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ABSTRACT

Climate change induces high and erratic rainfall which triggers landslides and floods. With the increasing population and food needs, households in mountainous, densely populated areas turn fragile ecosystems into farms. This exacerbates landslide and flood risks requiring Disaster Risk Reduction (DRR) measures. Tree planting and diversion channels are among the recommended measures for farmers but their adoption remains low. Current studies assessing barriers to adoption ignore farmers' opinions regarding the kind of trees or diversion channels preferred. We apply a Discrete Choice Experiment to evaluate how information delivered through videos impacts preferences for the DRR measures. Plot-level data were collected from 319 farmers from Kasese, Bundibugyo, Bushenyi and Buhweju in Uganda – districts prone to landslides and floods. The mixed logit model reveals a general preference for risk-reducing attributes of DRR measures. Using the conditional logit model to analyze split samples reveals that information influences preferences for tree planting, while preferences for diversion channels were hardly changed. Plot characteristics did not strongly explain the differences in preferences. Our study indicates that information specific to DRR measures in extension programmes would increase the adoption of such measures.

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1. Introduction

Climate change induces weather extremes such as more frequent and intense rainfall which triggers natural hazards such as soil erosion, landslides, and floods (Kondrup et al., 2022). Hazards refer to events potentially disrupting human beings and the natural system. They turn into disasters when they overwhelm the local community's efforts to cope with them and threaten socio-economic development (Barasa et al.,

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2022; Pal et al., 2023). The world is increasingly affected by geo-hydrological hazards such as landslides and floods. For instance, about 1.7 billion people were affected by such disasters, and over 410,000 fatalities were recorded between 2010 and 2020 (IFRC, 2020). In Sub-Saharan Africa, over 2.6 million people were internally displaced by disasters ('climate refugees') in 2021 alone (Serwajja et al., 2024). Between 2006 and 2019, approximately 1,200 deaths from landslides and floods were reported (CRED & UNDRR, 2021). Landslides and floods also affect farmers by killing livestock or damaging assets such as crops, and farm structures. This causes a significant loss of food and income (OPM, 2010). In addition, soil degradation is associated with both hazards and flooded areas are breeding grounds for pests and diseases. Moreover, several small-scale but regular landslides and flash floods[1] tend to be unreported in the national databases, yet they present large cumulative losses (Monsieurs et al., 2018; Sekajugo et al., 2022). Such hazards cover smaller areas (< 1.5 ha) and are usually difficult to identify with satellite imagery (Sekajugo et al., 2022). They can be confused with soil erosion, or are rapidly covered through revegetation, and land reclamation (Jacobs et al., 2017). This study focuses on floods and landslides (see Appendix 1 for the pictures of the two disasters) because: (a) they severely affect poor households in rural areas, (b) farmers are usually uninsured against them and attract less government (external) support if affected by such hazards, and (c) the rising human population pushes farming activities towards marginal lands like mountain slopes which increases the occurrence of this type of hazards (Hamdan, 2015; IPCC, 2022).

Applying Disaster Risk Reduction (DRR) measures at the farm level can reduce the devastating impact of these climate-induced hazards (Kondrup et al., 2022). Tree planting is recommended for risk reduction in low- and middle-income countries (Maes et al., 2017; Mertens et al., 2018). The measure involves establishing trees following the best practices such as the right tree species, recommended population, spacing, and maintenance (Lan et al., 2020). Tree planting reduces landslides and floods by improving drainage through deep percolation, decreasing the water's erosive velocity, stabilising the soil structure, and trapping eroded material (Kobayashi & Mori, 2017; Kumawat et al., 2020). Trees also offer several additional benefits, such as shade for crops and wood (Kumawat et al., 2020). Diversion channels (diversion/ retention ditches)[2] are soil and water management practices applied to reduce surface runoff and erosion on mountain slopes, thereby preventing sedimentation of rivers that would cause flooding (Kamruzzaman & Chowdhury, 2023; Mugonola et al., 2013). They are rectangular (or semi-circular) pits dug in the soil parallel to each other across the slope at a spacing of about 30 feet (Mati, 2012).[3]

Despite their potential for risk reduction, the actual adoption of tree planting and diversion channels remains low (Jacobs et al., 2019; Mertens et al., 2018; Mutyebere et al., 2023). Many studies on the adoption of DRR measures (e.g. Lan et al., 2018; Valibeigi et al., 2019) have assessed the barriers to adoption *ex-post,* but only a few provided an *ex-ante* assessment of farmers' opinions regarding the kind of tree planting or diversion channels preferred and how providing information might influence such opinions. Evaluating farmers' preferences for tree planting or diversion channels *ex-ante* would help policymakers understand and disseminate information in line with farmers' preferences to promote adoption and supply the right tree seedlings in disaster-prone areas. Moreover, most smallholder farmers in rural areas experience information asymmetries (compared to peri-urban centers) due to poor road networks that limit access by extension workers (Mutyebere et al., 2023). Thus, the farmer's problem can be thought of as the problem of optimal application of the two measures in the presence of limited knowledge about their beneficial impacts. Providing the right information could improve their knowledge and awareness. Most studies assessed how information can affect decision-making but they were not conducted in the farmer's setting. For example, Valibeigi et al. (2019) assessed the lack of information about disaster risks to explain poor perceptions of risk reduction measures in Iran. Further, Rousseau and Vranken (2013), Vanermen et al. (2021) and Boogen et al. (2022) suggested that providing information related to a product (or an intervention) to citizens reduces ill-informed choices. However, whether DRR-specific information can influence preferences for adopting tree planting and diversion channels is yet to be assessed.

This study aims to assess preferences for tree planting and diversion channels as DRR measures and to provide insights into the role of information on such preferences. We achieve this by combining customised information and a Discrete Choice Experiment (DCE) to evaluate the farmer's choice behaviour as regards DRR for different plots owned by the household. We assume that a household might own plots in different locations, with different land uses, and different levels of DRR measures already applied, where, some are exposed to floods and/ or landslides and others are not. Therefore, the choice of adoption of a DRR measure per plot differs. This study is premised on three specific questions. (i) What kind of tree planting, or diversion channels do farmers prefer as DRR measures? (ii) How do such preferences change when information about the DRR measure is provided? (iii) Does the influence of DRR information on preferences vary with the farmers' plot characteristics?

To address these research questions we conducted a survey, that included a DCE among smallholder farmers from the Rwenzori and Ankole in Western Uganda. These are remote, mountainous sub-regions that are densely populated and are prone to landslides and flash floods. As such, the findings are relevant for many regions that face similar challenges. Furthermore, study findings are relevant for Uganda's National Policy for Disaster Preparedness and Management (OPM, 2010) which stresses the importance of effective risk response efforts. Similarly, the study contributes to Uganda's National Development III and the country's Vision 2040 which emphasises addressing climate change challenges to fast-track sustainable socio-economic development (MWE, 2018). Focusing on smallholder farmers is key because they form a larger part of the Ugandan agriculture sector, yet it is a priority sector in achieving the nation's development targets. Moreover, the sector's National Adaptation Plan aims to fortify risk preparedness and response by increasing farmers' awareness about hazards (MAAIF, 2018).

2. Methods and materials

2.1. The study area

This study was conducted in Uganda in the western districts of Kasese (0.06 N, 30.06 E) and Bundibugyo (0.68 N, 30.02 E) in the Rwenzori Sub-region, and Buhweju (0.29 S, 30.29 E) and Bushenyi (0.48 S, 30.20 E) in the Ankole Sub-region (see Figure 1). Kasese and Bundibugyo districts are located on the slopes of Rwenzori Mountain. Buhweju and Bushenyi districts also have a hilly topography and experience offsite flooding,

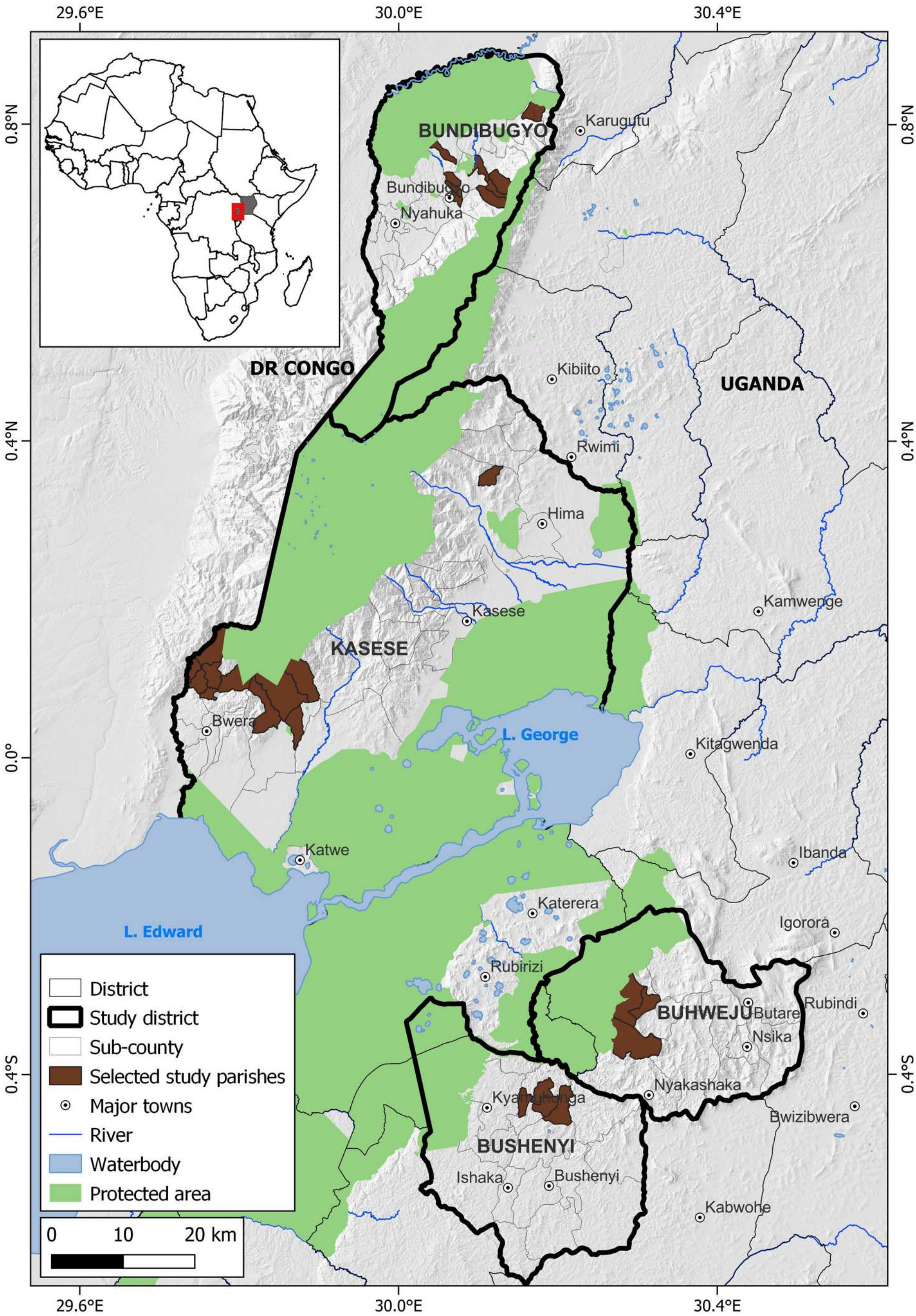


Figure 1. Location of study areas in Uganda, highlighting the four districts in which the data collection took place.

which is exacerbated by the increasing farming and urbanisation activities due to fast-growing populations in the region (Nseka et al., 2021; Tumwesigye et al., 2021; UBOS, 2022).

Overall, the mountainous area has a fragile environment due to its deeply incised valleys uphill of the mountain experiencing slope instabilities and mud flows. Further, the study area is characterised by gneiss, quartzite, fertile volcanic, and soft alluvial soils, high bimodal rainfall, and a dense river system which makes the area more susceptible to shallow landslides and flash floods (Lara et al., 2019; Mertens et al., 2018; Nseka et al., 2021). The area also experiences a combined occurrence of earthquakes, wildfires, landslides, and flash floods (Jacobs et al., 2016). It is mainly inhabited by smallholder farmers deriving their livelihoods from agriculture and animal husbandry (Serwajja et al., 2024). However, some farming activities involve clean weeding, deforestation, and bush burning which expose the slopes to the two hazards (Mertens et al., 2018).

2.2. Ethical consideration

This research was embedded in the D-SiRE project which was approved by the Uganda National Council for Science and Technology (Registration number NS126ES). An introductory letter was written to the respective district administration by Mountains of the Moon University to seek permission to reach study communities. The purpose of the study was explained to respondents before the interview. They were also informed of the freedom to stop the interview at any stage if they suspected that giving further information was harmful. We also sought consent to engage respondents above 18 years, and the answered questionnaires were anonymous.

2.3. Sample selection and data collection

A household survey that embedded two DCEs and an information intervention (see further) was conducted in November 2021 in a one-time field visit by well-trained enumerators, each at the level of a master's degree. A quantitative questionnaire was used during face-to-face interviews with the household head or representative. Smallholder farmers were selected from 32 landslide and flood disaster-prone parishes under the guidance of the D-SiRE project[4] following stratified random sampling.[5] Parishes were viewed as homogenous strata, but only from farming households, we randomly selected the study sample. We aimed to obtain 10 respondents per parish. However, in some parishes, we obtained fewer respondents due to practical reasons such as failing to reach the targeted homestead because of bad weather, poor roads, and difficult terrain. Therefore, more households were selected in a nearby parish. The actual number of households surveyed per district is as follows: Kasese (137), Bundibugyo (100), Buhweju (39), and Bushenyi (43). The variation in the number of respondents per district was influenced by the number of parishes prone to the two hazards. Additionally, the D-SiRE project, which contributed to mapping study parishes, operates in 17 parishes in the Ankole Sub-region (Buhweju and Bushenyi), compared to 38 in the Rwenzori Sub-region (Kasese and Bundibugyo).

2.4. Discrete choice experiment method

To examine the preferences of farmers for adopting DRR measures, and to explore the influence of information on such preferences, we used a DCE as a stated-preference elicitation method (Louviere et al., 2000; Louviere et al., 2010). To minimise the novelty bias among respondents when making choices (see Rousseau and Vranken (2013)), we focused on tree planting and diversion channels. The two are most recommended in the literature (e.g. Maes et al. (2017)) as a DRR measure. Overall, most DRR strategies are not yet employed in the region but amongst those that are taken up, tree planting and diversion channels are the most widespread (Mertens et al., 2018; Mugonola et al., 2013).

DCEs have their origin in the random utility theory (RUT), based on pairs of choice alternatives and extended by McFadden (1986). They are also theoretically based on consumer theory which assumes that utility is not derived from the whole product, but the sum of its attributes. In a DCE, people are presented with different alternatives of a good (described by attributes). Based on the economic concept of consumer sovereignty, individuals are assumed to behave rationally, their choices enact interests and rational decisions (Redmond, 2000). Therefore, they can assess the options available in a DCE and make choices based on utility maximisation. Through repeated choices, the individual's preferences for the attributes of the good as well as for the good as a whole can be evaluated (Atkinson et al., 2018; Caussade et al., 2005).

Several studies have applied DCEs for *ex-ante* evaluation of interventions to inform policies. For example, in health sciences and medicine (Dai et al., 2020; Dong et al., 2020; Zhao et al., 2018), in transport (Guo & Peeta, 2020), in market research (Rousseau & Vranken, 2013; Tian et al., 2022; Wesana et al., 2020), in agriculture (Gamboa et al., 2018; Lambrecht et al., 2015; Oyinbo et al., 2019), and in environment and nature studies (Mertens & Vranken, 2021; Vanermen et al., 2021; Vlaeminck et al., 2016; Zhang et al., 2019). However, no study has assessed farmers' preference for tree planting and diversion channels as DRR measures in the global south. Empirically, conducting DCEs requires the proper choice of attributes and levels, the experimental design of the choice cards, and proper DCE implementation (Champ et al., 2017; Jeanloz et al., 2016; Mariel et al., 2021).

2.4.1. DCE attributes

Based on a literature search (e.g. Maes et al. (2017)), a long list of attributes focusing on tree planting and diversion channels was compiled. This list was then discussed during two Focus Group Discussions (FGDs), one conducted in the Kasese and another in Bushenyi districts (Rwenzori and Ankole sub-regions respectively), each comprised of ten participants (local disaster experts, local leaders, and farmers). During the discussion, a PowerPoint Presentation on the list of attributes was given. Participants were asked to conduct a ranking exercise on a score sheet in the order of importance for the attributes and levels. After a break, participants discussed their scores and were asked to repeat the ranking if they felt that some scores would change. This information was used to select the final six attributes for each measure and their hypothetical levels (Table 1). As recommended by Mariel et al. (2021), the list was kept short to reduce the complexity of the choice tasks, respondent fatigue, and random non-deterministic choices.

The first DCE focused on tree planting as a DRR measure. Here, the six selected attributes include 'cost per tree seedling', 'erosion reduction', 'the number of trees', 'maintenance days', 'maturation period', and 'root and canopy structure'. The first attribute 'cost per tree seedling' refers to the amount of money, based on prevailing average prices of tree seedlings, that would be paid to purchase one tree seedling from a nursery

Table 1. Attributes and attribute levels used in the discrete choice experiment for tree planting and diversion channels.

Tree planting		Diversion channels	
Attribute	Attribute levels	Attribute	Attribute levels
Cost per tree seedling (UGX)	UGX 500 UGX 800 UGX 1100	Cost per div channel (UGX)	UGX 5000 UGX 10000 UGX 15000
Erosion reduction (%)	5% 10% 15%	Erosion reduction (%)	5% 10% 15%
Number of trees per acre	20 trees 30 trees 50 trees	Number of diversion channels per acre	1 diversion channel 4 diversion channels 8 diversion channels
Maintenance days per acre per month	1 day 5 days 10 days	Maintenance days per acre per month	1 day 5 days 10 days
Maturation period (years)	5 years 10 years 15 years	Grass strips on the diversion channels[a]	No strips* Low strips Moderate strips High strips
Root and canopy[a]	Deep & Small* Shallow & Small Shallow & Large Deep & Large	Location of diversion channels on the plot[a]	Random* Systematic At boundaries

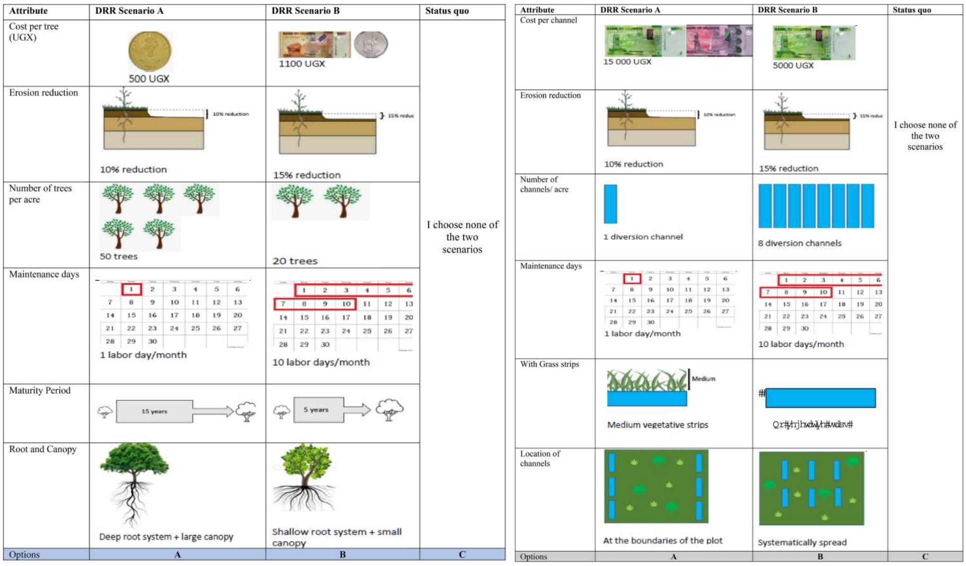
Note: *refers to the Base level; [a]Categorically-coded attribute.

bed. It is expressed in Uganda shillings (UGX), with levels defined as 500, 800, and 1100 UGX.[6] Non-indigenous species such as Pine (*Pinus patulla*) and Eucalyptus (*Eucalyptus grandis*) are sometimes given for free by the government and other organisations but sometimes, they are purchased from commercial nursery beds. The second attribute 'erosion reduction', is defined as the nutrient-rich fertile top layer in a given plot protected from soil erosion by tree planting compared to where the intervention is lacking. Expressed in percentage, trees reduce soil erosion through a root-binding effect, deep water percolation, and intercepted transport materials (Kumawat et al., 2020). The hypothetical levels used, as discussed in FGDs are 5%, 10%, and 15%: we expect farmers to choose higher levels. The third attribute 'number of trees per acre' refers to the numerical value of trees per acre of plot regardless of other tree characteristics. Purwaningsih et al. (2020) indicate that about 40 trees per acre can be planted in agroforestry to increase effectiveness in risk reduction. The levels used are 20, 30, and 50 trees but we expect fewer trees to be preferred to avoid competition with crops. The fourth attribute is 'maintenance days per month' which refers to the amount of labour in days[7] required to prune the trees to not only reduce competition with crops but also improve the growth vigor and maintain the structure for timber species. The hypothetical levels used are one day, five, and ten days. The fifth attribute 'maturation period' refers to the number of years a tree takes to establish the canopy and root structure to its potential based on variety, which are among the key criteria for effective DRR. Fast maturation is expected to be preferred to protect farmers against landslide and flood risks. The attribute levels applied are five, ten, and fifteen years. The sixth and last attribute 'root and canopy structure' refers to the architecture of roots and canopy which are important for DRR. A deep and strong root structure is key in soil anchoring and ensuring root binding of soil.[8] Also, a wide and thick canopy reduces raindrop intensity and thus reduces soil erosion (Lan et al., 2020). The attribute levels applied are shallow roots and small canopy, shallow roots and large canopy, deep roots[9] and small canopy, and deep roots and large canopy. Although the attribute might reduce light for crops around the tree, we expect trees with deep roots and a large canopy to be preferred by the farmers at risk of landslides and floods.

The second DCE focused on diversion channels. Here, the six selected attributes include 'cost per diversion channel', 'soil erosion reduction', 'number of diversion channels', 'maintenance days', 'location of diversion channels', and 'grass strips on the diversion channels'. The first attribute 'cost per diversion channel' refers to the amount of money paid to hire someone to dig a standard diversion channel. It is expressed in Uganda shillings (UGX), with levels defined as 5,000, 10,000, and 15,000 UGX based on the average prices suggested in the FGD. The second attribute 'erosion reduction' was considered with the same description, units, attribute levels, and expected preferences as described under the tree planting DCE. The third attribute 'number of diversion channels per acre' refers to the numerical value of channels per acre of plot regardless of other channel characteristics. About five diversion channels per acre are recommended (Mati, 2012). The attribute levels are; one diversion channel, four and eight channels. Five to eight channels are expected to be preferred because the more channels the more effective they are in DRR. The fourth attribute 'maintenance days per month' refers to the number of days required to remove soil and other materials from the diversion channel after heavy rains. The hypothetical levels, as discussed in the FGDs, are one day, five, and ten days. The fifth attribute 'location of diversion channels' refers to the area on the plot where channels are located. The levels used are random, in that the layout of one diversion channel on the plot relative to each other, does not follow a clear order; systematic, where there is a clear order, and located at boundaries, in that the channels are located in the plot boundaries. Random diversion channels are expected to be preferred because, in a rough and hilly terrain, it is difficult to follow systematic order. The sixth attribute 'grass strips on the diversion channels' refers to the practice of growing perennial grasses such as Napier grass *(Pennisetum purpureum)* on the upper side to stabilise the channels, intercept surface runoff, and trap materials being eroded and transported. The levels used are none, low, moderate, and high grass strips measured in terms of height and density of the grass. Moderate to high grass strips are expected to be preferred because they are more effective in erosion control (Kizito et al., 2022). Following Champ et al. (2017) and DeLong et al. (2021), all the attributes were illustrated as pictograms on the choice cards to facilitate the understanding by the less educated farmers.

2.4.2. Choice card design

The selected attributes and their levels were combined into hypothetical scenarios using a Bayesian D-efficient (a fractional factorial) design generated using Ngene 1.1.2 software (ChoiceMetrics, 2018). A D-efficient design aims to obtain efficient parameter estimates with low standard errors and low occurrence of dominant choice cards (ChoiceMetrics, 2018; Goos & Jones, 2011). We applied a multinomial logit probability specification to obtain a design that has a D-error of 0.0187 for tree planting and 0.0483 for diversion channels. D-errors are calculated given the design specifications and complexity of



(a). Example of the choice cards on tree planting

(b). Example of the choice cards on diversion channels

Figure 2. Example of the choice cards implemented during the discrete choice experiment.

each DCE. There is no critical threshold to identify an efficient design, rather, a design is considered efficient when the D-error is lower than the preceding design iteration (Chaloner & Verdinelli, 1995; ChoiceMetrics, 2018). The selected designs for each DCE respectively represent the lowest D-errors, and thus the most efficient designs. The design was tested in a pilot survey among 30 farmers in Bundibugyo District. Piloting in one district was considered appropriate because it was mainly done to verify the attribute relevancy and interpretability (Mariel et al., 2021), and to make reasonable assumptions about prior parameters when updating the design. Furthermore, piloting only in Bundibugyo was also determined by logistical and time constraints.

The final design included 12 choice cards per DCE which were allocated to four blocks of three cards each by the Ngene 1.1.2 software. Per plot, a respondent was asked to randomly select one of four blocks for which they proceeded to answer three choice cards. The DCE was repeated for a minimum of one plot and a maximum of three plots per respondent, depending on the number of plots ploughed by the household at the time of the survey. Each choice card (Figure 2) was comprised of two unlabelled hypothetical alternatives referring to the DRR measure, and the third (status quo) representing the farmers' current level of adoption. Including a status quo in DCEs reflects realistic choices that people make (Lancsar et al., 2017), and reduces bias due to forced-choice situations (Atkinson et al., 2018). Selecting the status quo throughout the DCE demonstrates a serial non-demanding behaviour sometimes known as protesters. According to Maaya et al. (2021) and Mariel et al. (2021), protesters should be dropped from the sample to obtain consistent estimates. The survey did not include a follow-up question about why the status quo was chosen to distinguish between true protesters and those choosing the status quo for a valid reason. Therefore, we removed all respondents with serial non-demanding behaviour, i.e. respondents who chose the status quo in all cards and on all plots, from the analysis.

2.4.3. Information treatment and DCE implementation

All farmers participated in two DCEs, one for tree planting and another for diversion channels. Each farmer was exposed to an information treatment after the first DCE to also evaluate preferences after treatment. Following other studies (Bazoche et al., 2023; Lin & Nayga, 2022), we applied a between-subject approach for the informational intervention as follows. A total of 162 respondents (51%) randomly assigned to the tree planting treatment group participated first in the DCE on diversion channels, then watched a video on tree planting, and finally participated in the DCE on trees. Similarly, each of the 157 respondents (49%) assigned to the diversion channel treatment group participated in the DCE on tree planting first, watched a video on diversion channels, and concluded with the DCE on diversion channels. Thus, each respondent in one treatment group (with information on one measure) also acted as a control (without information) for the other. Guided by Lecoutere et al. (2019), the two videos shown were self-made. As shown by the script (Appendix 2), each video included a short description of how farmers are affected by landslides and floods and highlighted some key aspects related to each specific DRR measure. Both videos showed testimonies of a model farmer and were played in the local language with an English translation of the key points running on the Android phone/ tablet screen. The survey started with the collection of data on household and plot characteristics. This was followed by the DCE-Video-DCE session. Both DCEs were conducted at the plot level up to three plots. In this way, we assumed that the adoption decisions for different plots owned by a household are correlated but the decision of one household is independent of another household.

2.5. Econometric analysis

The mixed logit model (MXL) was applied to estimate the farmers' preferences for the DRR measures in the full sample to evaluate the general preferences. MXL relaxes the independence of irrelevant alternatives (IIA) property and allows for preference heterogeneity[10] (Greene, 2002). The IIA property requires that the relative probability of choosing an alternative in a pair of alternatives should not change relative to each other if the third alternative is introduced or removed. In other words, the error terms should not be correlated across alternatives (Shi & Yin, 2018; StataCorp, 2023). Due to the low degrees of freedom stemming from fewer cards observed by the respondents, there were model identification and convergence problems experienced when estimating the subsamples using the MXL model, as explained by Vij and Walker (2014). Therefore, to investigate how preferences are impacted by the information provided, and how such impact varies across plot characteristics, a conditional logit (CL) model was applied. The CL model satisfies the IIA and homogeneity properties thus, is considered restrictive.

The CL model remains the typical estimation model for DCEs and can appropriately estimate the utility when a linear relationship between utility and the parameters of the deterministic components is assumed (McFadden, 1974). Maximum likelihood estimation of the CL provides efficient asymptotic and normally distributed estimates even with small samples. We account for heterogeneity in preferences in the MXL model for the full sample using a CL model, following Jumamyradov et al. (2023). In the subsamples, we also assessed three plot characteristics expected to influence choice behaviour in the presence of disaster risks. They include plots without any DRR measures implemented, plots at risk of landslides and floods, and plots both at risk and without any DRR measures implemented currently.

For the empirical analysis, the utility a respondent derives from the choice of a DRR measure is based on RUT (McFadden & Train, 2000), which is comprised of a deterministic (observable) component denoted by v, and a stochastic/ random (unobservable) component (ε). The utility (U) derived by a farmer for a given plot (represented by the farmer-plot combination *i)* from alternative j among the total set of alternatives in a choice card q is presented as follows:

$$U_{ijq} = v_{ijq} + \varepsilon_{ijq} = ASC + \beta_i x_{ijq} + \varepsilon_{ijq} \quad (1)$$

Where ASC is the alternative-specific constant that describes preferences for one of the alternatives over the status quo, x_{ijq} is a vector of the attributes of the alternatives, β_i are the preferences of each attribute, and are the random components, which are assumed to be independently and identically distributed (iid) across individuals and alternatives, and follow a type I extreme value distribution (Greene, 2002; Gujarati, 2004). Under the iid extreme value assumption, the probability that the farmer for a given plot (represented by the farmer-plot combination *i)* chooses alternative j in the choice card q is given by:

$$\boldsymbol{P_{ijq}} = \frac{\boldsymbol{e^{ASC+\beta_i x_{ijq}}}}{\sum_{\boldsymbol{k}=1}^{\boldsymbol{k}} \boldsymbol{e^{ASC+\beta_i x_{ikq}}}} \quad (2)$$

Where k, is the number of alternatives in each choice card. Equation (2) shows that the probability of choosing alternative j depends on the attribute levels of that alternative and other alternatives k in the choice card. Using the choice sequence for all the choice cards selected by an individual, we introduce the probability density function $h(\beta)$ for the coefficients of the attributes to obtain the unconditional probability, following Zhang et al. (2019):

$$\boldsymbol{P_{ij}} = \int \frac{\boldsymbol{e^{ASC+\beta_i x_{ijq}}}}{\sum_{\boldsymbol{k}=1}^{\boldsymbol{k}} \boldsymbol{e^{ASC+\beta_i x_{ikq}}}} h(\beta) d(\beta) \quad (3)$$

In both (MXL and CL) models, categorical attributes were dummy-coded for easy interpretation of attribute coefficients (Mariel et al., 2021). To make conclusions about the interest in the adoption of the two measures regardless of the attributes we also run a model with effect-coded categorical variables. While effect-coded ASC captures purely preferences for alternatives, dummy-coding not only captures pure preferences for the alternatives but is also confounded with the base levels of the dummy-coded attributes (Daly et al., 2016; Mariel et al., 2021).

3. Results

3.1. Socio-economic profile of the farming households and plot characteristics

Of the 319 households surveyed, seven respondents (2.19%) always chose the status quo in the tree planting DCE and thus were dropped. Likewise, six respondents (1.89%) were dropped because they always chose the status quo in the diversion channel DCE. Table 2 shows the household and plot characteristics of the final sample with 312 and 313

Table 2. Farming household and plot characteristics.

Variable	Tree planting			Diversion channels		
	Control	Treatment	Full sample	Control	Treatment	Full sample
Household Characteristics (Households)	154	158	312	159	154	313
Categorical variables (%)						
Gender (male household head)	88.96	82.91	85.90	81.76	89.61	85.62*
Farmer group membership (household)	37.01	37.34	37.18	35.85	38.96	37.38
Access to credit by the household	20.13	24.05	22.12	23.90	21.43	22.68
Extension visits to the household	25.97	29.75	27.88	28.93	25.97	27.48
Access to NGO support by the household	5.84	10.13	8.01	10.06	5.84	7.99
Mobile phone ownership (household head)	87.66	90.51	89.42	89.94	87.66	88.82
Household head's education (≤primary level)	63.64	63.29	63.46	64.15	62.99	63.58
Numerical variables (mean (Std dev))						
Age (household head)	45.78 (15.69)	44.63 (12.86)	45.19 (14.32)	44.55 (12.89)	45.46 (15.41)	45.00 (14.17)
Family size (number of persons)	6.95 (2.99)	6.89 (2.90)	6.93 (2.95)	6.88 (2.86)	6.92 (3.01)	6.90 (2.93)
Land size (acres of land)	3.06 (2.62)	3.00 (2.47)	3.03 (2.54)	2.96 (2.49)	3.04 (2.61)	3.00 (2.54)
Household income (Uganda shillings (UGX)/ six months)	386,263.00 (584076.00)	469,906.70 (946148.70)	428,621.00 (788353.20)	459,404.10 (943627.00)	380,094.20 (581920.90)	420,382.60 (786486.40)
Plot characteristics (plots)	**304**	**307**	**611**	**306**	**305**	**611**
Plots owned (not rented) (%)	97.70	97.39	97.55	97.39	97.70	97.55
Perceived at risk of landslide or floods (%)[a]	71.38	70.68	71.03	70.59	70.82	70.70
Plots with diversion channels (%)	33.88	35.50	34.70	35.95	34.75	35.35
Plots with trees (%)	39.80	38.11	38.95	37.91	39.02	38.46
Plot without trees and at risk (%)	40.13	39.74	39.93	39.54	40.33	39.93
Plot without div channels and at risk (%)	49.01	47.56	48.28	47.39	48.20	47.79
Plot steepness (steep) (%)	58.22	57.33	57.77	56.86	57.38	57.12
Plot landslide history (was affected) (%)	32.57	29.32	30.93	29.41	31.80	30.61
Plot flood history (was affected) (%)	15.79	17.92	16.86	18.30	15.74	17.02
Plot size (acres of land) (mean (Std dev))	1.37	1.33	1.35	1.32	1.35	1.34

Standard deviations in parentheses for numerical variables. *Significant gender difference ($p < 0.05$) between the control and treatment groups for diversion channels. [a]This is the share of plots reported to be at moderate or high risk of at least one of the two disasters.

respondents for the tree planting DCE and diversion channel DCE, respectively. The samples contain almost (but not entirely) the same respondents. Nevertheless, because the majority of the individuals are the same in both samples, we discuss the descriptives together/overall. Furthermore, we applied chi-square and t-tests to examine the differences between respondents randomly assigned to the treatment and the control groups in each DCE. Results for the tree planting sample show no significant difference between the control and treatment groups. However, for diversion channels, there is a significant difference for gender at $p < 0.05$ (slightly more female household heads in the control than treatment group).

In the full sample (control and treatment for each DRR measure combined), 86% of the households sampled had male household heads. The household heads were on average 45 years old, and the majority (64%) had primary-level education and below. On average, a household comprised of seven members, owned three acres of land, and earned a farm income of UGX 420,000 every six months.[11] About 89% of the households owned a mobile phone. In terms of institutional support, out of the entire sample, 37% of the households were members of a farmer group which helps them to save and share money and other resources. About 22% accessed credit from commercial institutions, 28% had extension visits, and only 8% received support from NGOs in the six months before the survey. The sample contained information about 611 plots and each household owned about two plots. The average plot size was about 1.3 acres and 97% of the plots were owned (not rented). The share of plots that are perceived to be at risk of at least one of the two hazards is 70%. Nonetheless, less than 40% of the plots had a diversion channel or tree. Furthermore, over 40% of the plots without trees and/or diversion channels were perceived to be at risk of both landslides and floods. Lastly, 57% of the plots were reported by the farmer to be steep, and 31% and 17% of the plots had already experienced landslides and floods, respectively.

3.2. Preferences for tree planting and diversion channels as DRR measures

Table 3 column (1) shows the preferences estimated using the MXL model for the full sample on tree planting, irrespective of whether respondents received information or not. The effect-coded ASC is significant suggesting that farmers generally prefer to plant trees compared to no trees. Moreover, farmers expressed a significant preference for a higher percentage of erosion control and more maintenance days. Results also confirm that farmers generally disliked trees with a longer maturation period. Additionally, farmers significantly preferred trees with deep roots and large canopies over trees with deep roots and small canopies, while they disliked trees with shallow roots and large canopies compared to the same base level. Lastly, the significant standard deviations indicate preference heterogeneity for all six attributes.

For the diversion channel DCE as indicated in Table 3 column (1), the preference for diversion channels was significant based on the ASC. Additionally, farmers preferred a higher percentage of soil erosion reduction, similar to the finding for tree planting. Furthermore, farmers expressed significant preferences for moderate and high grass strips compared to the absence of grass strips on the channels. Surprisingly, the parameter

Table 3. Mixed logit (full-sample) and Conditional logit model (Sub-samples) based on dummy-coding (effect-coding is used only to interpret the ASC).

	Tree Planting DCE									
	Full sample (1)		Information treatment (2)		Plot without trees (3)		Plot at risk (4)		At risk & without trees (5)	
Attributes and levels	Coeff (β)	Std. dev	Control (β)	Treatment (β)	Control (β)	Treatment (β)	Control (β)	Treatment (β)	Control (β)	Treatment (β)
ASC1 (effect-coding)	17.974***	14.455***	0.486***	0.483***	0.507**	0.357*	0.602***	0.920***	0.605**	0.854***
ASC2 (dummy-coding)	26.715***	19.155***	0.989***	1.144***	0.989**	0.814*	1.241***	1.978***	1.219*	1.635***
Cost per tree (UGX)	0.026	0.090*	0.023*	−0.006	0.007	−0.019	0.028*	−0.010	0.017	−0.026
Erosion reduction (%)	0.172***	0.225***	0.074***	0.085***	0.065***	0.077***	0.080***	0.071***	0.065**	0.052*
Number of trees per acre	−0.006	0.198**	−0.003	0.013	−0.020	0.016	−0.015	0.007	−0.018	0.010
Maintenance days /month	0.051**	0.126***	0.012	0.029**	0.008	0.032**	−0.000	0.027	−0.006	0.036*
Maturity period (years)	−0.037*	0.210*	−0.005	−0.026**	0.003	−0.011	−0.003	−0.039**	0.008	−0.026
Root and canopy[a]										
Shallow & large	−0.708**	0.460	−0.258	−0.611***	−0.188	−0.562***	−0.261	−0.554**	−0.211	−0.409
Shallow & small	−0.337	0.355	0.011	−0.347*	0.077	−0.169	−0.073	−0.389	−0.034	−0.015
Deep & large	0.509*	2.582***	0.175	0.252*	0.209	0.332*	0.181	0.389**	0.212	0.716***
Log-likelihood	−1224.360		−777.560	−786.120	−489.850	−504.280	−541.770	−519.540	−316.460	−295.160
# Observations	5,499	5,499	2,736	2,763	1,647	1,710	1,953	1,953	1,098	1,098
	Diversion channel DCE									
	Full sample (1)		**Information treatment (2)**		**Plot without div. (3)**		**Plot at risk (4)**		**At risk & without div (5)**	
Attributes and levels	**Coeff (β)**	**Std. dev**	**Control (β)**	**Treatment (β)**	**Control (β)**	**Treatment (β)**	**Control (β)**	**Treatment (β)**	**Control (β)**	**Treatment (β)**
ASC1 (effect coding)	8.958***	6.359***	0.546***	0.805***	0.330**	0.594***	0.768***	1.110***	0.536**	0.863***
ASC2 (dummy coding)	15.041***	12.020***	0.778***	1.394***	0.419	1.158***	1.162***	1.884***	0.858*	1.577***
Cost /channel (UGX)	0.436***	1.239***	0.163**	0.163**	0.212**	0.199**	0.169*	0.098	0.311**	0.117
Erosion reduction (%)	0.679***	1.344***	0.304***	0.246***	0.246**	0.250**	0.248**	0.264**	0.145	0.357***
No. of channels per acre	−0.009	0.336***	0.014	−0.027*	0.019	−0.051**	0.029	−0.027	0.045	−0.056**
Maintenance days/month	−0.018	0.145**	−0.011	0.008	−0.009	0.025**	−0.009	0.008	−0.016	0.027*
With grass strips[b]										
Low strips	0.176	0.746***	0.098	0.005	0.098	−0.164	0.131	0.134	−0.043	−0.026
Moderate strips	1.422***	1.064**	0.547***	0.488***	0.394**	0.353**	0.662***	0.600***	0.468**	0.360*
High strips	1.256***	0.188	0.462***	0.669***	0.434**	0.400**	0.439**	0.783***	0.488**	0.466**
Location of channels[c]										
Systematic	0.095	0.500	0.003	−0.050	−0.001	−0.143	0.034	0.016	−0.027	0.016
At boundaries	0.116	0.924	0.111	−0.176	0.031	−0.205	0.166	−0.144	−0.013	−0.167
Log-likelihood	−1216.410		−741.050	−702.340	−511.680	−472.120	−500.930	−473.270	−350.280	−324.160
# Observations	5,499	5,499	2,754	2,745	1,764	1,791	1,944	1,944	1,305	1,323

Base levels: [a]Deep roots & Small canopy, [b]No strips; [c]Random location. Sig. levels:* $p < 0.1$, ** $P < 0.5$, and *** $P < 0.01$. Acronyms: ASC-Alternative Specific Constant; div. – diversion channels.

estimate for the cost of digging a diversion channel is positive and significant. Preferences for the number of channels, the number of maintenance days, and the location of channels were insignificant. Nevertheless, the significant standard deviations suggest preference heterogeneity for most attributes, except the location of the diversion channels. To gain more insights into preference heterogeneity, we investigate the effect of information on preferences (Section 3.3) and how this effect is influenced by the plot characteristics investigated (Section 3.4).

3.3. Effect of information on preferences for tree planting and diversion channels

In the tree planting DCE, the CL model estimated for the control and treatment groups (sub-samples) reveals that the effect-coded ASC demonstrates a significant and positive preference for the proposed DRR measure (Table 3, column (2)). Respondents in the control group had a positive and significant preference for higher prices and a higher percentage of soil erosion reduction. Respondents in the treatment group demonstrated significant preferences for more maintenance days, shorter tree maturation, and trees with deep roots and large canopies. Additionally, only this group of respondents significantly disliked trees with shallow roots (irrespective of the canopy structure) over trees with deep roots and small canopy. In the diversion channels DCE, the preferences were similar for the control and treatment groups, except for the number of diversion channels. Both groups prefer higher prices, and higher percentages of soil erosion reduction, as well as channels with moderate or high grass strips compared to no grass strips. The treatment group prefers a significantly lower number of diversion channels, while this preference was not observed among the control group.

3.4. The effect of information on preferences across different plot characteristics

To gain insights into how the influence of information on preferences varies across plot characteristics, we estimated the CL model for the control and treatment groups for three plot characteristics[12] (Table 3, columns (3), (4), and (5)). In the tree planting DCE, the coefficients of the effects-coded ASCs are significant across all plot characteristics indicating a significant utility derived from tree planting for both the control and treatment groups. However, the significant preference for trees with deep roots and large canopies (over deep roots and small canopies) is observed only within treatment groups. Furthermore, this preference is consistent across the three plot characteristics, particularly even more significant ($p < 0.01$) within the sub-sample of respondents with plots at risk for landslides and floods, and currently without trees. Similarly, the same sub-samples have a significant preference for more maintenance days, except for plots at risk. Finally, while fast maturation is significant only for the treatment group with plots at risk, cost per tree seedling is significant for the control group in the same sub-sample. In the diversion channels DCE, there was a significant preference for fewer channels per acre by the treatment group for the sub-sample without diversion channels, and the sub-sample with plots at-risk and without diversion channels. The same sub-sample had significant preferences for more maintenance days.

4. Discussion

4.1. Preferences for tree planting and diversion channels as DRR measures

Generally, this study indicated a significant preference for the two DRR measures as opposed to not implementing them. Households have a preference for several coping mechanisms, which is in line with the findings of Kisira et al. (2023). Our findings also suggest that the two measures can be integrated to reinforce each other to increase effectiveness in disaster risk reduction (Kizito et al., 2022; Mati, 2012). However, more research is needed to assess whether households are willing to implement both measures simultaneously on a plot.

In the tree planting DCE, there was a significant preference for a higher percentage of soil erosion reduction. The result is not surprising, since soil erosion is the initiator of soil profile damage that results in landslides or floods (Kumawat et al., 2020). Erosion also increases the destructive power of a landslide by amplifying the debris mobility, travel distance, and impact (Pudasaini & Krautblatter, 2021). From an economic perspective, more maintenance days might be burdensome in terms of labour. However, as expected, farmers make trade-offs between purely the economic objective or both economic and conservation objectives. For the latter, the preference for more maintenance days through pruning might explain the respondents' desire to reduce competition with crops for light, and space such that both crops and trees grow together. For timber tree species, this practice may be done to maintain vigor and shape. Lastly, a significant preference for fast maturation indicates the desire for trees that take fewer years to establish the canopy and root structure for DRR, and other benefits like wood, fruits, and shade (Kobayashi & Mori, 2017).

In the diversion channel DCE, the attribute levels favorablle for DRR such as higher percentages of soil erosion reduction, and moderate and high grass strips were significant and positive. Grass strips are commonly established from native grass species such as Guatemala *(Tripsacum laxum)*, Napier grass *(Pennisetum purpureum)*, and Lemon grass *(Cymbopogon citratus)* (Ericksson & Kidanu, 2010). They provide ground cover, intercept runoff, and trap the eroded material. As a result, when reinforced with grass strips, there is an improvement in the effectiveness of diversion channels (Adere et al., 2024). Surprisingly, we find a significant preference for a higher price for digging a diversion channel. Lambrecht et al. (2015) and Oyinbo et al. (2019) also found positive and significant preferences for the price of inputs. They proposed several reasons, including (i) respondents not caring about the attribute; (ii) too small ranges of price attributes included in the choice card for realistic substitution between attributes to capture significant effects; and (ii) the correlation between input quality and price. The maximum price included in the DCE was UGX 15,000. The considered price range might be too small as the actual cost of digging a channel might be high. Also, Mati (2012) reported that a standard diversion channel usually comes at a high cost of digging. Further, farmers may assume that a higher price means better quality (deeper, longer, more stable) and effectiveness. Nonetheless, the reasons for choosing expensive diversion channels are inconclusive in our investigation, and further studies are required.

4.2. Effect of information on preferences for tree planting and diversion channels

We find significant preferences to adopt both tree planting and diversion channels by both the control and treatment groups. In the tree planting DCE, preference for DRR characteristics associated with improved effectiveness, such as increased tree maintenance days, fast maturation, and trees with deep roots and large canopies, was significant only for the treatment group. Such results indicate that information can play a role in making more informed choices about tree planting. The result suggests that most farmers are less informed about the DRR measures to apply and need more information as was suggested by Kamruzzaman and Chowdhury (2023). This is in accordance with the National Disaster Preparedness and Management Policy which lists disseminating disaster risk reduction information as a priority (OPM, 2010). However, policies such as the Uganda National Climate Change Policy (MWE, 2015), tend to disseminate general knowledge of climate change and associated risks, and pay limited attention to specific DRR measures. Informational campaigns, like the one administered in the video for this study, have been found effective in influencing respondents' preferences for agricultural and environmental conservation interventions. Usman et al. (2024) showed that 82% of secondary school students in Japan favoured adopting farming as a career after being given information on the benefits of farming. Similarly, Vanermen et al. (2021) found a significant effect of information on preferences for attributes that support forest soil biodiversity in Flanders (Belgium).

In the diversion channel DCE, preference for fewer channels per acre is the only attribute that is significant in the treatment group and not in the control group. This indicates that the information treatment has a limited impact on farmers' preferences for digging diversion channels. This does not mean that information always has a limited impact on preferences for adopting diversion channels *per se*. It rather signals that the information in the video used in this particular study had less effect on farmers' choices for diversion channels. Diversion channels serve only the purpose of soil and water conservation. Therefore, farmers might less easily be convinced to apply them based on additional information. On the other hand, information might convince farmers more easily to adopt tree planting as it is multi-purpose. Also, most farmers might already know how to apply diversion channels, and providing more information could hence be less impactful as explained by Mariel et al. (2021).

We also investigated whether selected plot characteristics provide more insights into the effect of information on preferences but found limited evidence. It could be because the household makes decisions in general without paying attention to specific plots, or other plot characteristics matter more than those investigated. Farmers at risk and without trees are expected to be more susceptible to disaster risks (Mertens et al., 2018). When still in doubt about the effectiveness of the available strategies, providing information about how trees with deep roots increase slope stability influences their preferences (Lan et al., 2020). Similarly, in the diversion channel DCE, the respondents with plots at risk and without diversion channels were influenced by the information to prefer more maintenance days and fewer diversion channels. As already indicated, if farmers are vulnerable to disasters, watching a video emphasising regular maintenance of diversion channels resulted in farmers preferring more maintenance days per month.

Moreover, according to a study by Vlaeminck et al. (2016), being at risk was found to determine the choice of a risk reduction strategy among the citizens of Uganda prone to landslide risk.

5. Limitations of the study

This study's major empirical limitation concerns two DCE dimensionality issues related to the unbalanced number of choice cards and attribute levels presented to respondents (Mariel et al., 2021). We delivered three choice cards per plot from four randomised blocks such that a respondent with three plots receives a total of nine choice cards per DCE. Since the analysis is done at the plot level there were not enough cards per plot especially for respondents with only one plot. In addition, a respondent was (erroneously) given the liberty to pick from any choice card block for the first plot, then pick another block for the second plot from the remaining blocks, and finally, a third block for the third plot. A block picked per plot was not replaced but blocks were not randomised after every picking. As a result, 40.1%, 31.3%, 18.3%, and 10.3% of respondents selected blocks one, two, three, and four, respectively, in the tree-planting DCE. Likewise, in diversion channel DCE, 39.6%, 31.1%, 17.5%, and 11.8% of respondents selected blocks one, two, three, and four, respectively. Therefore, estimating parameters on the whole range of attribute levels was difficult. Poor randomisation of blocks is associated with a lack of enough trade-offs on the attribute levels to provide sufficient information to obtain precise estimates of all parameters. The design would further improve if more choice cards (per block) were included and randomisation was properly done. However, this was not possible due to unforeseen mistakes made during the DCE implementation.

Fewer cards observed by the farmers led to poor identification of the models due to low degrees of freedom and the MXL failed to converge when estimating the sub-samples (Champ et al., 2017; Vij & Walker, 2014). Poor model identification arises due to small samples, or misspecification, in which the dataset lacks enough variability to support the estimation (Vij & Walker, 2014). This explains why we could not estimate more complex models like MXL with an interaction effect for an information treatment dummy, the same case with latent class models. Therefore, we only were able to estimate the MXL for the full-sample and CL models in the sub-samples, amidst the fact that the latter makes the unrealistic assumption of homogeneous preferences.

6. Conclusion

Using a DCE, the study aimed to investigate the characteristics of tree planting or diversion channels preferred by farmers as DRR measures and whether the preferences can be influenced by providing information. The results indicate general preferences for both tree planting and diversion channels, confirming that farmers value both measures. Preference heterogeneity was also observed for most attributes. There is generally a significant preference for higher percentages of soil erosion reduction. Moreover, smallholder farmers significantly preferred trees with deep roots, fast maturation, and regular maintenance, as well as diversion channels reinforced with moderate or high grass strips over no strips. Further, analyses of split samples revealed an effect of information on preferences for the attribute levels of tree planting, while the information effect on preferences for diversion channels was limited. Further, we found limited evidence to support our claim that the influence of information varies across plot characteristics.

Key policy implications can be derived from the results of this study. Preference for both tree planting and diversion channels suggests the need for a package of interventions by the extension agencies to enhance their effectiveness in disaster risk control and increase the adoption. Next, the study gives an important policy direction regarding the need for information provision. Current policies in Uganda are sometimes rather blunt, provide 'one size fits all' solutions, and often focus on improving general knowledge. Policy could take action to make advice more concrete so that adoption increases e.g. by informing about the relevance of planting trees and tree maintenance, and by promoting planting trees that are fast maturing and have deep root systems. Further, the results illustrate that integrating videos in extension tools can alter farmers' preferences (and thus the likelihood) to adopt DDR measures. In addition, short videos (distributed for example via social media) can be an option to disseminate useful information because, despite the limited accessibility of certain areas, many households still own a (smart) phone.

Further, this study also creates avenues on which further research should focus. Information provisioning impacts preferences for some DRR attributes, but not all. This does not mean that information always plays a limited role *per se*. The limited effect can potentially be attributed to inadequate information provided in the video. For example, in the video, it was not stressed that very steep plots might need diversion channels more randomly spread and a higher number of trees. The limited evidence of information could also be because we were not able to estimate complex models such as the latent class and the MXL with an interaction effect for the information treatment dummy.

Notes

1. Flash floods arise from an elevated terrain and can happen in any location resulting from heavy rainfall irrespective of any overflowing nearby water body. Shallow landslides, on the other hand, are the mass movement of rock, debris, or earth less than three meters deep, down the slope, movements deeper than three meters would be referred to as deep-seated landslides (Maes et al., 2018).
2. Diversion channels can divert excess water from the plot while retaining some amount but retention ditches retain all incoming runoff for infiltration and are used where there is no space for discharge runoff (Mati, 2012).
3. A standard diversion channel should be about 0.6–1.4 m bottom width, 1.2–2.8 m top width, 0.3–0.7 m deep, and up to 250 m long and about five channels per acre (Mati, 2012).
4. D-SiRE (Digital Citizen Science for Community-Based Resilience on Environmental Management) is a TEAM project under VLIR-OUS, in which citizen scientists known as geo-observers are recruited on recommendation by the local community, trained and report disaster events using smartphones. Thanks to the D-SiRE project that also provided the funding for this study.
5. See Catherine et al. (2008) and Khan et al. (2015) for further details on stratified sampling.
6. 1 USD = 3586 UGX at the time of the survey.
7. We assume that there is no additional cost associated with attribute other than 'cost of tree seedlings'.
8. A mature tree of about 10 years old, depending on the nature of the root structure and size of the canopy, can absorb in the trunk and branches about 1,500–2,000 liters of water which helps to keep the water table down (van Noordwijk et al., 2019).
9. Lan et al. (2020) describe a tree as having deep roots if they extend up to 2 m from the surface and shallow if less than 40 cm from the surface.

10. Preference heterogeneity arises due to individual taste differences for specific attributes but could also be due to scale heterogeneity, which is related to the fact that choice consistency varies across respondents, implying an individual-specific error variance (Gamboa et al., 2018).
11. Six months were used to evaluate income and other institutional factors like credit access, extension, and group membership in the study area because farmers depend on rainfed smallholder agriculture. They also have two seasons of planting in a bi-model rainfall pattern. Therefore, the period between planting, harvesting, and selling is equivalent to six months.
12. See Appendix 3 for plot steepness, landslide history and flood history

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Disclosure statement

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Author contribution

All authors contributed to the study as follows: **Rodgers Mutyebere:** Conception and design of the study, material preparation, data collection, analysis, and writing the manuscript. **Iris Vanermen**: data analysis, reviewing, and editing, **Kato Van Ruymbeke:** data analysis, reviewing, and editing, **Jean Bosco Nkurikiye**: data analysis, reviewing, and editing, **Ronald Twongyirwe**: Conception and design of the study, supervision, reviewing, and editing, **John Sekajugo:** GIS work**,** reviewing, and editing, **Clovis Kabaseke:** funding acquisition, project administration, reviewing, and editing, **Violet Kanyiginya:** reviewing, and editing, **Grace Kagoro-Rugunda**: funding acquisition, project administration, reviewing, and editing, **Matthieu Kervyn**: funding acquisition, project administration, reviewing, and editing, and **Liesbet Vranken**: Conception and design of the study, funding acquisition, project administration, supervision, reviewing, and editing. All authors approved the final manuscript.

Data availability

Data will be made available on request.

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Appendices

Appendix 1: field photos taken in 2022

(a). Diversion channels on a farm in the Rwenzori region (shown by the white arrows)
Source: Authors' field photos, 2022

(b). Tree planting for slope stability on a farm in the Ankole region (shown by the white arrows)
Source: Authors' field photos, 2022

Figure 3.

(a). Flash flood in Kasese District (Rwenzori sub-region) (shown by the white arrows)
Source: Authors' field photos, 2022

(b). Shallow landslide in Buhweju District (Ankole sub-region) (shown by the white arrows)
Source: Authors' field photos, 2022

Figure 4.

Appendix 2: scripts for the self-made videos

Tree planting

- The weather in this area is no longer reliable due to climate change and our crops and animals in Uganda are increasingly vulnerable to disaster risks such as floods and landslides.
- Imagine a farmer plants his crops every season but loses it all due to floods and landslides.
- Our soil is no longer fertile due to soil erosion.
- Our houses and other farm structures are destroyed by floods and landslides every rainy season.
- In some cases, our loved ones are killed by such disasters every year too.
- Our fore parents did not have such dangerous disasters although they lived in the same place.
- The government and other development partners such as universities, and NGOs have advised us to put disaster risk reduction strategies to reduce the impact of disasters such as floods and landslides.

- Tree planting is such an important strategy that I have chosen to apply on my farm to reduce the impacts of soil erosion, floods, and landslides.
- Ever since I applied the trees, I feel my household members and neighbours are safe from such disasters.
- However, when choosing to plant a tree, one should know that not all trees or tree attributes/characteristics are good.
- A good tree that is more effective to landslides and floods should have a deep and strong tap root system to prevent sliding of the soil block, and soil binding roots to prevent soil detachment. We also need to have a wider canopy to reduce the intensity of raindrops hitting the soil.
- As the roots of the tree holds the soil particles together, the canopy reduces raindrop intensity, tree trunks block material transportation, and dropping leaves provide a soil cover and soak the water.
- Compared to a bear ground, having trees saves me about 5%–15% soil loss every rainy season.
- I consider the cost of tree seedlings and the amount of labour required to maintain the tree. For me, the cost of buying and maintaining a tree is less important, as long as the tree keeps my family and the gardens safe from disasters. Normally, I choose indigenous tree species for agroforestry and are usually.
- I advise fellow farmers to choose the right population of trees in a given area if trees are to be effective for landslides without impacting farm yield negatively. On my farm, I apply about 30–50 trees per acre.
- Also, when choosing a tree, I consider its maturity period. For me, a tree should be able to grow and start reducing floods, landslides, or soil erosion by the time it is 5–10 years. A tree taking longer than that would leave my farm more exposed to landslides and floods for a long period.
- As I conclude, if every household plants the right tree variety in terms of the maturity period, root and canopy structures, and maintains the tree through pruning, we shall have the problem of climate change-associated disasters such as floods and landslides solved.

Diversion channels

- The weather in this area is no longer reliable due to climate change and our crops and animals in Uganda are increasingly vulnerable to disaster risks such as floods and landslides.
- Imagine a farmer who plants his crops every season but loses it all due to floods and landslides.
- Our soil is no longer fertile due to soil erosion.
- Our houses and other farm structures are destroyed by floods and landslides every rainy season.
- In some cases, our loved ones are killed by such disasters every year too.
- Our fore parents did not have such dangerous disasters although they lived in the same place.
- The government and other development partners such as universities, and NGOs have advised us to put disaster risk reduction strategies to reduce the impact of disasters such as floods and landslides.
- The use of diversion channels is an important strategy, among many available strategies that I have chosen to apply on my farm to reduce the impacts of soil erosion, floods, and landslides.
- Diversion channels are water harvesting structures that increase water availability for crop use and also divert and reduce the erosive speed of the surface runoff.
- Not all diversion channels are effective for disaster risk management and erosion reduction. I choose certain practices on diversion channels carefully.
- On my farm, most diversion channels have a high amount of Vegetative strips (in terms of volume) to trap the material transported and reduce the speed of water outburst at each diversion channel.
- Maintaining the diversion channels comes at a cost. To me, the price paid is less important as long as the channel effectively reduces the vulnerability of my plot to landslides and floods.
- Sometimes I spend over UGX 15,000 to dig or maintain a single channel per season. Or I spend about 10 days emptying it after every rainy season.

- I also make sure I have an appropriate number of channels in a given space/ size of the garden. On average, I apply about 4 horizontal diversion channels at a spacing of about 30 ft from one channel to the next.
- I also think carefully about the location of a diversion channel in my plot. While some people scatter them randomly without a clear plan, I put the main diversion channel at the boundary, and uniformly place the rest in the middle of the garden following an organised pattern.
- Lastly, with the recommended size (12ft × 2ft × 2 ft) before the next tie band can reduce about 5%–15% soil erosion per season (compared to areas without channels).

As I conclude, if every household applies the right number of diversion channels correctly in terms of recommended size, maintains them, plants grass strips on the channel, and chooses a systematic layout, we shall have the problem of climate change-associated disasters such as floods and landslides well solved.

Appendix 3

Table A1. The effect of information on farmers' preferences across plot steepness, landslide history, and flood history.

Tree planting DCE						
	Plots on steep slopes		Plots previously hit by landslides		Plots previously hit by floods	
Attributes and levels	Control (β)	Treatment (β)	Control (β)	Treatment (β)	Control (β)	Treatment (β)
ASC1 (effect-coding)	0.481**	0.674***	0.975***	0.932***	1.439***	0.780*
ASC2 (dummy-coding)	0.942*	1.549***	1.952***	1.911**	2.801***	1.718**
Cost per tree (UGX)	0.021	0.029	−0.017	0.012	−0.011	−0.055
Erosion reduction (%)	0.084***	0.085***	0.092***	0.072**	0.063*	0.116***
Number of trees per acre	−0.012	0.026	−0.033	0.014	−0.084***	0.054
Maintenance days /month	0.021	0.018	0.005	0.018	−0.024	0.035
Maturity period (years)	−0.009	−0.033*	−0.021	−0.028	−0.063**	−0.080***
Root and canopy[a]						
Shallow & large	−0.270	−0.636**	−0.162	−0.297	0.094	−0.371
Shallow & small	−0.008	−0.480**	−0.151	−0.221	0.107	−0.349
Deep & large	0.359*	0.311*	0.302	0.327	0.105	0.088
Log-likelihood	−441.396	−413.145	−237.636	−209.598	−118.463	−124.402
# Observations	1,593	1,584	891	810	432	495

Diversion channel DCE						
	Plots on steep slopes		Plots previously hit by landslides		Plots previously hit by floods	
Attributes and levels	Control (β)	Treatment (β)	Control (β)	Treatment (β)	Control (β)	Treatment (β)
ASC1 (effect coding)	0.856***	0.860***	0.646**	0.946***	0.271	1.126***
ASC2 (dummy coding)	1.413***	1.435***	1.212*	1.879***	0.377	2.030**
Cost /channel (UGX)	0.227**	0.047	0.392***	0.165	0.375	−0.066
Erosion reduction (%)	0.239**	0.377***	0.118	0.075	0.395	0.138
No. of channels per acre	0.038*	−0.036*	0.051	0.015	0.056	−0.010
Maintenance days/month	−0.019	0.011	−0.058**	−0.024	−0.004	−0.021
With grass strips[b]						
Low strips	0.093	0.209	−0.283	−0.035	−0.006	0.058
Moderate strips	0.555***	0.606***	0.533**	0.423	0.565	0.356
High strips	0.564***	0.877***	0.463*	0.798***	0.799**	0.989**
Location of channels[c]						
Systematic	−0.062	−0.040	−0.241	−0.261	−0.207	−0.115
At boundaries	0.052	−0.374**	−0.052	−0.591***	−0.318	−0.275
Log-likelihood	−384.779	−392.287	−204.568	−228.549	−114.048	−114.908
# Observations	1,566	1,575	810	873	504	432

Base levels: [a]Deep roots & Small canopy, [b]No strips; [c]Random location. Sig. levels:* $p < 0.1$, ** $P < 0.5$, and *** $P < 0.01$. Acronyms: ASC-Alternative Specific Constant; div.– diversion channels.