the extent of salt damage varies among farmers in this area), while the remaining three disasters widely and equally affect farmers in this area. Thus, WII for salt damage might not be suitable for this area. However, if an equipment that can measure detailed salinity in water is put to practical use in this area, it could possibly make the WII for salt damage feasible in this area. On the other hand, WIIs for the remaining three disasters might be appropriate for this area. Although additional information is needed to design actual WII packages that are suitable for farmers in the area, these results could assist the Government of Myanmar and other organizations in this task, since the relationship between the quantity of WII packages demanded and the premium rate is vital for designing effective products and developing sales strategies.

A major limitation of this study must be noted when considering the results: our method of informing farmers about WII. On the basis of preliminary surveys, we designed features of the hypothetical WII—including the trigger conditions—and then explained these through a poster and handouts with illustrations. These explanations could be further improved. For example, some technical terms could be modified, as these may reduce farmers’ understanding of WII, and thus might affect their preferences in future WII packages. The second limitation is that farmers’ characteristics are not introduced explicitly into the analysis, although

Table 4 Simulated probabilities of selecting WII packages by disaster type, coverage rate, and premium rate. Bold values indicate simulated probabilities of 0.5 or more

	Disaster type: cyclone				Disaster type: flood				Disaster type: drought				Disaster type: salt damage			
	Coverage				Coverage				Coverage				Coverage			
Premium	40%	60%	80%	100%	40%	60%	80%	100%	40%	60%	80%	100%	40%	60%	80%	100%
1%	0.404	0.480	0.546	0.603	0.405	0.491	0.563	0.624	0.421	0.501	0.569	0.627	0.241	0.302	0.361	0.417
4%	0.265	0.327	0.385	0.438	0.257	0.326	0.390	0.446	0.273	0.339	0.399	0.454	0.157	0.203	0.251	0.298
8%	0.184	0.234	0.282	0.328	0.175	0.230	0.282	0.331	0.189	0.241	0.292	0.338	0.109	0.145	0.183	0.221
12%	0.141	0.182	0.223	0.263	0.132	0.177	0.221	0.263	0.144	0.187	0.230	0.271	0.083	0.112	0.144	0.177

we considered the heterogeneity in farmer preferences for WII attributes using the RPL model. To extract detailed information from the estimated models, farmers' characteristics should be set as independent variables, shifting the means of random parameters in the RPL model. The last limitation of this study is that insurance providers were not considered: economic conditions of supplying WII are also vital to design WII suitable for this area. Further studies are needed to overcome these limitations.

Appendix

For the DCE questions in a multinomial choice format, farmers were asked to select one package that they would like to purchase from three alternatives: two hypothetical WII packages (profiles) and an opt-out (none of these) option. A

profile consists of three attributes that are the same as those used in the DCE questions under a binary choice format. The format of a profile is the same as that in the binary choice format (see Fig. 1). This style of questioning is repeated four times per respondent, while changing the profiles shown. A total of 32 choice sets were generated using a rotation design approach (Chrzan and Orme 2000; Johnson et al. 2007). These were then divided randomly into eight versions (i.e., four DCE questions for each of eight versions).

Table 5 shows the conditional logit and random parameter logit model estimates of the responses to DCE questions in a multinomial choice format, where the model specifications follow that of the binary choice format: the systematic component of the utility for WII packages is also the same as that of the binary choice format; the systematic component of the utility for the opt-out option is normalized to 0; and independent variables are defined in the same manner as in the binary choice format.

Table 5 Conditional logit and random parameter logit model estimates of the responses to multinomial discrete choice experiment questions

Variable	Conditional logit (CL)			Random parameter logit (RPL)		
	Estimate	S.E. ²	P value	Estimate ³	S.E. ²	P value
Parameter (CL)/fixed parameter (RPL)						
ASC ¹	−0.1905	0.1839	0.300	0.0884	0.3370	0.793
Parameter (CL)/mean (RPL)						
CYCLONE	0.1695	0.0790	0.032	0.4293	0.1813	0.018
FLOOD	0.2604	0.0678	0.000	0.6970	0.1449	0.000
DROUGHT	0.1721	0.0766	0.025	0.4442	0.1597	0.005
COVERAGE	0.8786	0.1982	0.000	0.3686	0.2786	0.186
PREMIUM	−10.3556	1.1686	0.000	2.6469	0.2411	0.000
Standard deviation (RPL)						
CYCLONE				1.7838	0.3463	0.000
FLOOD				0.7335	0.2981	0.014
DROUGHT				1.4530	0.3098	0.000
COVERAGE				0.8063	0.1209	0.000
PREMIUM				2.5141	0.2527	0.000
Summary statistics						
Number of respondents			317			317
Number of observations			1268			1268
Log-likelihood value at 0			−1393.0			−1393.0
Log-likelihood value at convergence			−1301.1			−1125.4
Adjusted McFadden's R ²			0.062			0.184

¹ASC stands for an alternative specific constant, which is included in WII alternatives. ²S.E. stands for a robust standard error. ³Means and standard deviations for COVERAGE and those for PREMIUM refer to those of the underlying normal distribution, respectively (see the subsection "Specification of empirical discrete choice models.")

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