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YSSP Report
Young Scientists Summer Program

Exploring farmers' willingness to pay for index-based insurance in Nepal

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Abstract

This study explores smallholder farmers' willingness to pay (WTP) for hypothetical index-based flood insurance (IBFI) for crops in flood-prone areas of the Karnali river basin in western Nepal. A structured questionnaire was developed to elicit data from 705 farmers. By employing logistic regression analysis, the study identifies factors probably affecting farmers' WTP. As the most significant factors the study finds the age, the years of agricultural experience, the basis risk sensitivity, the education and the flood frequency experience during the past five years. Additionally, the study identifies that the education, participation in local scheme for disasters, risk aversion and trust towards insurance companies might be related to the lack of interest in the general concept of flood insurance for crops. The findings of this study implicate that factors affecting the WTP and interest in insurance are important to be considered when designing insurance products for climate related risks.

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Abbreviations

CDMC	Community Disaster Management Committe
CRRA	Constant Relative Risk Aversion
CVM	Contingent Valuation Method
DRF	Disaster Risk Financing
IBCI	Index-Based Crop Insurance
IBFI	Index-Based Flood Insurance
IBI	Index-Based Insurance
INGO	International Non-governmental Organisation
mMPL	modified Multiple Price List
OLS	Ordered Lottery Selection
WTP	Willingness To Pay

1 Introduction

Some of the developing countries are expected to confront high impacts from climate change (Joshi et al., 2017). Climate change will have a significant effect on households' income and assets, especially in rural areas (Tiwari et al., 2014), where smallholder farming presents the main source of livelihood. The yields in developing countries and particularly in South Asia are expected to be negatively affected by climate change (Nelson et al., 2009).

Agriculture has always been a risky business threatened by a variety of hazards that affect the production and consequently livelihoods (Yanuarti et al., 2019). The agricultural shocks coming from the natural hazards such as floods and droughts depress the investments and risk-taking (Hill et al., 2013).

This research is focused on Nepal, a country ranked in 2017 as the fourth most affected country in the climate risk index (Eckstein et al., 2019). A significant portion of the population in Nepal depends on agriculture-related activities (Tiwari et al., 2014), as agriculture is the primary source of livelihood for two-thirds of the Nepali population (Ghimire, 2014). Given this importance of agriculture, it is concerning that the agriculture in Nepal is profoundly affected by natural hazards resulting in a risky business (Ghimire et al., 2016b). Therefore, managing climate-related agricultural risks in Nepal is of high importance (Ghimire et al., 2016a). One of the ways to manage these risks in agriculture is through agricultural insurance.

Agricultural insurance contributes to the financial security of smallholder farmers against extreme shocks but also encourages credit and investments (Morsink et al., 2016). For instance, climate risk management contributes to the improvement of livelihoods in the bad cropping years and taking productive risks in the good years (Norton et al., 2014). Hence crop insurance as a means for climate change adaptation supports rural economies by stabilising the livelihoods of communities and individuals (Afroz et al., 2017).

The Asian Development Bank (ADB, 2019), suggests a promotion of insurance as an option to reduce the risks of natural hazards that the Nepali farmers are and will face. Indeed, given the impacts of climate change, there has been an increasing interest in agricultural insurance in Nepal over the last decade (Ghimire et al., 2016a). For instance, in 2013 directives and guidelines were introduced to non-life insurance companies to develop appropriate products for crops and livestock (Ghimire et al., 2016a,b; Timsina et al., 2018; ADB, 2019). In 2013, the insurance scheme was 50% subsidised (Ghimire et al., 2016a), increasing to 75% in the fiscal year 2014-2015 (ibid.). In other words, the farmer contributes 25% of the premium while the government funds 75% (ADB, 2019). The first results for agricultural insurance are positive (ADB, 2019); however with a varying level of success for livestock and crop insurance. While livestock insurance seems more attractive to farmers the uptake of crop insurance is minimal (ADB, 2019). Therefore, the government of Nepal has an interest in the increase uptake of crop insurance (Timsina et al., 2018).

This study deals with a specific type of insurance, index-based insurance. In this type of insurance, the payments are triggered according to a highly correlated with the actual losses index (Carter et al., 2014). Developed to confront moral hazard, high operational costs and adverse selection issues that appear in traditional indemnity insurance products (Castellani and Viganò, 2017), index-based insurance is considered a promising and ambitious tool for agriculture (Fonta et al., 2018). The significant reduction in the transaction costs is the main advantage of this type of insurance, especially for developing countries (Hochrainer et al., 2009). The main disadvantage is the introduction of basis risk (ibid.).

The risk of a significant difference between the index-losses and the actual-damages is named basis risk (Andersen, 2002; World Bank Group, 2014). In other words, basis risk is the imperfect correlation between the trigger values and the actual damages (Hochrainer et al., 2009; Morsink et al., 2016). The payments can be lower or higher than the losses occurred (Castellani and Viganò, 2017; Morsink et al., 2016). For instance, a policyholder might not get compensation for the occurred losses in case the index did not get triggered (World Bank Group, 2014). However, a policyholder might get compensation without damages having occurred (ibid.).

Stated willingness to pay (WTP) studies are a useful tool to provide valuable information especially when a market for a particular product does not yet exist, even though they do not represent real situations (Hill et al., 2013). Previous WTP studies in some countries and have shown high levels of demand for insurance, even though actual demand studies have lower percentages (Marr et al., 2016). A considerable number of empirical studies assess the farmers' WTP for crop insurance by employing stated preferences methods. For instance, List et al. (2019) examined the role of index-based insurance for floods among other mitigation preferences to assess farmers' WTP in their study in Amazonia; Hill et al. (2013) used WTP to estimate which farmers would be early adopters of a weather index-based insurance products in rural Ethiopia; Afroz et al. (2017) used a logistic regression model to examine the factors affecting farmers WTP for crop insurance for flood risk in Malaysia.

Even though it is a promising tool, index-based insurance has shown limited uptake (Elabed and Carter, 2015), with open questions regarding the demand for index-based insurance of farmers in developing countries (Norton et al., 2014), requiring further empirical evidence. Additionally, understanding the impacts of index-based insurance is limited (e.g the impact of insurance in wealth) (Marr et al., 2016). Therefore, there is a need for further empirical research to verify to what extent index-based insurance is beneficial for smallholder farmers (ibid.).

In Nepal, "*Agriculture insurance should evolve from a pure indemnity product involving farm-level loss assessment to an index-based product.*" (ADB, 2019, p. 55). Moreover, it is suggested to pilot[1] "*...selected DRF instruments and agriculture insurance products that can be readily demonstrated and scaled up, e.g., parametric insurance.*" (ADB, 2019, p. 21). Similarly is suggested to assess farmers' willingness to participate in weather index insurance (Ghimire et al., 2016c).

This study examines the farmers' WTP for hypothetical index-based flood insurance (IBFI) in the lowlands of the Karnali river basin in Nepal, including the factors that might be leading to farmers' lack of interest in flood insurance for crops, and identification of factors possibly affecting the farmers' WTP for IBFI for crops by the use of logistic regression analysis. The logistic regression follows a specific stepwise procedure to find out the most

[1]Parametric insurance is synonym for index-based insurance.

relevant variables by a sub-model selection.

The remainder of the report is organised as follows: Section 2 reviews studies of the existing literature of agricultural insurance in developing countries and presents the selected factors examined in this study. Section 3 introduces the study area and Section 4 the data collection. Section 5 presents the methods, Section 6 presents the results and discussion followed by the conclusions in Section 7.

2 Literature

As introduced earlier, the study explores the factors possibly affecting farmers' WTP for a hypothetical IBFI. The factors examined in this study are based both on indicators from the existing literature on agricultural insurance in developing countries and information gained during the scoping trip in April 2019 (to be described in Sections 4 and 5.1). In total thirty indicators were identified and examined. The existing literature studies are presented in Table 1. The identification of the factors to be examined is presented in this section and in the descriptive statistics Table 8.

Table 1: Literature on agricultural insurance in developing countris studies

Authors	**Country**	**Insurance type**	**Hazard**
Afroz et al. (2017)	Kedah Malaysia	WTP for crop insurance	Flood
Budhathoki et al. (2019)	Nepal	WTP for area-based crop yield insurance	Natural hazards
Chantarat et al. (2009)	Northern Kenya	WTP for index-based livestock insurance using remotely sensed vegetative cover	Livestock mortality
Cole et al. (2013)	India	Demand for index-based crop insurance	Rainfall
Fonta et al. (2018)	Southwestern Burkina Faso	WTP for weather index-based crop insurance	Dry spell
Hill et al. (2013)	Ethiopia	WTP for weather index insurance	Rainfall
Jin et al. (2016)	China	Weather index crop insurance	Drought
Marr et al. (2016)	Systematic review on index-based insurance in developing countries		

In their study on estimation of WTP for weather index-based crop insurance in West Africa, Fonta et al. (2018) found that male-headed households had higher WTP than female-headed households. In contrast, Budhathoki et al. (2019) in their study conducted in Tharu[2] community in the lowlands of Nepal observed that female household heads were willing to pay more for wheat insurance than male household heads. This research was also conducted in a part of the lowlands of Nepal; therefore, this study examined not only the gender but belonging to Tharu community. In their study on WTP for crops insurance in Malaysia,

[2]Tharu are indigenous communities living in the Karnali area and depending on farming activities for their finances (Rai et al., 2020).

Afroz et al. (2017) found that younger household heads were willing to pay more than the elderly. The number of household members was negatively correlated with WTP for paddy rice in the study of Budhathoki et al. (2019). Therefore, age and family size are also included in the analysis of this research study.

The years of farming experience had a positive effect in WTP of crops insurance in the studies of Afroz et al. (2017) and Jin et al. (2016). Farmers with larger farms are willing to pay more than farmers with small farms (Jin et al., 2016; Afroz et al., 2017; Fonta et al., 2018). Budhathoki et al. (2019) found that households with larger plots of lands had a positive relationship with WTP for paddy rice but did not have an effect on WTP for wheat insurance. In the same vein, agricultural experience and cultivated land size are included in the analysis of this research study.

While researching index-based livestock insurance in Kenya, Chantarat et al. (2009) found wealthier households to have a negative relation between herd size and WTP. They explained that more affluent households might be able to self-insure. Similarly, Afroz et al. (2017) and Jin et al. (2016) found that farmers' household income was negatively related to WTP for crop insurance. In contrast, Fonta et al. (2018) observed that wealthier households are willing to pay more. Budhathoki et al. (2019) found that households with higher income had a positive relationship with WTP for paddy rice but did not have an effect on WTP for wheat insurance. Hence, the income level ranges of the household of the participant are identified and included in the analysis of this study[3].

People are more likely to buy insurance during the period they have taken a loan and have higher liquidity (Patt et al., 2009). In their study in India, Cole et al. (2013) found that demand is reduced when there are liquidity constraints. According to the systematic review of Marr et al. (2016) on index-based insurance for smallholder farmers in developing countries, most studies showed a positive relationship between liquidity and insurance uptake. However, the literature has mixed output regarding credit constraints (ibid.). Having access to formal credit mechanisms such as having a bank account increased the WTP in the study of Hill et al. (2013). Credit and liquidity characteristics are taken into account in this study to identify the abovementioned characteristics. The respondents were asked if they had a bank account, if the household had a loan currently, the number of loans taken during the last three years. Moreover, the respondents were asked the level of difficulty in case they needed to borrow. The number of local saving groups that the farmer participated and the Community Disaster Management Committee (CDMC) fund's participation are included in the analysis of the study.

The relation between exposure to risk and demand for insurance is ambiguous (Marr et al., 2016). According to Budhathoki et al. (2019), farmers who had experienced floods in the last five years had lower WTP for rice insurance. The number of floods the respondents had experienced during their farming years, the number of floods the respondents had experienced the last five years and if the farmer had ever experienced a flood that destroyed all their crops are questions included in the analysis of this study as indicators for the risk exposure.

Marr et al. (2016) state that the demand for insurance is expected to be lower in the

[3] The income level range in the sample of this study does not include potential remittances received.

presence of other risk mitigation strategies such as other means of income, planting a variety of crops and receiving remittances, three variables which are included in this study.

Regarding the behavioural indicators of Marr et al. (2016), poor understanding of insurance and experience with insurance were mentioned as factors resulting in low uptake. Fonta et al. (2018) found that knowledge of crop insurance was positively correlated to WTP, meaning that the more the farmers were informed, the higher the demand. In the same direction, Cole et al. (2013) in their study in India found that villages with previous experience with insurance had higher insurance demand. Trust is also related to understanding, while mistrust reduces the demand (Marr et al., 2016). In their study Cole et al. (2013) found that the level of trust significantly affects the demand. In this study, experience with any type of insurance, awareness of the existing crop and livestock agricultural insurance scheme and the level of trust towards a hypothetical index-based flood insurance product that would be sold by a private company are factors included in the analysis.

An increase in basis risk reduces demand (Marr et al., 2016). Cole et al. (2013) asked their respondents insurance questions and found that the understanding and the demand for insurance were positively correlated. Following similar approaches as those of Hill et al. (2013) and Cole et al. (2013) a series of questions to capture the understanding on IBFI was asked to the respondents of this study, which is explained in section Section 5.4. Inspired by Hill et al. (2013), this study attempts to get a sense whether the respondents have a sensitivity towards basis risk[4]. The approach is explained in Section 5.7.

Education has an ambiguous effect and sometimes insignificant to insurance take up (Marr et al., 2016). Household heads with no formal education had higher WTP in the study of Fonta et al. (2018). In contrast, Hill et al. (2013) found that educated farmers will likely be the first adopters of insurance. Furthermore, Cole et al. (2013) observed that math skills, probability skills and financial literacy of the respondents were positively correlated with insurance demand. The math questions used in this study were adopted from Cole et al. (2013) and/or Hill et al. (2013), whereas the probability questions utilised a similar approach as the two previous mentioned studies. The financial literacy questions were adapted from Lusardi and Mitchell (2011) and/or Cole et al. (2013). The math, probability and financial literacy questions used in this study are explained in section Section 5.2.

In their study on WTP for index-based livestock insurance, Chantarat et al. (2009) found that demand decreases with ambiguity aversion. Utilising similar approach as Chantarat et al. (2009) ambiguity aversion data were collected. The ambiguity aversion approach used in this study is explained in section Section 5.2. A considerable number of studies contradict the theory that insurance demand increases with risk aversion (Marr et al., 2016). For instance, Hill et al. (2013) following the Ordered Lottery Selection (OLS) method of Binswanger (1980) to elicit risk preferences found that risk-averse respondents were related to low insurance uptake. Jin et al. (2016) eliciting farmers risk preferences and index insurance uptake in their study in rural China adopted the modified by Brick et al. (2012) Multiple Price List (mMPL) of Holt and Laury (2002) risk aversion method. In contrast, they found that the more risk-averse farmers had higher chances of willing to pay for index insurance.

[4]The basis risk sensitivity variable stands for downside basis risk.

In this study to identify risk aversion, both OLS and mMPL methods were adopted, which is explained in Section 5.3.

3 Study area

The research was conducted in the lowlands of the Karnali river basin (Fig. 1) in the Terai plains[5]. The Karnali river, one of the three large river systems of Nepal, has its origins in the Tibetan plateau and joins the Sharda river in India (Rai et al., 2020). The Karnali river catchment area in western Nepal is approximately 49000 km^2 (Bhandari et al., 2018). The river reaches the Terai plains through Chisapani gorge and before outflowing to India gets divided into two streams and connects again in India, creating an inland delta (ibid.).

The communities in the lower parts of Karnali river basin below Chisapani are exposed to frequent flood events with most recent examples the floods of 2014 and 2017 (Rai et al., 2020).

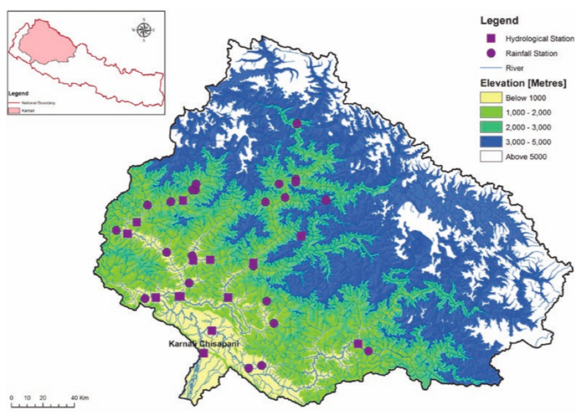
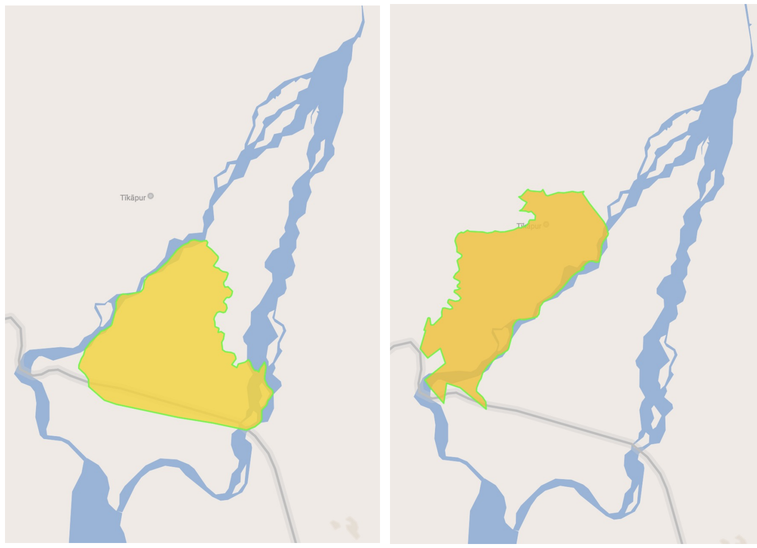


Figure 1: Karnali river basin in western Nepal, adopted from Bhandari et al. (2018)

4 Data collection

The data were collected from two municipalities along the western distributary of the inland delta in the lowlands of the Karnali river in Nepal, as presented on the maps of Fig. 2. The communities in the lower Karnali river basin below Chisapani in Kailali and Bardiya districts are exposed to frequent flood events (Rai et al., 2020). This research study partnered with Practical Action, an international Non-Governmental Organisation (INGO) with a local presence in the case study area. As a national partner, Practical Action and their local partner organisation guided decision making and access in the field.

[5]As this study does not represent all agricultural zones and inundation types of the country, the data are not representative of Nepal or other developing-countries context.



(a) Municipality of Rajapur **(b)** Municipality of Tikapur

Figure 2: Case study areas, maps retrieved from https://www.citypopulation.de (2020)

Due to the research focus on agricultural insurance, the municipality of Tikapur was chosen to be the primary case study area. Tikapur seemed to have the highest number of experienced farmers with agricultural insurance (crop or livestock) in comparison to other visited municipalities and information gained during the scoping trip in April 2019. However, due to the time and resources available during the main fieldwork, the research was extended to the municipality of Rajapur.

The research data were collected from four wards (5, 6, 7 and 8) in the municipality of Tikapur of Kailali district and three wards (1, 3 and 4) in the municipality of Rajapur of Bardiya district. The data were mainly collected from 13 communities of the municipality of Tikapur and three communities of the municipality of Rajapur, which were indicated by Practical Action and Practical Action's local partner as flood vulnerable. Additionally, part of the collected data were with farmers having previous experience with agricultural insurance (crops or livestock) from the abovementioned wards.

The survey took place during mid-October to end of November 2019. During the piloting week of the main fieldwork a team of enumerators[6] was trained and the questionnaire was tested in the field and adjusted when necessary. In total, 705 questionnaires were collected. The survey was conducted with farmers who were the household's heads or a member that knew about the financial decisions of the household, were about 25 years old or older, had a farming experience of more than five years, had experienced a flood event with agricultural losses in the past (due to the research focus on floods and agriculture) and lived in the area at least five years.

[6]The enumerators were leading the interviews and were suggested by Practical Action and their local partner.

5 Methods

5.1 Questionnaire design

The data are extracted from the structured questionnaire developed for the main fieldwork data collection phase. The questionnaire was designed based on existing literature for agricultural insurance in developing countries studies, as presented in Section 2. Additionally, relevant information gained during the scoping trip, which contributed to the contextual understanding of the case study area was incorporated into the questionnaire. For instance, during the scoping trip information regarding the existence of the local financial schemes (or saving schemes) was obtained, e.g. the scheme for disasters.

5.2 Mathematical skills, financial literacy skills and ambiguity aversion

In this study, four math questions were adopted from Cole et al. (2013) and/or Hill et al. (2013), while two probability questions were asked to the participants utilised similar approach as the two previous mentioned studies. Additionally, utilising similar approach as Lusardi and Mitchell (2011) and/or Cole et al. (2013) four financial literacy questions were asked to the participants[7]. Following the same approach as Chantarat et al. (2009) the ambiguity aversion of the respondents was identified. The questions and the scores of correct answers are presented in Section 5.2.

The respondents performed better in probability and financial literacy than the math questions. Besides, 79.4% of the respondents were categorised as ambiguity averse as they chose the bag with the known instead of the bag with the unknown probabilities.

Table 2: Math and probability skills, financial literacy and ambiguity aversion

Math skills	**% Correct responses**
$4 + 3$	73.9
$35 + 82$	18.2
$3 * 6$	34.0
1/10 of 400	16.0
Probability skills	
Showing a clear red bag with 3 blue and 1 pink counters. Chances of getting a pink counter.	64.7
Showing the previous red bag and a clear green bag with 5 blue and 1 pink counters. Bag with more chances of getting a pink counter (red or green).	76.6

[7] At the beginning of this part it was explained that the questions might be difficult and the participant did not have to answer any question if they do not wish.

Continued.

Financial literacy skills	
Suppose that you borrow 100 NRP with interest rate 2% per month. How much would you have to give back after 2 months if you have not paid back anything until then? More, less or exactly 102 NRP ?	55.9
Suppose that you need borrow 1000 NRP to be paid back in one month. There are two options. Option 1: Someone lends you the money asking you to pay back 1050 NRP. Option 2: Someone lends you 1000NRP with 10% interest. Which option would you choose?	55.5
If you have NRP 1000 in a savings account and you earn 1% of interest per annum, and the prices of good and services increased 2% over a one year period, can you buy more, less or the same amount of goods as you could today?	22.6
Is it safer to plant one single crop, multiple crops or it does not matter?	54.2
Ambiguity aversion	**Ambiguity averse**
Showing a transparent blue bag with 4 pink and 3 blue counters and an non transparent orange bag with unknown number of blue and pink counters. Participant's choice of a counter colour followed by a choice of bag (blue or orange) to pick a counter with the chosen colour.	79.4

5.3 Attitudes towards risk

Risk aversion was measured following two methods[8]; the Ordered Lottery Selection (OLS) by Binswanger (1980) in the form of Clarke and Kumar (2016) and the Multiple Price List (mMPL) by Holt and Laury (2002) modified by Brick et al. (2012).

Both methods assume a constant relative risk aversion (CRRA) where the utility is in a power form. The CRRA utility function gives the utility of the income (Brick et al., 2012), which is defined by:

$$U(x) = \frac{x^{1-r}}{1-r} \tag{1}$$

where r is the coefficient of relative risk aversion, and x is the payoff in the option (Brick et al. (2012) citing Andersen et al. (2008), Jin et al. (2016) citing Anderson and Mellor (2008)). The power utility for each lottery preference gives a CRRA range. A value of $r<0$ indicates risk loving preference, a value of $r>0$ a risk averse and a value of $r=0$ a risk neutral preference (Brick et al., 2012; Jin et al., 2016). The CRRA ranges are presented in the left column in Table 3.

The OLS by Binswanger (1980) method presents a list of all the lottery options to the participant asking them to choose one set of options[9] (Jacobson and Petrie, 2009). In the

[8]The games were hypothetical (not real payoffs) in the neighbourhood of the average monthly income.

[9]In this study the enumerator read the questions sequentially to avoid putting participants will low literacy rate at unease. Each option had 50% probability of one hypothetical payoff and 50% of another hypothetical payoff.

Table 3: Risk aversion methods

CRRA ranges	Risk aversion classes	Distribution of sample (Valid %)
OLS based on Binswanger (1980) in the form of Clarke and Kumar (2016)		
$(+\infty, 7.51)$	Extreme risk averse	58.5
(7.51, 1.74)	Severe risk averse	7.6
(1.74 , 0.81)	Intermediate risk averse	8.2
(0.81 , 0.32)	Moderate risk averse	9.3
(0.32, 0)	Slight-to-risk neutral	7.2
$(0, -\infty)$	Neutral-to-negative	9.3
mMPL based on Holt and Laury (2002) in the form of Brick et al. (2012)		
CRRA ranges	Risk aversion classes	Distribution of sample (Valid %)
$(-\infty, -1.4)$	Highly risk loving	11.4
$(-1.4, -0.4)$	Very risk loving	4.3
$(-0.4, 0)$	Risk loving	3.6
$(0, 0.2)$	Risk neutral	11.9
$(0.2, 0.4)$	Slightly risk averse	13.0
$(0.4, 0.6)$	Risk averse	8.3
$(0.6, 0.7)$	Very risk averse	5.6
$(0.7, +\infty)$	Highly risk averse	42.0

mMPL method, the respondent has to choose among a series of eight choices between two options (Brick et al., 2012). The first option declines systematically while the second is an expected payoff[10] which remains unchanged (ibid.).

Data of both measures of risk aversion were collected in this study. The distribution of the valid sample is presented in Table 3. Both methods found the highest percentages to be in the highest risk aversion class.

5.4 Ways of explanation of index-based flood insurance (IBFI)

To explain insurance and specifically IBFI to the farmers, two separate approaches were employed. One approach was through an explanation flyer that the enumerator used as a guide. The other approach was through sessions with groups of farmers, where a hypothetical IBFI product was presented while playing a game. The enumerator would skip the explanation part during the interview if the farmer played the game before the interview, as the farmer was assumed to have already been introduced to IBFI.

Hypothetical index-based flood insurance for crops was explained from the enumerator or during the game session to the participants using the sketch presented in Table 4 as a

[10] In this study, the payoffs and games were hypothetical.

guide. The yellow and red water levels in the sketch represent the trigger water levels in the hypothetical measurement station. When the water level reaches the yellow level, payments for partial losses of the insured crops are assumed to follow. When the water reaches the red level, payments for total losses of the insured crops are assumed to follow.

5.5 Understanding of IBFI

Having explained insurance and briefly introduced the hypothetical IBFI presented in Section 5.4 a set of understanding questions[11] was asked to the respondents to explore whether their understanding of the hypothetical IBFI was correct.

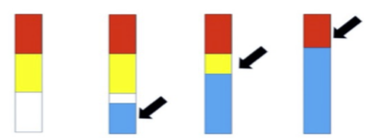
The enumerator would introduce a hypothetical IBFI question. In that question, the farmer is assumed to have bought flood insurance for their crops. Various scenarios of the water level in the hypothetical measurement station were assumed to occur in combination with various scenarios in the field of the farmer. The farmer was asked if they would get paid under a variety of combinations of the abovementioned scenarios and how much they would get paid. Two examples of the questions are presented in Table 4.

Table 4: Understanding of index-based flood insurance

Imagine you bought flood insurance for your crops for the next monsoon period. If the yellow level is reached (then this means there was a big flood), the company will pay you money for loss of half of your seasonal production. If the red level is reached (extremely big flood) the company will pay you money for loss of all your seasonal production. If the water stays in the white area, there will be no payments.

Imagine it rained and the water reached the yellow area. All of your crops are destroyed. Will you get paid?

If yes, how much will you get paid?



In total, a set of twelve understanding questions was asked the participants using a similar sketch as the one during the explanation. The scores of the correct answers are presented in the descriptive statistics Table 8 and are included in the regression analysis in Sections 6.3 and 6.4.

5.6 Willingness to pay for IBFI

Hypothetical IBFI for crops was introduced with the approaches explained in Section 5.4. The respondent was asked during the interview if they would be willing to buy such type of flood insurance in case it existed in their area and was offered to them at an affordable price.

[11] The studies of Hill et al. (2013) and Cole et al. (2013) inspired the formulation of the "*Understanding IBFI*" questions.

The next question further asked if the farmer would be willing to buy if the government subsidised this type of flood insurance, as presented in Table 5.

Table 5: Willingness to pay for index-based flood insurance

	Yes (Valid %)	**No (Valid %)**
1. After being explained, would you be willing to buy such type of flood insurance, if it existed in your area and if it was offered to you to an affordable price?	594 (84.5)	109 (15.5)
2. After being explained, would you be willing to buy such type of flood insurance, if it existed in your area and if it was offered to you to an affordable price or being subsidised (shared part of participation costs) from the government?	656 (93.0)	49 (7.0)

Approximately 84.5% of the respondents would be willing to buy IBFI for crops, which was increased to 93.0% in the question where subsidy was assumed to be offered. The results suggest a significant demand for IBFI for crops in the case study area.

5.7 Willingness to pay for flood insurance and basis risk

Following the approach of Hill et al. (2013), three hypothetical questions were asked to the participants regarding their willingness to purchase flood insurance for crops and the sensitivity towards basis risk, which are presented in Table 6. The respondents were asked if they would renew their flood insurance for their crops after:

- one monsoon cropping season where it was assumed that flood insurance was bought, but no flood event occurred
- five monsoon cropping season where it was assumed that flood insurance was bought, but no flood event occurred
- one monsoon cropping season where it was assumed that flood insurance was bought, a flood event occurred in the farmer's field, but the farmer received no payment[12].

In total 76.8% farmers would be willing to purchase insurance after having bought flood insurance for their crops for one monsoon period and not experiencing flood event that year. 52.1% would continue buying insurance after five years of purchasing insurance but not experiencing a flood event during these years. One possible explanation could be that a considerable number of farmers might have under-evaluated the benefit of protection, therefore would not wish to continue purchasing flood insurance after five years when no flood event occurred during these years.

[12]The questions were about a hypothetical scenario. Therefore, the option "*I don't know*" was included in the options of the questionnaire, as it is possible that the respondent might not be sure in advance about their reaction in such a hypothetical and not real scenario. The "*I don't know*" responses were the lowest percentage compared to the rest of the proposed options.

Table 6: Willingness to pay for flood insurance and sensitivity towards basis risk

1. Imagine you bought flood insurance for the next cropping season/monsoon season and you paid the money requested to buy insurance coverage for your crops. There was not flood event this cropping season. Would you be willing to continue buying insurance the next cropping season?	Yes (%)	No (%)		Don't know (%)
	76.8	14.1		9.1
2. Suppose you bought flood insurance for five cropping seasons, and you paid the money requested to buy insurance coverage for your crops. There was no flood event for five cropping seasons. Would you be willing to continue buying insurance after five cropping seasons?	Yes (%)	No (%)		Don't know (%)
	52.1	31.8		16.1
3.Imagine you bought flood insurance for your crops for the next cropping season/monsoon season and you paid the money requested to buy insurance coverage for your crops. There was flood on your field but you received no payment. Would you be willing to continue buying insurance after one cropping season, where you had flood on your field and received no payment?	Keep (%)	Doubt (%)	Definitely not buy (%)	Don't know (%)
	20.4	12.5	65.2	1.8

Basis risk is an important topic to be included in future studies to understand its effect on demand for insurance (Cole et al., 2013). In the scenario where the farmer experiences downside basis risk; the situation were the farmer has paid premium, experienced damages and does not receive compensation, the farmer might end up in a worse situation than not having bought insurance at all (Morsink et al., 2016). Understanding the relation of downside basis risk and demand might contribute to the estimation of the sustainability of an index insurance market (Hill et al., 2013). Therefore, in this study, the farmers' sensitivity towards downside basis risk was identified by the third abovementioned hypothetical question. In the remainder of this analysis, the basis risk variable stands for downside basis risk.

Approximately 20.4% of the farmers would continue buying flood insurance after experiencing basis risk. 77.7% would definitely not renew or doubt if they would renew their contract after experiencing basis risk. The result indicates that the majority of the farmers had a sensitivity towards basis risk. The basis risk sensitivity is included as an independent variable in the regression analysis, which is explained in Sections 6.3 and 6.4.

5.8 Exploring the lack of interest in flood insurance

A group of 44 farmers is identified that might have no interest in flood insurance for crops. These 44 respondents in Table 5 would not be interested in purchasing IBFI with or without subsidy. The same 44 respondents in the first question of Table 6 did not reply that they would renew their contract, had they bought flood insurance for one cropping season, and a flood event did not occur during that season[13]. The same response[14] was for the second question in Table 6, asking if they would renew their contract after purchasing for five years and no flood event occurred. Finally, the same 44 respondents did not reply that they would keep[15] their contract in the scenario where they had bought flood insurance for one year for their crops and faced basis risk (third question in Table 6).

The 44 farmers did not reply positively in any of the abovementioned five questions. One explanation could be that these 44 respondents might not be interested not only for index-based but in the general concept of flood insurance for crops.

A new variable for the "*interest*" in flood insurance observations was generated. The 44 "*non-interested*" observations were coded with 0 and the remaining 661 observations of the study were coded with 1. A bivariate analysis explored the factors leading to the non-interest in flood insurance for crops. The bivariate analysis explored the interest in flood insurance with each of the indicators examined in this study. The analysis is presented in Section 6.2.

5.9 Setting up the logistic regression models

The data were analysed using logistic regressions to identify the factors possibly affecting the farmers' WTP for IBFI. The Wald test in SPSS is used to identify the joint significance of the independent variables[16]. The dependent variable was the WTP for IBFI first question in Table 5. The variable was coded with 1 when the farmers replied "*yes*" and 0 when the farmers replied "*no*".

The sample in the regression analysis was consisted of 661 observations, as the 44 non-interested in flood insurance for crops observations, which were identified in Section 5.8, were subtracted from the regression analysis. These 44 respondents might not be interested in the general concept of flood insurance for crops not only for index-based.

Initially 109 observations replied "*no*" to the dependent variable in Table 5. Therefore, subtracting the 44 observations, 65 "*no*" answers were included in the regression analysis. These 65 observations under specific circumstances could be potentially interested in the general concept of flood insurance or IBFI specifically, as they replied positively to at least one out of the five questions analysed in Section 5.8. For instance, a significant number of these 65 farmers changed their answer for their WTP for IBFI from "*no*" to "*yes*" when the subsidy was assumed to be offered.

Two initial logistic regression models were set up in SPSS, including 30 independent variables. By the use of the full model of "*Enter*" method in SPSS, one regression model included the risk aversion measured by the OLS method. The second model included the risk aversion measured by the mMPL method. The thirty independent variables were coded either continuous or dichotomous, as presented in Table 8.

[13] The reply was "*no*" or "*I don't know*".

[14] The reply was "*no*" or "*I don't know*".

[15] The reply was "*no*", "*doubt*" or "*I don't know*".

[16] The analysis was conducted by the use of SPSS 26.0 software.

By the logistic regression the probability that the insurance is accepted is estimated as a function of the independent (explanatory) variables. A prediction rule can be based on this probability estimate, by assigning the value "*insurance will be taken*" if this probability is larger than a cut value; otherwise, the value "*insurance will be refused*" is assigned. A selection procedure for the cut value was followed to approach the best prediction for the WTP. The relation between the choice of the cut value and the correct prediction is shown in Table 7.

Table 7: Selecting the cut value for the initial and simplified regression models

	OLS				**mMPL**			
Cut value	Correct prediction (%)			Nr. of	Correct prediction(%)			Nr. of
Initial models	Yes	No	Overall	Obs.	Yes	No	Overall	Obs.
0.5	99.4	13.1	90.5	589	99.3	13.7	89.8	461
0.7	95.5	31.1	88.8	589	95.9	27.5	88.3	461
0.8	87.5	52.5	83.9	589	86.6	56.9	83.3	461
0.85	82.0	65.6	80.3	589	79.3	68.6	78.1	461
0.9	**70.6**	**77.0**	**71.3**	589	**66.6**	**76.5**	**67.7**	461
Simplified model								
0.8	88.3	52.3	84.6	630	-	-	-	-
0.85	81.8	66.2	80.2	630	-	-	-	-
0.9	**69.2**	**78.5**	**70.2**	630	-	-	-	-

Five calculations for each initial model were performed with cut values 0.5, 0.7, 0.8, 0.85 and 0.9. By increasing the cut value, the correct prediction for the "*no*" answers improved. However, the correct prediction for the "*yes*" worsened. The 0.9 cut value seemed to be the best for the OLS model. The model had a correct prediction of "*yes*", "*no*" and "*overall*" higher than 70%. On the other hand, the best prediction for the mMPL model was difficult to be identified. The 0.85 cut value resulted in a correct prediction of "*no*" less than 70%. In contrast, a cut value of 0.90 resulted in a correct prediction of "*yes*" and "*overall*" less than 70 %.

The OLS method included 589 observations (72 missing cases) in the initial models' analysis. The mMPL model included 461 observations (200 missing cases) in the initial models' analysis. Often participants shift between lotteries repeatedly when employing the multiple price list method is often observed (Brick et al. (2012) citing Andersen et al. (2006)). The inconsistent observations of the mMPL method of this study were coded as missing values during the analysis. Therefore the mMPL initial model included a considerable higher number of missing cases in comparison to the OLS initial model.

Taking into account the considerable higher number of observations used in the initial OLS model and the higher than 70% correct prediction with a cut-off value of 0.9, the OLS initial model was used for the further steps of the analysis of this study.

A simplified OLS model was set up, which included the 15 variables with the highest significance levels of the initial OLS model. The simplified model of the fifteen variables resulted in the identification of the most significant indicators amongst all. The final calculations are presented in Sections 6.3 and 6.4. The same cut value of 0.9 was kept for the simplified OLS model with correct prediction in the neighbourhood of 70% and higher. The included observations of the simplified model were 630 with 31 missing cases, as shown in Table 7.

6 Results and discussion

6.1 Descriptive statistics

The descriptive statistics of the sample of 705 observations and the coding in SPSS are presented in Table 8. The selected variables in this study are presented in groups of background (1), agricultural characteristics (2), wealth (3), credit and liquidity (4), risk exposure (5), risk mitigation (6), experience with insurance (7), index-based insurance (8), educational background (9) and risk preferences (10).

Background (1): The average age of participants was 42.7 (SD 12.7) years old, slightly higher than the study of Rai et al. (2020) in the lower Karnali river basin in Nepal, which was 38.08. Approximately, 53.8% of the participants' were Tharu ethnicity, lower than the study of Budhathoki et al. (2019) in another Terai region of Nepal, whose sample was consisted of 78.4% Tharus ethnicity respondents. In Tharu communities "*women are more empowered and highly aware of agricultural insurance and climate hazards*"(Budhathoki et al., 2019, p.8). Of the total respondents, 67.9% were female, close to the study of Rai et al. (2020), where the female participants were 62.0%. The average family size of the study was 6.22 (SD 3.12), which is in agreement with the study of Rai et al. (2020) in the Karnali river basin that reported an average household size of 6.48.

Agricultural characteristics (2): In developing countries, farmers are predominantly smallholder households (Collier et al., 2009). In many countries, smallholder farmers' farms are less than 2 hectares, while 95% of the smallholder farms are smaller than 5 hectares (FAO, 2014; Andrade, 2016). On average, the farmers in this study cultivated a cultivated land size area[17] of 20.3 (SD 25.2) Kattha[18]. 58.5% of the farmers in this study cultivate a land size area less than 15 Kattha ($\approx 0.51ha$). 93.9% cultivate less than 60 Kattha ($\approx 2ha$) and 99.3% less 150 Kattha ($\approx 5.1ha$) which indicates that the majority of the sample was smallholder farmers. In the data analysis, there is no separation between smallholders cultivating for livelihood or commercial purposes. Finally, almost half of the respondents reaching 48.2% had more than 20 years of agricultural experience.

Wealth (3): Of the respondents 48.7% reported that their household's income range[19] was less than 5000 Rs./month[20]. Each income range was coded as a continuous variable.

[17] The midpoints of the land size ranges were coded as presented in Table 8. The last class > 150 Kattha was coded as 165.0 Kattha.

[18] 1 Kattha = 0.034 ha (Budhathoki et al., 2019).

[19] Income ranges in the sample do not include potential remittances.

[20] 1£ = 144.22 Nepali Rs on 14-10-2019 (https://www.xe.com, 2020).

Table 8: Descriptive statistics

Group & Indicator	Variable measure	Description & coding in SPSS	Valid N & Valid %	Mean	SD
Background (1)					
Gender	Dichot.	Male (=1), Female (=0)	226 (32.1)	0.32	
Age	Contin.			42.7	12.7
Ethnicity	Dichot.	Tharu (=1), Other (=0)	379 (53.8)	0.54	
Household members	Contin.			6.22	3.12
Agricultural characteristics (2)					
Agricultural experience	Contin.			2.29	0.77
		5 – 10 (=1)	133 (18.9)		
		11 – 20 (=2)	231 (32.9)		
		> 21 (=3)	339 (48.2)		
Cultivated landsize	Contin.			20.3	25.2
		< 5 (=2.5)	192 (27.3)		
		5 – 10 (=7.5)	141 (20.1)		
		10 – 15 (=12.5)	78 (11.1)		
		15 – 20 (=17.5)	59 (8.4)		
		20 – 30 (=25.0)	90 (12.8)		
		30 – 45 (=37.5)	66 (9.4)		
		45 – 60 (=52.5)	34 (4.8)		
		60 – 90 (=75.0)	24 (3.4)		
		90 – 120 (=105.0)	10 (1.4)		
		120 – 150 (=135.0)	4 (0.6)		
		> 150 (=165.0)	5 (0.7)		
Wealth (3)					
Income without remitt. (monthly)	Contin.			1.69	0.80
		< 5000 (=1)	343 (48.7)		
		5000 – 15000 (=2)	267 (37.9)		
		15000 – 25000 (=3)	66 (9.4)		
		> 25000 (=4)	28 (4.0)		
Credit & liquidity (4)					
Had a bank account	Dichot.	Yes (=1), No (=0)	387 (55.2)	0.55	
Loan currently	Dichot.	Yes (=1), No (=0)	493 (69.9)	0.70	
Loans last 3 years	Contin.			3.08	2.26
Borrowing difficulty	Contin.			2.01	0.79
		Easy (=1)	212 (30.2)		
		Average difficulty (=2)	270 (38.5)		
		Very difficult (=3)	219 (31.2)		
Number of local financial schemes	Contin.			1.99	1.72
		0 (=0)	177 (25.3)		
		1 (=1)	137 (19.6)		
		2 (=2)	138 (19.7)		
		3 (=3)	117 (16.7)		
		4 (=4)	59 (8.4)		
		5 (=5)	38 (5.4)		
		More than 5 (=6)	33 (4.7)		
Participate in CDMC	Dichot.	Yes (=1), No (=0)	130 (18.9)	0.19	

Continued.

Group & Indicator	Variable measure	Description & coding in SPSS	Valid N & Valid %	Mean	SD
Risk exposure (5)					
Floods experienced	Contin.			6.30	4.21
Floods exper. last 5 years	Contin.			1.69	0.95
Floods destroyed all crops	Dichot.	Yes (=1), No (=0)	684 (97.0)	0.97	
Risk mitigation (6)					
Mixed Crops	Dichot.	Yes (=1), No (=0)	627 (89.4)	0.89	
Other means of income	Dichot.	Yes (=1), No (=0)	413 (58.7)	0.59	
Remittances	Dichot.	Yes (=1), No (=0)	204 (29.0)	0.29	
Experience with insurance (7)					
Insur. exper. in general	Dichot.	Yes (=1), No (=0)	367 (52.1)	0.52	
Agricultural insurance scheme aware	Dichot.	Yes (=1), No (=0)	443 (62.9)	0.63	
Trust	Contin.			0.72	0.60
		Don't trust (=0)	252 (35.8)		
		Medium (=1)	396 (56.3)		
		Highly (=2)	56 (8.0)		
Index-based insurance (8)					
Understanding of IBFI				10.6	2.87
Basis risk sensitivity	Contin.			2.46	0.82
		Keep (=1)	144 (20.8)		
		Doubt (May/May not) (=2)	88 (12.7)		
		Definitely not renew (=3)	460 (66.5)		
Educational background (9)					
Education	Contin.			0.78	0.89
		No education/ No formal education (=0)	330 (46.8)		
		Primary school (=1)	235 (33.3)		
		Secondary school (=2)	108 (15.3)		
		High school (=3)	26 (3.7)		
		University or higher (=4)	6 (0.9)		
Math	Contin.	Average score		1.42	1.26
Probability	Contin.	Average score		1.41	0.73
Financial lit.	Contin.	Average score		1.88	1.07
Risk preferences (10)					
Ambiguity aversion	Dichot.	Not Amb. Av. (=0), Ambiguity averse (=1)	560 (83.3)	0.83	
Risk aversion OLS	Contin.			3.73	1.76
		Neutral to negative risk averse (=0)	65 (9.3)		
		Slight to risk neutral (=1)	50 (7.2)		
		Moderate risk averse (=2)	65 (9.3)		
		Intermediate risk averse (=3)	57 (8.2)		
		Severe risk averse (=4)	53 (7.6)		
		Extreme risk averse (=5)	409 (58.5)		

Continued.

Group & Indicator	Variable measure	Description & coding in SPSS	N & Valid %	Mean	SD
Risk aversion mMPL	Contin.		n=555	1.61	2.62
		Highly risk loving (=-4)	40 (7.2)		
		Highly risk loving (=-3)	23 (4.1)		
		Very risk loving (=-2)	24 (4.3)		
		Risk loving (=-1)	20 (3.6)		
		Risk neutral (=0)	66 (11.9)		
		Slightly risk averse (=1)	72 (13.0)		
		Risk averse (=2)	46 (8.3)		
		Very risk averse (=3)	31 (5.6)		
		Highly risk averse (=4)	233 (42.0)		

The mean of the income ranges was 1.69 (SD 0.80), which indicates that the income of the respondent's households was on average between the first two classes (< 5000 and 5000 − 15000 Rs./month). The result is lower than the average monthly household income in rural areas of 20.997 Rs.[21] in fiscal year 2014/2015 (NRB, 2016).

Credit & liquidity (4): Out of the sample, 55.2% had a bank account. 69.9% of the respondents' households had a loan at the period of the survey. The average number of loans during the last three years was 3.08 (SD 2.26). Of the respondents, 31.2% replied that it is very difficult to borrow if someone needed, 38.5% categorised the difficulty to borrow as average and 30.2% as easy. The respondents were asked if their community had any saving schemes. The farmers who replied that their community had saving schemes were asked further if they participated in any of these schemes. The farmers who replied positively were further asked the number of the schemes they participated. The number of the saving schemes the farmer participated was used in the regression analysis[22]. The average number of schemes the farmers participated[23] was 1.99 (SD 1.72). Approximately 18.9% of the respondents replied that they participate in the fund for disasters (CDMC)[24].

[21] Average monthly household income with remittances in rural areas was 27511 Rs. out of which the remittances were 6514 Rs. (NRB, 2016). In this analysis, the potential remittances were not included in the income. Therefore the data are compared with the income without remittances of the NRB (2016) survey, which is 27511-6514=20.997 Rs.

[22] The number of schemes was coded as continuous. The sixth option indicated participation to more than five schemes.

[23] 167 farmers replied that their community has a saving scheme, but they do not participate. Ten farmers replied that their community does not have a saving scheme. These 177 observations were coded that they participate to zero number of schemes at the "*Number of local saving schemes*" variable. Six observations replied that they do not know if their community has saving schemes and were coded as missing values "*Number of local saving schemes*" variable.

[24] 109 farmers replied that their community does not have a CDMC fund. These observations were coded as zero at the CDMC participation variable, meaning that they do not participate in the CDMC. Sixteen observations replied that their community does not have saving schemes or that they do not know if their community has saving schemes. These 16 observations were coded as missing values at the CDMC participation variable.

Risk exposure (5): On average, the respondents had experienced 6.30 (SD 4.21) flood events during their farming years. During the last five years, the respondents had on average experienced 1.69 (SD 0.95) flood events. 97% of the respondents had experienced a flood that destroyed all their crops during their farming years.

Risk mitigation (6): Of the farmers 89.4% plant mixed crops, 58.7% of the respondents' households had other means of income apart from agriculture, and 29% of the respondents' households received remittances from abroad.

Experience with insurance (7): Of the respondents, 52.1% had experience with insurance in general. 62.9% had heard about the existing crops and livestock insurance scheme. Approximately 56.3% replied that they would have medium trust towards a private insurance company which would potentially sell an index-based flood insurance product.

Index-based insurance (8): On average, the participants replied a mean of 10.6 (SD 2.87) correct out of 12 hypothetical IBFI understanding questions. The result suggests a good understanding of the hypothetical IBFI for crops. 66.5% of the respondents would definitely not renew their contract if they had bought flood insurance for their crops, experienced flood in their field and did not receive payment indicating a sensitivity towards basis risk.[25].

Educational background (9): Of the participants, 46.8% did not have formal education. The average math score was 1.42 (SD 1.26) out of four correct answers. Respondents performed better on probability questions reaching 1.41 (SD 0.73) out of two correct answers. This is similar to the study of Cole et al. (2013) in India, which revealed higher percentages in probability scores than math questions. The average score of the financial literacy skills was 1.88 (SD 1.07) out of four correct answers[26].

Risk preferences (10): Of the respondents 83.3% were identified as ambiguity averse[27]. The six CRRA ranges of the OLS method in Table 3 were coded as continuous with values ranging from zero to five. Similarly, the CRRA mMPL risk aversion ranges were coded from minus four to four. The OLS risk aversion method reported a mean of 3.73 (SD 1.76) indicating that the average participant was severely risk-averse. The mMPL risk aversion method had a mean of 1.61 (SD 2.62), indicating that the average participant was risk-averse.

6.2 Analysing factors leading to lack of interest in flood insurance

Forty-four observations are identified that might have no interest at all in flood insurance for crops, as explained in Section 5.6. The 44 observations that might have no interest at all in flood insurance were coded as 0, while the remaining 661 observations were coded as 1.

A bivariate analysis was performed to observe the relationship between indicators that

[25] Basis risk was coded as a continuous variable with increasing basis risk sensitivity; values 1,2,3. The "*I don't know*" option of the basis risk question explained in Section 5.7 was treated as a missing value in the regression analysis. Therefore, the valid (%) responses of Table 6 and Table 8 are slightly different.

[26] The math scores varied between 0-4 correct answers, probability between 0-2 and financial literacy between 0-4 correct answers in the regression analysis.

[27] This is the valid percent excluding the "*I don't know/I don't want to reply answers*", which were coded as missing values. This is why there is a difference with the Section 5.2 where the percentage presented was out of the whole sample including the "*I don't know/I don't want to reply answers*".

might be related to the lack of interest in flood insurance for crops variable. The bivariate analysis was performed between the interest in flood insurance variable and each of the variables of the ten abovementioned groups examined in this study[28]. Eight indicators are significantly correlated with the interest in insurance variable, as shown in Table 9.

Table 9: Bivariate analysis for the non-interested in insurance variable

Indicator	**Significance level**	**Correlation coefficient** (Spearman's ρ)
CDMC	0.016	0.092*
Trust	0.001	0.123**
Understanding IBFI	0.001	0.125**
Math scores	0.013	0.094*
Probability scores	0.021	0.087*
Financial literacy	0.012	0.095*
Risk aversion (OLS)	0.026	-0.084*
Risk aversion (mMPL)	0.015	-0.103*

* Correlation is significant at the 0.05 level (2-tailed)
** Correlation is significant at the 0.01 level (2-tailed)

The interest in flood insurance variable was positively correlated with the participation in the local community disaster fund (CDMC)($\rho = 0.092$, $p \leq 0.05$). The results suggest that the farmers who did not participate in the CDMC fund might not be interested in flood insurance either. One possible explanation could be that these farmers might not have interest in the informal risk-sharing mechanisms for disasters (such as the CDMC) or the formal ones (such as the insurance). A considerable number of farmers replied that their community does not have a CDMC[29]. Hence, another possible explanation could be that when farmers are not familiar with informal mechanisms for disasters, they might not be interested in formal ones too.

The interest in flood insurance variable was positively correlated to the trust towards a private company, which would hypothetically provide the IBFI described ($\rho = 0.123$, $p \leq 0.05$). The result indicates that farmers who have low trust towards private insurance companies might not be interested in flood insurance. One possible explanation could be previous bad experiences with insurance, resulting in low trust and low interest. The risk aversion measured by the OLS method ($\rho = -0.084$, $p \leq 0.05$) and the mMPL method ($\rho = -0.103$, $p \leq 0.05$) were both negatively correlated with the interest in insurance, which indicates that the higher the risk aversion the less the interest in flood insurance. One possible explanation for the negative relationship could be that farmers with high risk

[28]The bivariate analysis was between the "*Interest in insurance*" variable and the independent variables identified to be used in the regression analysis. However, the basis risk variable was not part of the bivariate analysis as this variable contributed to the identification of the 44 non-interested in insurance observations.

[29]The farmers who replied that their community does not have a CDMC were coded as not participating in CDMC.

aversion might perceive insurance as a lottery and not as a protection mechanism and do not want to engage with it. A considerable number of studies contradict the theory that insurance demand increases with risk aversion (Marr et al., 2016). Technology adoption studies have shown that risk-averse households might not be early adopters of new technologies (Hill et al., 2013). As a result, another possible explanation for the negative relation of interest in insurance and risk aversion could be that flood insurance might be perceived as new technology, and the farmers have a low interest because they might not trust it.

The understanding of IBFI was positively correlated with the interest in flood insurance ($\rho = 0.125$, $p \leq 0.01$). The result suggests that those who were not interested in flood insurance might have low understanding of IBFI. Among the significant variables were also the math ($\rho = 0.094$, $p \leq 0.05$), probability ($\rho = 0.087$, $p \leq 0.05$) and financial literacy scores ($\rho = 0.012$, $p \leq 0.05$). Farmers with low scores in those three variables might not be interested in insurance. The education level was positively and significantly related to the understanding of IBFI, the math, probability and financial literacy scores as shown in Table 10. Therefore, the results suggest that there is a relation between education and interest in flood insurance.

Table 10: Bivariate analysis for the education variable

	Spearman's ρ	**Sign.**
Education & Understanding IBFI (N=705)	0.172**	0.000
Education & Math scores (N=705)	0.606**	0.000
Education & Probab. scores (N=705)	0.332**	0.000
Education & Finan. Lit. scores (N=705)	0.302**	0.000

** Correlation is significant at the 0.01 level (2-tailed)

6.3 Sub-model selection during regression analysis

The dependent variable question was asking the participants if they would be willing to buy such type of flood insurance (after having been introduced to IBFI) in case it was offered at an affordable price. The dependent variable of the regression analysis is the first question presented in Table 5. The positive answers of the dependent variable were coded with 1 and the negative with 0. The regression analysis included 661 observations[30]. Out of 661 observations 594 replied "*yes*" to the dependent variable and 65 replied "*no*".

The logistic regression analysis was conducted into two phases. The initial model included thirty independent variables to identify the fifteen factors with the highest significance level. The initial model's regression analysis results are presented in Table 11. The results of the initial model set up the simplified model; therefore, the simplified model was set up including

[30]The 44 non-interested in flood insurance observations identified in Section 5.8 were excluded from the regression analysis as explained analytically in Section 5.9.

fifteen variables. The simplified model resulted in the identification of the most significant variables of all. The simplified model's results are presented in Section 6.4.

Table 11: Logistic regression analysis initial model

	Group	Indicator	β	Sign.	exp(β)
1	Background (1)	**Gender**	**-0.579**	**0.161**	**0.560**
2	"	**Age**	**-0.040**	**0.008**	**0.960**
3	"	**Ethnicity**	**-0.713**	**0.059**	**0.490**
4	"	HH size	-0.029	0.568	0.971
5	Agricult. characteristics (2)	**Agricult. experience**	**0.377**	**0.080**	**1.458**
6	"	Cultivated landsize	-0.002	0.786	0.998
7	Wealth (3)	Income	0.117	0.613	1.125
8	Credit & Liquidity (4)	**Bank account**	**-0.320**	**0.319**	**0.726**
9	"	Loan currently	0.229	0.506	1.257
10	"	Loans last 3 years	-0.068	0.336	0.934
11	"	**Borrowing difficulty**	**-0.264**	**0.208**	**0.768**
12	"	**Nr. of schemes**	**-0.140**	**0.157**	**0.869**
13	"	CDMC	0.334	0.457	1.397
14	Risk exposure (5)	**Floods experience**	**0.06**	**0.262**	**1.062**
15	"	**Floods last 5 years**	**0.366**	**0.078**	**1.441**
16	"	Floods destr. all crops	0.630	0.415	1.877
17	Risk mitigation (6)	**Mixed crops**	**-1.848**	**0.086**	**0.158**
18	"	**Other means of income**	**0.405**	**0.255**	**1.500**
19	"	Remittances	-0.300	0.441	0.741
20	Insurance (7)	Experience insurance	-1.112	0.724	0.894
21	"	**Agric. insurance scheme aware**	**0.541**	**0.091**	**1.717**
22	"	Trust	0.208	0.443	1.232
23	IBFI (8)	**Understanding IBFI**	**0.058**	**0.832**	**1.060**
24	"	**Basis risk sensitivity**	**-0.857**	**0.001**	**0.424**
25	Educ. background (9)	Education	0.058	0.832	1.060
26	"	**Math scores**	**0.381**	**0.065**	**1.464**
27	"	Probability scores	0.085	0.727	1.089
28	"	Financ. literacy scores	0.127	0.406	1.135
29	Risk preferences (10)	Ambig. aversion	-0.053	0.895	0.948
30	"	Risk aversion OLS	0.035	0.670	1.036

The fifteen variables with the highest significance level identified in the regression analysis of the initial model had significance level ≤ 0.262. The variables were the gender, age and ethnicity, agricultural experience, bank account, borrowing difficulty, number of local financial schemes the farmer participated, number of floods the farmer had experienced in total and during the last five years, planting mixed crops, other means of income, awareness of the existing agricultural insurance scheme, understanding of IBFI, basis risk sensitivity and math scores. The variables belonged in the presented groups of background data, agricultural characteristics, credit and liquidity, risk exposure, risk mitigation, insurance, IBFI and education.

6.4 Factors affecting the WTP for IBFI

The simplified OLS model was set up with the fifteen variables identified in the initial OLS model in Section 6.3. The simplified model indicated five factors might affecting the WTP for IBFI with significance level ≤ 0.05 as shown in Table 12. The five variables were the age, the agricultural experience, the number of floods experienced during the last five years, the math scores and the basis risk sensitivity, which belonged in the presented groups of questions 1, 2, 5, 8 and 9, accordingly.

Table 12: Logistic regression analysis simplified model

	Group	Indicator	β	Sign.	exp(β)
1	Background (1)	Gender	-0.458	0.226	0.633
2	"	**Age**	**-0.033**	**0.011***	**0.967**
3	"	Ethnicity	-0.542	0.098	0.582
4	Agricult. characteristics (2)	**Agricult. experience**	**0.395**	**0.049***	**1.484**
5	Credit & Liquidity (4)	Bank account	-1.999	0.495	0.819
6	"	Borrowing difficulty	-0.325	0.096	0.722
7	"	Nr. of schemes	-0.107	0.226	0.898
8	Risk exposure (5)	Floods experience	0.049	0.325	1.050
9	"	**Floods last 5 years**	**0.374**	**0.047***	**1.454**
10	Risk mitigation (6)	Mixed crops	-1.982	0.056	0.138
11	"	Other means of income	0.097	0.745	1.102
12	"	Agric. insurance scheme aware	0.532	0.070	1.702
13	IBFI (8)	Understanding IBFI	0.046	0.345	1.047
14	"	**Basis risk sensitivity**	**-0.083**	**0.001*****	**0.436**
15	Educ. background (9)	**Math scores**	**0.421**	**0.010****	**1.523**

* $p \leq 0.05$,
** $p \leq 0.01$
*** $p \leq 0.001$

The age was negative and significant ($p \leq 0.05$). The result indicates that younger farmers have higher odds of willing to pay for IBFI than older farmers. One explanation could be that younger farmers might be more open to new technologies such as IBFI. The result agrees with the findings of Afroz et al. (2017) study on WTP for crops insurance in Malaysia that found younger farmers to be willing to pay more than the elderly.

The agricultural experience was positive and significantly related to WTP ($p \leq 0.05$). The result suggests that the higher the farming experience, the higher the odds the farmer is willing to pay for IBFI. One possible explanation might be that farmers with higher agricultural experience might have higher experience with agricultural losses during their farming years (Jin et al., 2016). The result is in agreement with the findings of Afroz et al. (2017) and Jin et al. (2016).

The number of floods experienced during the last five years was positive and significant ($p \leq 0.05$). The result suggests that farmers with a higher number of floods experienced during the last five years have higher odds of willing to pay for IBFI. One possible explanation could be that the experience with losses recently might increase the demand for protection. A further possible explanation could be that the higher number of floods experienced during the last five years might indicate a higher risk exposure and consequently need for protection. The result contrasts with the findings of Budhathoki et al. (2019). Their study conducted in the lowlands of Nepal found that the number of floods during the last five years was negatively related to the WTP for paddy rice.

The math scores had a positive and significant ($p \leq 0.01$) relation with WTP for IBFI. The higher the math scores, the higher the odds of willing to purchase IBFI. The result is in agreement with the study of Cole et al. (2013) in India, who found that farmers who performed better in math scores had a higher WTP. Bivariate analysis between the math scores and education level in the sample of this study revealed a positive and significant relation between the two variables[31]. Consequently, the results suggest that the higher the education level of the farmers, the higher the odds of willing to pay for IBFI. As a result, the findings can be related to the findings of the studies of Hill et al. (2013) in rural Ethiopia and Jin et al. (2016) in China. Both studies indicated that educated farmers might be early adopters of insurance. In contrast, the study of Fonta et al. (2018) found that educated farmers are willing to pay less than farmers with no formal education.

Finally, the basis risk sensitivity variable had a negative and significant relation with the WTP. The variable had the highest significance level among all ($p \leq 0.001$). The result indicates that farmers with low basis risk sensitivity have higher odds of willing to pay for the hypothetical IBFI.

7 Conclusions

This study was conducted in the lowlands of the Karnali river basin in western Nepal. The empirical data of 705 questionnaires were collected from smallholder farmers exposed to frequent floods, and their willingness to pay for IBFI was explored.

The presented study contributes to the literature in three ways. First, the study identifies factors that might be related to a lack of interest in the general concept of flood insurance for crops not specifically IBFI, which is to the best of our knowledge, one of the first attempts in the available literature. Second, the study explores the factors affecting the farmers' WTP for a hypothetical IBFI product. The role of basis risk sensitivity on the WTP was included as one of the independent variables. To our knowledge this is one of the first studies to examine the basis risk indicator as an independent variable in a logistic regression analysis of a stated preference study, regarding the WTP for hypothetical IBFI. Therefore, further empirical evidence is needed to identify the role of basis risk when assessing the factors affecting the WTP for index-based insurance stated preference studies. Third, a number of independent variables examined in this study is large and informed by a comprehensive overview of the variables identified through the literature and fieldwork.

[31] In the sample of 661 observations a bivariate analysis showed that there was a positive and significant relationship between the education and math score variables (spearman's rho coeff. 0.602, sign. 0.000).

The study found the following factors for the lack of interest in flood insurance: the non-participation in local groups for disasters, lower trust towards insurance companies, higher risk aversion and lower education.

An initial model of 30 independent variables was set up for the interested in flood insurance farmers. The 15 variables with the highest significance level of the initial model set up the simplified model. The simplified model of 15 independent variables indicated five factors possibly affecting farmers' WTP for hypothetical IBFI. Younger farmers, farmers with more agricultural experience, farmers who experienced a higher frequency of floods during the last five years, farmers with higher education level and farmers with low basis risk sensitivity have higher odds of being the first adopters of a potential IBFI product in the examined area.

Education about the risks and the role of insurance would possibly lead to higher interest in flood insurance for crops generally and WTP for IBFI specifically. One possible way to deliver education about insurance to farmers might be through workshops and trainings. Furthermore, farmers with high basis risk sensitivity have higher odds of not willing to pay for index-based flood insurance. Therefore, a particular emphasis to minimising basis risk should be given when designing these types of products.

According to (Hill et al., 2013), WTP studies might not definitely represent actual behaviour and the insurance products offered might be oversimplified. However, this type of studies can be quite informative for a product that does not exist in the market (ibid.). Therefore, this study explored the WTP for a hypothetical index-based insurance product. It is also important to mention the limitations of this research which are mainly related to data collection. The explanation of insurance and index-based insurance were approached in a simplified way which may have resulted in the loss of some information. Due to the complexity of the topic, significant effort was made to communicate this type of mechanisms simply but presenting the main characteristics. Moreover, it is acknowledged that there might have been some loss of information in the way the research material was translated into documents, explained to enumerators or in real time translation during for instance the game sessions. Additionally, there might be differences in the way the enumerators explained and presented the material to research participants or the responses they received. However, these limitations present a reality of empirical research on the ground and in a context different to those of a researcher, and every effort was made to minimise these. During the training of the research team, a considerable time was spent to approach the explanations and questions similarly in order to ensure the consistency across different enumerators once in the field. This is a reality of on-the-ground research of this type and as previously mentioned, an effort was made to reduce these or similar challenges.

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