International Journal of Disaster Risk Reduction 136 (2026) 106070

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Farmers' social networks and adoption of disaster risk reduction measures: An experimental study in Uganda

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A R T I C L E I N F O

Keywords:
Citizen scientists
Disaster risk reduction measures
Landslides
Floods
Experimental study
Western Uganda

A B S T R A C T

Action against the severe impacts of climate change requires strengthening the local community's resilience to hazards such as landslides and flash floods. Therefore, improving farmers' knowledge to adopt farm-based Disaster Risk Reduction (DRR) measures is key. In addition, mountainous areas limit accessibility by external, less-facilitated government extension workers mandated for information transfer. Other informal, local social networks can play a role to promote DRR measures' adoption, but their effectiveness remains unclear. Using an experimental study involving 533 rural households, we investigated the effectiveness of different channels of information transfer: we tested whether a network of Citizen Scientists (CS) - an example of local social networks, can promote adoption of tree planting and diversion channels as DRR measures in the disaster-prone Western Uganda region. We also examined whether the CS network was more effective, than conventional outreach formal extension workers in influencing farmers' behaviour. Analyzing the treatment effect using the Analysis of Covariance, findings indicate that knowledge transfer through CS – either in one-on-one or group sessions - is more effective in enhancing tree adoption than transfer through external agents. For diversion channels, only group sessions facilitated by CS significantly increased their adoption but not the sessions by external agents or CS-facilitated one-on-one sessions. Therefore, social networks promise a bright future for knowledge transfer but may not be a 'silver bullet' to information access problems. Long-term impact of knowledge transfer, adoption by others in the farmers' networks, and integrating social networks like CS into the formal extension programs should be investigated.

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https://doi.org/10.1016/j.ijdrr.2026.106070
Received 15 May 2025; Received in revised form 17 December 2025; Accepted 21 February 2026
Available online 27 February 2026

1. Introduction

Climate-related hazards account for most of the world's disasters, which are estimated to have caused economic losses totaling to US$ 171.3 billion in 2020 [1]. In addition, between 2010 and 2020, about 1.7 billion people were affected and over 410,000 deaths recorded world-wide [2]. In Sub-Saharan Africa, 2.6 million people were internally-displaced by climate hazards in the year 2021 alone [3]. Therefore, there is urgent need to take action to combat severe impacts of climate change (Sustainable Development Goal 13) [4,5]. This can be achieved through strengthening communities' adaptive capacity and resilience to climate hazards. While hazards refer to events that can potentially disrupt human beings and the natural system, they turn into disasters when they exceed the community's coping capacity and hamper socio-economic development [6]. Moreover, disasters impact people disproportionately, with the poor, women, young, elderly, and those on the fringes of societies in low- and middle-income countries more affected due to limited resources [7]. Affordable and scalable solutions are urgently needed for the local communities to address such escalating risks [8]. Thus, there is a need to improve knowledge and awareness of disaster risk reduction (DRR), which is not yet attained by many countries, as indicated in the UN [9] report.

In low- and middle-income countries, people predominantly depend on agriculture for their livelihoods, amidst climate challenges, demographic, socio-economic, and political bottlenecks [7]. Climate hazards such as extreme rainfall events, threaten food security through damaging crops and animals, change the copping seasons, and lowering soil and water quality [10]. Therefore, promoting affordable land use practices such as farm-based DRR among local communities is crucial [11]. The aim should be to build a resilient agriculture sector that withstands hazards such as shallow landslides and flash floods.[1] However, such efforts are often hampered by inadequate awareness attributed to information asymmetries, in which rural areas have limited access to information compared to urban and peri-urban centres [12].

Traditional agricultural extension services, usually provided by the government, remain the main conduit of technical information in rural communities in low- and middle-income countries [13]. However, due to the ragged terrains of mountainous areas characterized by landslides and flash floods, accessibility by external knowledge transfer agents is much more limited. Most studies focus on traditional climate action strategies but often ignore the crucial role of social capital and the potential to leverage social networks and civic engagement in information sharing [14]. Non-governmental, informal knowledge transfer approaches that are targeted to specific climate interventions, relying upon local social networks, and are trusted by the farmers can be important for the adoption of DRR measures' adoption.

Social networks refer to social capital comprising of individuals interacting consciously, and are referred to as social information networks when their main role is information exchange [15]. A study by Ulibarri et al. [16] stressed that the role of social capital in climate adaptation should not be underestimated as it enhances adoption at local scales, especially where formal extension services are limited. Social networks can be bonding (strong ties) or bridging/professional networks (weak ties) [17,18]. Bonding networks, also known as informal social networks, refer to social linkages between actors of the same sub-group, usually from the same geographical location, such as family members, neighbours, and friends. Bridging/professional networks, also known as formal networks, are comprised of less related actors, such as extension workers, and universities. If citizen science projects are occurring in a region, and then the network of involved citizen scientists (CS) could play a crucial role in knowledge transfer. CS are members of the general public (non-professional scientists) who collect data and monitor scientific initiatives in their communities in collaboration with professional scientists [9,19]. CS are an example of a local, informal social network, and are trusted because they are usually selected from local communities, but also have links with professional scientists since they are part of a citizen science project [20,21].

CS have great potential to add to the scientific expertise at a local-scale regarding DRR by providing real-time data and sharing knowledge in disaster-prone regions [22,23]. While Assumpção et al. [24] explored the opportunities and challenges of citizens' contribution to flood modelling, Jacobs et al. [25] examined the role of CS in participatory sensing of disasters in a remote setting. The study indicated that CS are motivated by intrinsic and extrinsic factors but that motivation differences can result in reporting biases. Further, Jacobs et al. indicated that citizen science provides an option for transferring technical information about DRR measures from professional scientists to local communities, though this was qualitatively investigated. Ashepet et al. [26] examined the factors driving and limiting participation of two CS networks in Uganda, namely one aimed at reducing aquatic parasitic diseases by monitoring freshwater snails, and another, monitoring natural hazards. The study established that gaining knowledge and the feeling of concern for others are key motivators. Brees et al. [27] assessed the potential of citizen-driven monitoring of freshwater snails in schistosomiasis research in Uganda. The findings indicated that the approach could provide spatio-temporal solutions to data scarcity about reducing snail-borne diseases. Other studies [23,28–30] also focused on motivation, and CS' contribution to data collection, monitoring, reporting, and improving hazard data inventories. As such, citizen science in most low- and middle-income countries has focused on motivation and the role of CS in crowdsourcing where its role has been limited to visual observation, monitoring, and reporting of agro-environmental problems [21]. They focus on the role of citizen science as a one-way flow of information, mainly as data collectors. However, its potential in knowledge transfer from professional scientists to communities in order to promote good land use practices such as DRR measures is yet to be tested. Therefore, through an experimental study, we address the first research question of whether informal social networks can influence the adoption of DRR and whether this form of knowledge transfer is more effective than traditional (formal) extension networks that rely external agents. Further, it is known that the way knowledge is shared is important in navigating the knowledge landscape effectively to connect various actors to make rational decisions [31]. Therefore, we

[1] While shallow landslides refer to the mass movement of the earth (less than 3 m deep) down the slope, flash floods result from water overflow from elevated terrains after heavy rains [88].

address a second research question of whether the impact of knowledge transfer vary with the communication format, i.e., when information is delivered in individual compared to group sessions.

This study makes a significant contribution to the literature by quantitatively testing the deployment of local, non-expert citizens (CS) as an alternative channel of knowledge transfer compared to the traditional extension approach, to promote the adoption of DRR measures. Further, the study builds on Lecoutere et al. [32] and Van Campenhout et al. [33] about how to develop effective videos to disseminate information about agricultural innovations among smallholder farmers. However, our study takes it one-step further by comparing the effectiveness of informal and formal networks for knowledge transfer through video-mediated individual and group extension sessions.

Information specific to an innovation plays a key role for adopters to make informed decisions [31]. With the right and timely information, farmers could are informed about the right DRR measure, timing, and procedure of application. Moreover, specific information also influences one's attitude and subjective norm regarding the application of DRR measures [12]. According to Caffaro et al. [34], tradition extension workers typically deliver general (agronomic) information. Unfortunately, key policies often focus on disseminating general information about climate risks, and DRR strategies. Therefore, information targeting specific DRR measures remains a binding constraint to the adoption [35]. In addition, people tend to trust their local social networks for obtaining (and verifying) information about agricultural innovations [36]. Accordingly, the two hypotheses tested in this study are: (1) Farmers are willing to apply DRR strategies but lack specific information about them; (2) Information transfer by local actors, such as CS, influences the adoption decisions more than information provided by external agents.

This research focuses specifically on Western Uganda as a case study region, but the study is also relevant to many other countries facing similar challenges. Over 68% of Ugandans depend on rain-fed agriculture, but it is highly vulnerable to climate change [37]. The country experiences high and erratic rains, especially in mountainous areas where unsustainable land use practices such as extensive deforestation and bush burning are common [3]. Amid underreporting in Uganda, the annual economic loss due to landslides is estimated at US$1.05 million [38], while that of floods at US$ 62 million (World Bank Group, 2020). Agriculture remains one of the key sectors targeted for poverty eradication and economic growth [39], but the sector is severely affected by climate related hazards such as landslides and floods. Hence, there is a need to prioritize sustainable land use practices by promoting farmers' awareness about affordable DRR strategies such as tree planting and diversion channels – one of the goals of Uganda's national land use policy [40]. Studies about enhancing the adoption of DRR measures, like ours, support the national efforts to promote effective risk response as indicated in Uganda's National Policy for Disaster Preparedness and Management (OPM, 2010). They are also in tandem with the agriculture sector's National Adaptation Plan, which aims at increasing farmers' preparedness and response to natural hazards [37].

2. Materials and methods

2.1. Study area

The study area is situated in the Western Uganda districts of Kasese (0.06° N, 30.06° E), 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 (Fig. 1). D-SiRe[2] project played a key role in the selection of districts and mapping the disaster hotspots per parish. The project has been running since 2017 and is aimed at understanding the spatio-temporal distribution, damages, vulnerabilities, and risks associated with natural hazards in the region (Sekajugo et al. [23], (2024)). The selected districts comprise of areas prone to small but frequent shallow landslides and flash floods due to their location on mountain and hill slopes. The area is characterized by fertile volcanic, ferralitic, and peat soils, with alluvial soils along water bodies especially in Bundibugyo District [41]. The area also has a high bi-modal rainfall, with the first rains between March and May, and the second rains between August and December [42,43]. The mean annual rainfall ranges between 700 and 2000 mm in the Ankole Sub-region [43], while that of the Rwenzori is between 1250 and 2600 mm [44]. Buhweju and Bushenyi districts have received less attention in most disaster risk studies, yet they are also exposed to landslides and floods [29].

The study area is predominantly inhabited by smallholder farmers, who mainly derive their livelihood from subsistence farming [3, 45]. Unfortunately, some farming activities are associated with environmental-unfriendly land use practices such as deforestation, clean weeding, and bush burning, exposing the area to disaster risks [41]. Moreover, with Uganda's fast-growing population estimated at 3% per annum, people are forced to do farming in marginal areas on the mountain slopes and floodplain [46]; [47]). Thus, a combination of tectonic activities, soft soils, high rainfall, and slope disturbance by human activities escalate landslides and flood risks [48].

2.2. The citizen scientists' network in Uganda

A network of thirty CS was established within the framework of the D-SiRe project. The network builds on the initiative by a team of researchers from Mountains of the Moon University (MMU) and Belgian partners under another VLIR-UOS South Initiative (SI) project titled 'Enhancing community-based natural resources and hazard management in Rwenzori Mountains' (2017-18). Currently, the network monitors and reports the occurrence of hazards in the mountainous Rwenzori region, Ankole, and Kigezi highlands in Western

[2] D-SiRe is Digital citizen Science for community-based Resilient environmental management. It is a VLIR TEAM project implemented by the University of Leuven (KU Leuven) and Vrije Universiteit Brussel (VUB) in Belgium, and Mountains of the Moon University (MMU) and Mbarara University of Science and Technology (MUST) in Uganda.

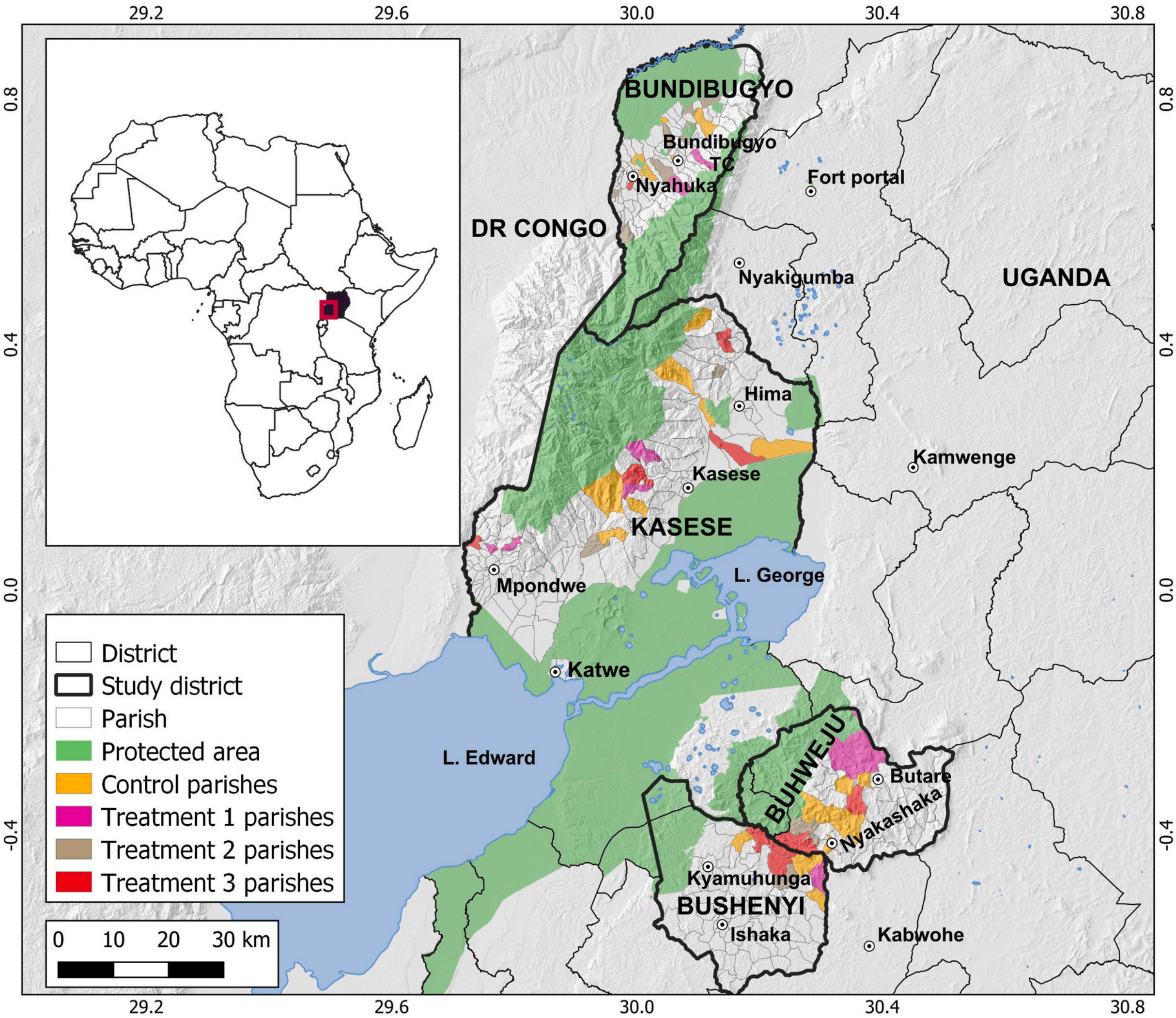

Fig. 1. Location of the study areas in Uganda, highlighting the four districts in which data collection took place.

Uganda. The CS were selected by district stakeholders, local people and civil society organizations based on the level of education (at least senior four), knowledge of smartphone technology, being native of the parish, and spirit of volunteerism.

Since the CS are part of communities where the citizen science project has been operating since 2017, most community members are aware of who the CS are and what they do. Kanyiginya et al. [28] observed high frequent reporting of hazards near the geographical boundaries of the CS's home and by CS with additional leadership positions. This could be linked to social responsibility, self-transcending values, CS having a stable residence in the community and the wider social network to facilitate information flow [30,49]. As soon as hazard events occurred, community members would call the CS due to the perception that CS's reports would reach humanitarian agencies [23]. However, the community can be frustrated if they continuously report hazards and this is not followed by tangible action [26]. This hampers enthusiasm to participate in citizen science projects and as such, it is important to pair data collection with tangible benefits for local communities.

In the context of the citizen science project considered in this study, each CS was equipped with a smartphone and trained to collect real-time and -space data about processes and impacts of droughts, earthquakes, floods, hailstorms, landslides, lightning, windstorms, and pests and diseases. Collected data were uploaded to Kobo Toolbox – an open-source mobile data collection tool that allows users to complete pre-designed forms. This was followed by data validation to enhance quality, accuracy, and completeness prior to analysis. Motivated by non-monetary incentives - such as the feeling of concern, and being able to participate in solving community problems - CS received only a modest monthly compensation, covering internet data for report submission, and transport to hazard sites. Using a multi-method approach to assess the inventories of natural hazards in Kigezi highlands, Kanyiginya et al. [28] highlighted the added value of the citizen science network: CS submitted 12 times more reports than those found in the national archives and literature for the same study period. Moreover, field report validation by Sekajugo et al. [23] confirmed high reliability, although some records were incomplete. Beyond their data collection effort, the CS also shared videos and disseminated specific information about the best practices for tree planting and diversion channels.

2.3. Sampling and experimental design

To examine the potential of local social networks, particularly citizen science, in knowledge transfer for adopting DRR measures, we tested the effectiveness of information videos transferred by CS or external agents. For the latter, we opted for someone qualified in agriculture extension but teaching at the university. We randomly assigned 55 parishes to three treatment groups and two control groups. The experimental unit is a household and the random assignment allows researchers to attribute the impact of a particular treatment precisely [50].

In the treatment group 1 (T1), each respondent watched a video screened by a CS in a one-on-one session (at home), while in treatment group 2 (T2), all respondents (per parish) watched the video shown by the CS in a group of about ten, gathered in one place. T1 and T2 were intended to test the effect of individual versus group learning. In treatment group 3 (T3), respondents also watched in groups of about ten but the video was shown by the university staff (external agent). T3 is intended to compare the effect of an external agent (less known to farmers) compared to the CS from a local social network (T2). Lastly, of the two control groups, the first (C1) comprised of households selected from parishes not having a CS but susceptible to landslides and floods, and the second (C2) comprised of the parishes covered by the project's CS. Using two control groups was done to test the effect of the mere presence of CS in a parish. As such, this study focused on 44 parishes covered by the CS of the D-SiRe project and 11 other parishes under the first control group.

To reduce the information spill-over from treated to the control groups, parishes bordering the treated parishes were not selected as control groups [50,51]. From each parish, we aimed to select randomly ten households spread over at least three villages. However, because of practical reasons such as failing to reach the targeted homesteads due to bad weather, poor roads, and difficult terrain, fewer households were obtained in some parishes, but then more were selected in a nearby parish. The actual sample size per district was as follows: 200 households from 20 parishes in Kasese, 162 households from 16 parishes in Bundibugyo, 113 households from 11 parishes in Buhweju, and 78 households from 8 parishes in Bushenyi. Selection of the number of parishes and therefore the sample of respondents per district is not proportional because it was not based on any statistical procedure. It was determined mainly by the prevalence of landslides and flash floods that influenced the allocation of CS under D-SiRe project, as further explained by Jacobs et al. [25], and Sekajugo et al. [23].

2.4. Developing the informational videos

The choice of a video-mediated information transfer approach was motivated by two factors. First, the study builds on the CS' experience because they already own Android smartphones given by the project, which they use for the day-to-day reporting of hazards and during their interactions with local communities. Thus, showing the video to farmers is relatively easy since they have adequate knowledge of the gadgets and the local people. Second, recent studies pointed out that videos can hasten the shift to a more effective knowledge-driven extension [32,33,52,53].

We prepared a video script guided by insights from literature such as Lecoutere et al. [32] and Van Campenhout et al. [33] about how to make effective and affordable videos in a local setting. The key insights include using male and female role models, using local language, and short videos to increase learning and retention. One video was in Rukonzho (mainly spoken in Kasese District), another in Rubwisi (in Bundibugyo District), and Runyankole (Buhweju and Bushenyi districts). The video in Runyankole was 10 min long, Rubwisi 14 min, and Rukonzho 17 min long. The main information in all videos was the same but the differences in length could be attributed to linguistic, cultural, and syntactic differences specific to each ethnic group. Each video had an English translation of the key points running on the Android tablet screen (see Maredia et al. [52]). All the videos played the testimonies of farmers, and were acted at the same model farm, with the 'husband and wife' appearing in the video together to avoid gender bias by the intended respondents [32]. The farmers who acted as role models and the demonstration farm were selected from the local setting susceptible to hazard risks similar to those targeted in the study area (see van Campenhout [54]). Each video was in the form of informational campaigns and started with a description of a diversion channel and then tree planting,[3] and concluded with a recap about the two measures.

The video addressed the escalating incidence of climate-related hazards in the region, associated damage and the role of farmers in both contributing to and suffering from these events. Furthermore, the video introduces DRR measures - such as tree planting and diversion channels – which farmers can adopt to mitigate the hazard effects. It highlights the best practices of the DRR measures, emphasizing the importance of correct application procedures, the right timing of activities, and regular maintenance to ensure their effectiveness. The video concludes with an appeal to all farmers in hazard-prone mountainous areas, urging them to adopt the DRR measures to enhance resilience against climate-induced hazards. The video was pretested with ten farmers in Bundibugyo to examine the clarity of its content. The feedback led to corrections thereby improving the quality and relevance of the final videos. Piloting in Bundibugyo District alone was considered appropriate because the pre-test was just to verify question interpretability but also was determined by logistical and time constraints.

[3] Diversion channels, also known as retention ditches, are semi-circular or rectangular pits dug parallel to each other across the slope, at a distance of about 30 feet to divert/retain surface runoff [80]. Tree planting refers to establishing trees in landslide-prone areas or riverbanks prone to flooding following the best practices such as the optimal number, correct spacing, and regular maintenance.

2.5. Information intervention and data collection

The intervention in this study was a video shown by CS or university staff (representing the external agent). The two categories were trained in extension approaches that covered the basic steps of conducting a video-mediated extension session. A short training manual, prepared following FAO [55] guidelines, focused on how to introduce, conduct, and conclude video sessions. The manual further included content about handling individual differences, adult learners, group dynamics, and managing conflicts. In August/September 2022, we collected the pre-treatment data from the 553 farmers in a baseline household survey. The questionnaire included household information such as household income, family size, ownership of mobile phones, and access to extension services, credit, NGO support, age, gender, and education of the household head. Such general household information is usually collected at baseline in experimental studies to verify effective randomization of households involved [56,57]. Specific plot characteristics can influence a household's decisions regarding the adoption of land management practices for the plot, as established by Adere et al. [58]. Therefore, following the study by Mutyebere et al. [59], we collected plot-level data such as plot ownership, steepness, disaster history, and perceived risk. We also asked the respondents if or not they were planning to plant trees or dig diversion channels per plot to determine the intention. Further, we asked them to estimate the number per plot of the two DRR measures to determine the actual adoption.

We informed respondents of the video session (time, mode - individual or group, and place where the video session would take place). Before the sessions, the facilitator (CS or university staff) introduced him/herself and aligned the participants' expectations. The facilitator selected the right video depending on the language spoken by the individual/group. During the actual session, the video would be paused to allow the participants to ask clarification questions (see e.g., Kadiyala et al. [60]). The respondents mainly inquired about the dimensions of a diversion channel, the actual number per acre, and size of an acre in local terms. Videos were shown to the respondents the same day after the baseline survey. Since the CS who facilitated the video sessions are originally from the parishes and since they are linked to the D-SiRe project, they were expected to visit farmers regularly after the video to encourage them to apply the DRR measures, unlike the external agents. In addition, most CS saved the video on their smartphones for reference. Further, the training manual stressed follow-up visits. However, to ensure uniform information intervention across the treatment groups, standard protocols were implemented. These included uniformity of the video content, identical gadgets used, equal duration per session, and comparable pre-training provided to both the CS and external agents. In addition, we did not ask the CS to follow up with the treated farmers during the trial period to prevent contamination by CS visiting control parishes or parishes treated by university staff.

A midline survey was conducted within one week after the video session (also in August/September 2022) involving 293 out of 333 respondents who watched the video (treatment group), representing an attrition rate of 12%. The midline survey intended to verify the respondents' understanding of the content in the video. It also aimed to test the immediate effect of informational videos on the adoption intention. The questions included were about the role of grass strips established on the sides of a diversion channel. Respondents were also quizzed about the role tie bands – a small raised part left at a short distance within a diversion channel to avoid water accumulating on one side of the channel. Other questions focused on the width of the diversion channel, when to remove silt that accumulates in the channel, the number of trees recommended per acre, tree maintenance, and the desired root structure for DRR. Between the intervention (August/September 2022) and the endline survey in May 2023 (eight months), there are two rainy (planting) seasons, and a farmer could adopt tree planting or diversion channels. The endline survey involved 549 respondents, indicating a 0.7% attrition rate. Low attrition was attributed to the short trial period and prior phone calls to respondents before the visit. In addition, we used CS as field guides in the parishes they are attached to or neighbouring, hence they knew the respondents' whereabouts. Further, Fig. 2 summarizes the steps in implementing the experiment, highlighting the data collection rounds, key variables per collection round, and the sample size involved.

2.6. Data analysis

We conducted data analysis at the plot level for individual farmers (households) by examining the intention to apply and the actual adoption of trees or diversion channels as the outcome variables. We consider actual adoption as well as intention to adopt as one's actual behaviour (adoption of DRR measures, in this case), which is usually determined by intentions about the action [61]. Therefore, the stronger the intentions to apply the DRR measures, the more likely will be the actual adoption [12]. We used Stata 17.0 software for descriptive and econometric analysis. Following other studies such as Duflo et al. [62], Van Campenhout et al. [33], and Oyinbo et al. [56], we conducted balance checks using key household and plot characteristics to verify if randomization was achieved. This was intended to avoid selection bias arising from the possible different starting points between the treatment and control groups. Like Katongole [63] and Oyinbo et al. [56], we applied the Analysis of Variance (ANOVA) to test systematic differences and a Joint F-test for the orthogonality test. While ANOVA tests if individual variables are independent, the Orthogonality test determines if they are jointly independent. To test orthogonality, we regressed each pre-treatment variable on the treatment status, a procedure applied in other studies like van Campenhout [54] and Oyinbo et al. [56]. We analyzed the treatment effect due to the informational videos using the Analysis of Covariance (ANCOVA) which combines regression and ANOVA and the method has also been widely applied in studies such as Kosova [64] and Oyinbo et al. [56]. The method is useful when evaluating experiments to account for variation arising from covariates that affect the outcome variable, thereby increasing the precision of the treatment effect [65]. Thus, ANCOVA models

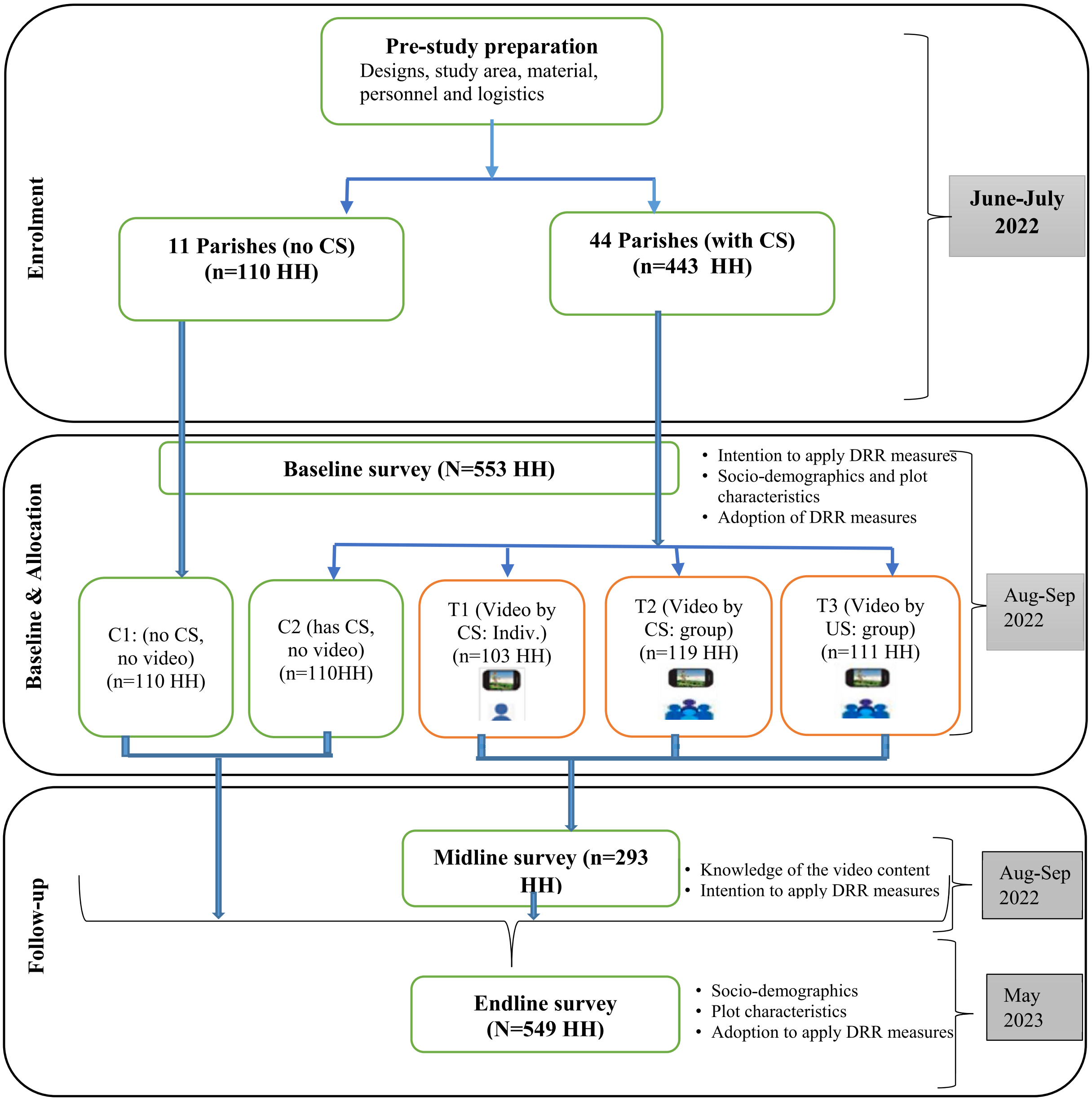

Fig. 2. Steps taken in implementing the experimental study, HH: Household, CS: citizen scientists, US: University Staff.

nuisance variables that might influence the outcome of interest but are difficult to control during the experiment. Furthermore, ANCOVA ensures higher statistical power than Difference-in-Difference (DiD) when the outcome variable demonstrates low autocorrelation[4] [56,66]. We estimated the intent-to-treat (ITT) effect with pre-treatment characteristics as control variables in the ANCOVA specification. ITT method analyses results in a randomized study by including all the participants in the statistical analysis based on the groups they were originally assigned [67].[5] In the ANCOVA specification, we include the pre-treatment farmer, household, and plot characteristics that might be correlated with the actual adoption - our dependent variable. This corrects the imbalances (that might exist) in the baseline characteristics despite randomization [68]. Equation (1) shows the ANCOVA model specified for this study.

$$y_{ij,endline} = \beta_0 + \beta_1 C2_{ij} + \beta_2 T1_{ij} + \beta_3 T2_{ij} + \beta_4 T3_{ij} + \beta_5 y_{ij,baseline} + \beta_6 X_{ij} + \varepsilon_{ij} \quad (1)$$

[4] Autocorrelation refers to the relationship between the variable's current value and the past value.

[5] ITT is important because excluding respondents who did not adopt can negatively impact the results of a study.

Where $y_{ij,endline}$ is the dependent variable (number of trees planted or number of diversion channels implemented) for the focal plot by household i in parish j in the endline survey, and $y_{ij,baseline}$ refers to the dependent variables at the baseline survey. X_{ij} represents the pre-treatment household characteristics including gender of the household head, group membership, access to credit, extension, NGO support, education of the household head, house type, leadership position, mobile phone ownership, and training. Plot characteristics such as plot steepness, landslide risk, floods risk, landslide history, and flood history were also considered. These variables provide descriptive statistics and balance tests for comparisons among the treatment and control groups as is usually applied in other similar studies such as van Campenhout [54] and Oyinbo et al. [56]. ε_{ij} is the random component clustered at the parish level to justify the cluster randomization [50,62,69]. Cluster randomization was conducted to prevent self-selection bias, and unobserved heterogeneity that results in identification problems predominant in impact evaluations compromising the internal validity [56]. Lastly, $C2_{ij}$, $T1_{ij}$, $T2_{ij}$, and $T3_{ij}$ are the binary indicators of respondents in C2[6] and the three treatment groups, and $\beta_1 - \beta_4$, refer to the corresponding coefficients indicating the ITT effect for C2, and the three treatment groups.

For robustness check, we conducted a DiD analysis to estimate the pre- and post-treatment mean differences in the dependent variables between treatment and control groups.[7] DiD helps to identify the treatment effect as the differences in the changes over time and across groups [50]. It examines the differences between the pre-treatment and post-treatment averages of the dependent variable, and also the differences between the treatment and the control group, known as the treatment effect [70]. The model is suitable when no eventual consequences related to the dependent variables occurred between baseline and endline surveys in both the control and treatment groups, also known as the parallel trend assumption. Therefore, DiD accounts for the counterfactual outcomes - what would the treatment outcome be post-treatment if treatment had not occurred [70]! It also controls for time-invariant[8] unobserved heterogeneity not controlled by randomization [56]. Other studies such as Sugg et al. (2023) and Watanabe & Fujimi (2025) also used the DiD method to determine the intervention effect across treatment groups. Furthermore, a study by Oyinbo et al. [56] used DiD to check the robustness of the ANCOVA results, and found contrasting results. Thus, this study's DiD specification is given in Equation (2):

$$y_{ijt} = \rho_0 + \rho_1 C2_{ij} + \rho_2 T1_{ij} + \rho_3 T2_{ij} + \rho_4 T3_{ij} + \rho_5 post_t + \rho_6 C2_{ij}{}^{*}post_t + \rho_7 T1_{ij}{}^{*}post_t + \rho_8 T2_{ij}{}^{*}post_t + \rho_9 T3_{ij}{}^{*}post_t + \rho_{10} X_{ij} + \varepsilon_{ij} \quad (2)$$

Where y_{ijt} is the dependent variable in the focal plot for household i in parish j at time t (time of the endline survey). The coefficients represented by $\rho's$ stand for the ITT effects for C2 and the treatment groups, $post_t$ captures the observations in the follow-up period. The rest of the variables in Equation (2) are already defined in Equation (1). Following studies like Athey & Imbens [71] and Oyinbo et al. [56], we checked for differential attrition - respondents dropping at different rates across the treatment and control groups - which would compromise the randomization. We applied a joint F-test with interaction terms between the treatment status (variable) and the baseline characteristics. We also conducted power calculations by opting for a 1:1 ratio that maximizes statistical power [72]. A meaningful effect size of 25% was applied using the average number of trees (outcome variable) and its standard deviation at the power of 0.8 and 0.05 alpha value, also used in other impact studies such as Oyinbo et al. [56]. Lastly, since we had two outcomes in our ANCOVA model (number of trees and number of diversion channels) and multiple treatment/control groups (T1, T2, T3, C1 &C2), conclusions from such an experimental setting are prone to type 1 error (based on false positives i.e. obtaining significant results when in reality they are not) [56]. Therefore, following other studies (e.g. Ref. [56,73]), we applied the false discovery rate (FDR) – adjusted p-values (also known as q-values) to correct for multiple hypothesis testing,- an approach extensively discussed by Anderson [74].

3. Results

3.1. Differential attrition, statistical power, and multiple hypothesis testing

Checking for differential attrition revealed no statistically significant difference from zero for respondents not included in the endline survey, suggesting no systematic attrition. However, in the midline survey, the joint F-test of the interaction between T2 and the treatment dummy is statistically different from zero, indicating differential attrition compared to the base category (Table A.1 in appendices). T2 respondents were asked to join groups in one place to watch the video afterwards, while in other groups videos were screened immediately after the baseline survey. Thus, in T2 some respondents could have failed to join due to poor weather, poor roads, and the lack of time. Furthermore, a 25% effect size and a mean of 44.31 trees (and a standard deviation of 82.18) would give a standardized minimum detectable effect of 0.13. Thus, with 110 households allocated to each of the three treatment and two control groups, only a 0.51 power was achieved. Lastly, correcting for multiple hypothesis testing (Table A.2) reveals that the FDR-adjusted p-values (q-values) are also significant for the number of trees (but at $p < 0.1$), and not for diversion channels.

3.2. Pre-treatment socio-demographic profile of the farming households and plot characteristics

We investigated if there were systematic differences across the two control and three treatment groups to examine randomization and check potential selection bias. Based on the ANOVA test, Table 1 Column 7 reveals no systematic difference except plot ownership

[6] C2 could be substituted by C1 when C2 is used as the base category in checking robustness.

[7] DiD is a method that identifies the impact by considering two differences: (1) the difference between the treatment group and the control group, and (2) the difference between before and after the intervention.

[8] There is nothing that is changing over time that is affecting the treatment groups and control groups differently, hence the same trend.

Table 1
Pre-treatment household and plot characteristics of sampled farmers across treatment and control groups.

Variable	Full sample (1)	Control one (C1) (2)	Control two (C2) (3)	Treatment one (T1) (4)	Treatment two (T2) (5)	Treatment three (T3) (6)	Systematic difference (*p*-value) (7)
Household Characteristics (Households)	**549**	**107**	**112**	**100**	**119**	**111**	
Gender (male HH head) (1/0)	0.83(0.38)	0.86(0.35)	0.81(0.39)	0.76(0.43)	0.82(0.39)	0.89(0.31)	0.11
Group membership (household) (1/0)	0.61(0.49)	0.59(0.49)	0.59(0.49)	0.61(0.49)	0.66(0.48)	0.59(0.49)	0.79
Access to credit by the household (1/0)	0.26(0.44)	0.27(0.45)	0.17(0.38)	0.28(0.45)	0.29(0.46)	0.29(0.45)	0.21
Extension visit to the household (1/0)	0.30(0.46)	0.34(0.47)	0.21(0.41)	0.31(0.46)	0.31(0.46)	0.35(0.48)	0.19
NGO support for the household (1/0)	0.06(0.23)	0.05(0.21)	0.08(0.27)	0.03(0.17)	0.08(0.28)	0.05(0.21)	0.34
Extended family in the village (1/0)	0.87(0.33)	0.83(0.38)	0.88(0.32)	0.86(0.35)	0.88(0.32)	0.90(0.30)	0.59
HH head's educ. (≤primary level) (1/0)	0.65(0.48)	0.58(0.50)	0.73(0.44)	0.71(0.46)	0.63(0.48)	0.62(0.49)	0.09
House type (permanent) (1/0)	0.46(0.50)	0.36(0.48)	0.50(0.50)	0.54(0.50)	0.41(0.49)	0.50(0.50)	0.06
Leadership position (HH head) (1/0)	0.42(0.49)	0.45(0.50)	0.36(0.48)	0.39(0.49)	0.46(0.50)	0.44(0.50)	0.46
Phone ownership (HH head) (1/0)	0.90(0.30)	0.90(0.31)	0.88(0.32)	0.90(0.30)	0.89(0.31)	0.95(0.23)	0.55
Training attended (HH head) (1/0)	0.40(0.49)	0.33(0.47)	0.40(0.49)	0.45(0.50)	0.36(0.48)	0.47(0.50)	0.18
Age (household head (years))	50.06 (13.45)	48.82 (12.95)	49.67 (13.74)	52.12(14.04)	49.19(13.68)	50.74(12.80)	0.39
Family size (number of persons)	6.03(2.50)	5.78(2.52)	6.06(2.37)	6.07(2.44)	5.89(2.77)	6.35(2.36)	0.50
Joint orthogonality p-value of F-test							0.79
Plot characteristics (plots)	**1001**	**189**	**195**	**173**	**239**	**205**	
Plot ownership by the household (1/0)	0.93(0.25)	0.96(0.20)	0.90(0.30)	0.91(0.29)	0.97(0.97)	0.93(0.26)	0.03**
Plot is steep (1/0)	0.78(0.41)	0.74(0.44)	0.75(0.43)	0.82(0.39)	0.78(0.42)	0.81(0.39)	0.23
Perceived at risk of landslides (1/0)	0.41(0.49)	0.38(0.49)	0.42(0.49)	0.49(0.50)	0.38(0.49)	0.42(0.50)	0.14
Perceived at risk of floods (1/0)	0.35(0.48)	0.39(0.49)	0.32(0.47)	0.34(0.48)	0.36(0.48)	0.33(0.47)	0.69
Plot landslide history (affected) (1/0)	0.38(0.48)	0.31(0.46)	0.37(0.49)	0.43(0.50)	0.38(0.49)	0.39(0.49)	0.21
Plot flood history (was affected) (1/0)	0.39(0.49)	0.41(0.49)	0.39(0.49)	0.34(0.48)	0.42(0.50)	0.37(0.48)	0.47
Plot size (acres)	1.67(1.37)	1.78(1.75)	1.58(1.16)	1.55(1.15)	1.82(1.39)	1.58(1.31)	0.13
Intention to plant trees (1/0)	0.79(0.41)	0.72(0.45)	0.76(0.43)	0.88(0.33)	0.81(0.39)	0.77(0.43)	0.30
Intention to dig diversion channels (1/0)	0.70(0.46)	0.67(0.47)	0.67(0.47)	0.77(0.42)	0.62(049)	0.74(0.44)	0.35
Adoption of trees (1/0)	0.31(0.46)	0.33(0.47)	0.32(0.47)	0.28(0.45)	0.36(0.48)	0.26(0.44)	0.16
Adoption of diversion channels (1/0)	0.36(0.48)	0.32(0.47)	0.34(0.48)	0.33(0.48)	0.38(0.45)	0.42(0.49)	0.21
Number of trees	44.31 (82.18)	43.17 (61.94)	48.22 (52.40)	57.35(91.67)	42.27(110.36)	33.10(63.75)	0.66
Number of div channels	4.12(3.09)	4.05(3.17)	4.25(3.72)	3.63(2.80)	4.08(3.46)	4.40(3.72)	0.68
Joint orthogonality p-value of F-test							0.75

Note: Sig: levels: **P < 0.05; Standard deviations are in parentheses; *p*-values in column 6 are from the ANOVA test for systematic differences based on treatment groups, except the joint test *p*-values of the F-statistic.

($p < 0.05$). Further, we conducted a joint test to check if the baseline characteristics were jointly statistically significant. The *p*-value of the joint F-test is not significantly different from zero. Therefore, we cannot reject the null hypothesis that the baseline characteristics are orthogonal to the treatment indicator.

Of the entire (full) study sample (Table 1 Column 1), 83% of the household heads were male, they were on average 50 years old, 65% had primary-level education and below, 90% owned a mobile phone, and only 39% attended formal training six months before the study. Each household is comprised of at least six members. Only 46% of households had a permanent residential house made of bricks, cement, and iron sheets compared to non-permanent houses constructed from simple local materials such as trees, reeds, and mud/earth. As a proxy for social support, 87% of the households had relatives in the same village. As institutional support, 60% of the households belonged to a farmer group that helps them in saving and borrowing. Households' access to credit stood at only 26%, extension services at 30% and NGO support at 6%. Overall, 1001 focal plots were considered by the study upon which the intervention is based. Of the total plots, 93% were owned (not rented), and the average size of the plot stands at 1.67 acres (0.7 ha). Moreover, 78% were reported steep, 41% and 35% of the plots are at risk of landslides and floods, respectively. Furthermore, 38% and 39% had experienced landslides and floods, suggesting high vulnerability to the two hazards. Unfortunately, only 31% of the plots had trees (on average, 44 per plot). Likewise, only 36% had diversion channels (on average, four per plot). However, farmers had plans (intention) to plant trees on 79% and dig diversion channels on 70% of the plots.

3.3. Intention to adopt and actual adoption of tree planting and diversion channels

Table 2 reports the intention to plant trees or implement diversion channels using the baseline and midline survey data, and the actual adoption using the baseline and endline survey data. In the midline survey conducted within a week after the information treatment, the intention to plant trees increased to 87% of the plots, compared to 80% in the baseline[9] (Column 1). Similarly, respondents expressed a higher intention to dig diversion channels (on 92% of the plots) than in the baseline (75%) (Column 2). In the midline survey, we also assessed the respondents' general understanding of the content in the video. Shown in Table A.3, the percentage of correct answers per question is high (ranging from 71% to 96%).

Table 2 further shows that the actual adoption (number) of trees per plot increased to 59 per plot (87 per ha) in the endline survey from 44 per plot (65 trees per ha) in the baseline, indicating an increase of 15 trees per plot (22 trees per ha) (Column 3). In addition, the average number of diversion channels increased from 4.1 per plot (5.9 per ha) at baseline to about 4.5 per plot (6.7 per ha), an increase of 0.4 (0.8 per ha) in the endline survey (Column 4). Investigating the sub-groups based on the treatment status revealed a significant increase in the intention to plant trees for T3. Likewise, a significant increase was observed in T1, T2, and T3 in the intention to dig diversion channels. Lastly, there was a significant increase in T1 and T2 for the actual adoption (number) of trees, and T2 for diversion channels.

We applied a two-sided *t*-test to investigate the equality of means, and the *p*-values are presented in the lower part of Table 2. The intention to plant trees and dig diversion channels is not significantly different across treatment sub-groups. For the actual adoption, the average number of trees planted is significantly higher in T1 than in T3 ($p < 0.05$), and significantly higher than in C1. However, the average number of diversion channels applied is significantly smaller in T1 than in T2 and T3 ($p < 0.05$), indicating individual face-to-face sessions by CS influenced the tree planting behaviour positively, but not the implementation of diversion channels.

3.4. Treatment effect: number of trees planted/number of diversion channels applied

Results of the ANCOVA specification (Equation (1)) are reported for the actual adoption of tree planting and diversion channels. They are based on a specification with C1 as the base category and include the pre-treatment control variables. For the ANCOVA results with C2 as a base category, we refer the reader to Table A.4, while Table A.5 provides the results when C1 is the base category and without control variables.

The ANCOVA estimates of actual adoption are rather similar to the results obtained using the DiD specification (in Equation (2)) as shown in Table A.6 (C1 as the base category and with control variables) and Table A.7 (C1 as the base category without control variables). Table 3 shows that information treatment significantly increases the level of adoption of tree planting in both T1 and T2 compared to the both control groups and T3. The increase is not statistically different between T1 and T2. In T1 and T2, the CS showed informational videos during face-to-face one-on-one (individual) sessions and in groups, respectively. The informational video shown by CS to farmers in groups (T2) significantly increased the adoption of diversion channels compared to regions where no CS were active (C1).

4. Discussion

The descriptive analysis revealed that the proportion of plots to which farmers intended to plant trees and apply diversion channels is high, 80% and 75%, respectively. This would be a promising result but only if such self-reported intentions turned into actual implementation, which is usually not the case according to a study by Mutyebere et al. [12]. Furthermore, the actual adoption of tree planting and diversion channels (at endline) is still low, at 48% and 46% of the plots, respectively. Considering how prone to disaster risks the selected area is, the result is extremely worrying. Previous studies, such as Mertens et al. [41] and Jacobs et al. [25] posted similar results about the low adoption of DRR measures in the area. A study by Kesternich et al. [75] indicated that intention – behaviour gap complicates policy recommendations to stimulate climate change adaptation. They argue that intentions rarely serve as good predictors for realized actions. The gap can be attributed to inadequate technical ability, financial resources, and low response efficacy regarding the DRR measures [41]. Iinterventions that strengthen the connection between intentions and actual adoption

[9] Intention to plant trees and dig diversion channels reported here (including the baseline value) is only for the farmers that participated in the midline but what is reported in Table 1 is for the total sample.

Table 2
(a) Intention at baseline and midline survey, (b) Actual adoption at baseline and endline survey.

	Intention (1/0)		Actual adoption (number)		
Treatment status	Trees(1)	Div. channels(2)	Treatment status	Trees(3)	Div. channels (4)
Follow-up – Baseline =Mean difference (*p*-values for the paired *t*-test denoted by stars)					
Full sample: Mean (SD)			Full sample: Mean (SD)		
Midline survey	0.87 (0.33)	0.92 (0.25)	Endline survey	58.82(122.07)	4.50 (3.31)
Baseline survey	0.80 (0.39)	0.75(0.43)	Baseline survey	44.30 (82.17)	4.12 (3.09)
Difference	0.06**	0.17***	Difference	14.51**	0.38**
T1: Mean (SD)			T1: Mean (SD)		
Midline survey	0.81(0.39)	0.90(0.20)	Endline survey	87.29(175.35)	3.75(2.73)
Baseline survey	0.86(0.34)	0.76(0.42)	Baseline survey	57.34(91.67)	3.63(2.80)
Difference	−0.05	0.14***	Difference	29.94*	0.12
T2: Mean (SD)			T2: Mean (SD)		
Midline survey	0.88(0.32)	0.97(0.17)	Endline survey	64.89(162.93)	5.09(3.13)
Baseline survey	0.76(0.43)	0.80(0.40)	Baseline survey	42.27(110.36)	4.075(2.46)
Difference	0.12	0.16**	Difference	22.62*	1.02**
T3: Mean (SD)			T3: Mean (SD)		
Midline survey	0.92(0.26)	0.92(0.26)	Endline survey	47.11(82.06)	4.981(3.57)
Baseline survey	0.76(0.43)	0.73(0.44)	Baseline survey	33.09(63.75)	4.39(3.72)
Difference	0.16**	0.19***	Difference	14.02	0.58
			C1: Mean (SD)		
			Endline survey	42.44(45.36)	4.09(3.35)
			Baseline survey	43.16(61.93)	4.05(3.17)
			Difference	−0.72	0.03
			C2: Mean (SD)		
			Endline survey	55.01(87.12)	4.53(3.46)
			Baseline survey	48.22(52.39)	4.24(2.72)
			Difference	6.79	0.28
***p*-values of two-sided *t*-test**					
T1≠T2	0.38	0.74	T1≠T2	0.36	0.01**
T1≠T3	0.92	0.59	T1≠T3	0.04**	0.01**
T2≠T3	0.28	0.89	T2≠T3	0.36	0.84
			C1≠C2	0.30	0.47
			T1≠C1	0.03**	0.52
			T1≠C2	0.14	0.14
			T2≠C1	0.28	0.11
			T2≠C2	0.65	0.36
			T3≠C1	0.74	0.11
			T3≠C2	0.52	0.41

Note: Sig. levels * $P < 0.1$, **$P < 0.05$, and ***$P < 0.01$; SD is standard deviation in parentheses; Intention captured at baseline is only for those who participated in the midline survey; no control group for intention to adopt.

Table 3
ITT effects on adoption of tree planting and diversion channels: Actual number at baseline and endline survey (with control variables and C1 as the base category).

Treatments	Tree planting (1)	Diversion channels (2)
ANCOVA results		
Control two (C2)	6.65(11.08)	−0.09(0.51)
Treatment one (T1)	71.23**(31.42)	−0.39(0.39)
Treatment two (T2)	39.18**(18.77)	0.78**(0.37)
Treatment three (T3)	10.01(12.88)	0.61(0.40)
Baseline control means (C1)	43.16(7.29)	4.16(0.28)
N	366	353
***p*-values of two-sided *t*-test**		
T1 ≠ C2	0.01**	0.50
T1 ≠ T2	0.23	0.00***
T1 ≠ T3	0.05*	0.01***
T2 ≠ C2	0.01**	0.06*
T2 ≠ T3	0.04**	0.64
T3 ≠ C2	0.77	0.13

Note: ITT is Intention to Treat; Standard errors in parentheses are clustered at the parish level; Sig. levels: *$P < 0.1$, **$P < 0.05$, and ***$P < 0.01$; N is number of plots.

behaviour are therefore crucial [76]. Besides addressing social-psychological factors such as self-efficacy, enhancing farmers' technical ability through effective training, and improving access to inputs such as tree seedlings to cash-strapped smallholder farmers could play a role [77]. After all, a wider intention – behaviour gap is more evident among people with limited resources [76].

The recommended number of trees per hectare in an agroforestry system is 100 [78]. Still, more might be required depending on the extent to which land is exposed to disaster risks [79]. The result from the baseline survey indicates that tree planting currently stands at 65 trees per hectare, indicating a deficit of 35 trees. Similarly, 12 diversion channels (30 feet long) per hectare are recommended [80]. The study established an average of six diversion channels applied in the study area, indicating that farmers have only fulfilled half of the requirements. Moreover, the statistics presented are taken from only 31-36% of the plots, on which adoption was reported, leaving many plots exposed to natural hazards. Though still below the recommended level, as shown in the endline survey, the number of trees per hectare increased by about 33% and 9% for diversion channels. More tree planting was observed eight months after the information intervention by the CS compared to parishes where there were no CS, where there were CS but no information provision took place, and to parishes where external agents delivered information. This could be explained by regular follow-ups and reminders for farmers to apply the DRR measures due to CS' well-established relationships with farming communities as they are part of their informal social networks [20,21]. A study by Rustinsyah et al. [81] argued that social networks, as a form of social capital, are shaped by civic participation, trust, reciprocity. Therefore, due to continuous information provision by CS, some farmers might have implemented the DRR measures in groups. In addition, as CS being part of D-SiRe project and were recruited locally, they could have established contacts, especially with district disaster committees and NGOs, to lobby for support related to tree planting, diversion channels, besides other relief items [23]. Sharing information from experts to farmers through CS is an example of tangible actions that can be paired with conventional data collection roles to enhance enthusiasm to participate in citizen science projects in low- and middle-income countries as suggested by Ashepet et al. [26].

In this study, the first hypothesis was that farmers wish to apply DRR measures but lack of technical information. Based on the results we accept the hypothesis because there was a significant treatment effect attributed to information in general compared the control groups - irrespective of whether there were CS present in the parish or not. Further, the second hypothesis, which proposed that knowledge transfer by local people such as CS influences adoption decisions more than by external agents, is also supported by the study findings. Testing the potential of the CS network in knowledge transfer revealed the network's promising future for farm-level DRR in disaster-prone rural settings in low- and middle-income countries. This agrees with other studies such as UN [9] and Tumusiime et al. [19], which posted a positive contribution of the CS in the scientific initiatives but mainly focused on data collection and monitoring. Furthermore, a study by Lukyanenko et al. [82] indicated citizen science as a significant contributor to sharing information and argued that the network opens a unique opportunity to improve local information systems. Our study has extended the discourse by highlighting the potential of CS to play a significant role in knowledge transfer for the adoption of land use practices such as DRR measures.

The follow-up questions in the midline survey indicated that both the CS and the external agent facilitate knowledge acquisition regarding technical aspects related to DRR measures. However, the empirical results revealed that local social networks, i.e. the CS, are more effective than external agents in knowledge transfer, for tree planting, irrespective of whether this information was delivered in one-on-one or group sessions. For diversion channels, CS were only more effective in knowledge transfer than external agents if the information was communicated using group sessions. CS approach being more effective was hypothesized due to being a trusted source of information and knowledge, and having close network ties with local communities. For example, tree planting, offers several functions such as food, and shelter, in addition to cultural, regulatory, and other ecological functions ([83]; Purwaningsih et al., 2020). Farmers should be guided on the tree with specific characteristics for DRR to avoid choosing the wrong species, which also agrees with a study by Mutyebere et al. [59]. This is also in line with a study by Kamruzzaman & Chowdhury [31] which identified the need to train farmers in Bangladesh on effective control measures for flash floods. Such efforts are re-echoed in the Uganda's National Disaster Preparedness and Management Policy whose main priority is to disseminate specific information for disaster risk reduction (OPM, 2010). Specific information is key because language, socio-cultural, and economic benefits associated with DRR measures vary across the local communities. For instance, in the Rwenzori Sub-region, people (specifically the Bakonzho) traditionally plant trees like bamboo around the watersheds to control floods. They believe such trees can only be effective if planted by famous Indigenous specialists [84]. Thus, sharing knowledge about the best practices when applying such measures could be more effective when done by someone with indigenous knowledge like the CS. In diversion channels, CS being only effective when the information is delivered in group sessions suggests that learning in groups plays a crucial role in facilitating further group actions such as mobilizing collective labour for labour-intensive land use practices, diversion channels being one of them. It also indicates that CS' effect can be higher through group actions, such as digging diversion channels at a village level. A study by Bukenya et al. [85] also established group method of extension as more effective in transferring agroforestry information and attributed it to different tools, and interaction during group sessions. Moreover, Dhehibi et al. [86] recommended promoting participatory extension approaches to not only improve farmers' access to training information in a cost-effective but also allow post-training discussions. Specific procedures such as size, dimensions, layout and design of diversion channels effective for DRR in mountainous terrains needs more post-training interactions and demonstration among group members.

5. Limitations of the study

This study investigated the effectiveness of farmers' social networks like CS in knowledge transfer for the adoption of tree planting and diversion channels through an experimental study. The findings promise a bright future for disaster-prone rural areas with limited accessibility for traditional extension workers. In regions where citizen science projects are being implemented, CS can provide local, context-specific knowledge transfer that addresses socio-cultural, and economic needs [84]. While our results provide useful insights, an eight-month period between the information intervention and the endline survey was limited due to time and logistical constraints. In this period, only the immediate impact was assessed but not the gradual (long-term) effect. It is one thing to plant a tree but another to grow it but the study did not examine whether (or not) the trees and diversion channels were sustained after the project.

The major goal of CS under the D-SiRe project was to map and report hazards. However, it was also assumed that, since they also form part of the farmers' local social network, through regular visits, information sharing could occur. The information intervention was done in August/September 2022 but the citizen science network was officially closed in December 2022 and the modest monthly compensation for internet data and transport ended. This might have led to insufficient interactions, which negatively affected the results. Therefore, the potential of knowledge transfer through CS might be higher than this study predicts. Further, our unit of analysis was limited to the households (and plots of the respondents) that formed the treatment and control groups. Muange [36] indicates that the uptake of agricultural technologies can occur through social learning networks or mere copying from neighbours. Hence, there is a need to investigate the adoption by others in the farmers' social networks.

The sample size was limited to 553 respondents, which was small for the three treatment and two control groups. We had a design power of 0.51, though, it is often advisable to aim for a power of 0.8 [72]; [56]). This would require the full sample of 1085 households, and 217 households per trial arm. This was not feasible because of logistical and financial constraints. We could not afford the first data collection round to obtain the means and standard deviations for power calculations. Nevertheless, we believe our results provide a good basis for analysing the role played by citizen science in promoting proper land use practices such DRR measures through knowledge transfer. Follow-up research with appropriate design power would be needed to confirm our findings.

To test the effectiveness of social networks in information provision, we rely on CS on one hand, and the university staff, on the other hand, to bring information to rural households. While the latter is an external advisor, their competencies and experience might differ from extension officers. Both are highly educated about extension approaches and trained professionally to deal with farmers' problems. University staff are perhaps less known (related) to local farmers, while extension workers apply more practical farmer-centred learning and offer hands-on support through regular visits [87]. While the university staff and CS were both trained to ensure they had the same background knowledge, university staff cannot entirely be compared with the formal extension worker, hence the observed outcomes might be different if information was brought to the farmers by extension workers. However, the choice to rely on university staff and not formal extension officers was due to financial limitations.

6. Conclusion and policy recommendations

Climate change is increasingly associated with small-scale but frequent geo-hydrological hazards such as shallow landslides and flash floods. Although, these events tend to be underreported, their cumulative impacts result in considerable economic losses, especially in mountainous farming regions. Adoption of affordable and scalable farm-based solutions, such as tree planting and diversion channels remains limited due to low levels of awareness. Formal information networks such as government extension workers are frequently constrained by geographical inaccessibility and financial barriers. Therefore, his study aimed to test whether farmers' social networks can help to promote the adoption of good land use practices such as DRR measures through knowledge transfer. We assessed the effect of relying on a network of CS, an example of an informal social network linked to professional scientists, and trusted by farmers, in sharing knowledge regarding shallow landslide and flash flood risk reduction. Furthermore, we examined whether communication impact of knowledge transfer varies with the communication format, i.e., when information is delivered in individual compared to group sessions.

The results indicate high intentions to apply DRR measures but low actual adoption, revealing an intention - behaviour gap. The study suggests the need to enhance farmers' technical ability through effective training, and improving access to inputs and tools for cash-strapped farmers as strategies to reduce the gap. Compared to external agents, CS can facilitate significant knowledge acquisition about key technical aspects regarding proper land use practices to reduce landslide and flood risks. One-on-one information and group sessions by CS were effective for the adoption of tree planting compared to group sessions by external agents or with no information provision (even when a citizen science project was taking place in the region). For diversion channels, group sessions facilitated by CS were more effective than one-to-one sessions but not significantly better than group sessions facilitated by external agents. This indicates that, being labour-intensive, diversion channels could better be promoted through group actions at the village level. These insights are particularly relevant to community-based facilitators such as extension workers, NGOs, and future CS projects. However, using social networks like the CS to transfer knowledge may not be a 'silver bullet' to poor access to extension services. The dynamics and expectations should be realistic (because citizen science projects are not omnipresent) and their integration into the extension system should be gradual.

The major aim of the Uganda's land use policy is to ensure sustainable and optimal land use by raising awareness on the proper utilization and avoiding degradation. The study findings suggest that government policies should focus on how professional networks such as extension services and informal (local) social networks like CS can form synergies to raise awareness about good land use practices in disaster-prone areas. There is need to institutionalize and integrate local, informal social networks into formal government structures to promote sharing technical knowledge, starting with the local government councils. For example, in partnership with training institutions such as universities, the government can train secretaries for production and environment, and opinion leaders at the village council level, in basic video-mediated extension methods. Then, facilitate them with smartphones to become contact persons, supervised by the formal extension workers. Link the secretaries to production departments, environment and natural resources departments, and disaster management committees at the district level. Such local social networks can ensure real-time reporting about the occurrence and damage by natural hazards. They could also facilitate sharing knowledge with farmers about risk reduction strategies. Lastly, the promising impact of CS in knowledge transfer revealed by this preliminary experimental study suggests the need for further research applying Randomized Control Trials (RCT) to offer a robust justification of the causal-effect relationship.

CRediT authorship contribution statement

Rodgers Mutyebere: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ronald Twongyirwe:** Project administration, Funding acquisition, Conceptualization. **John Sekajugo:** Writing – review & editing, Software, Methodology. **Clovis Kabaseke:** Writing – review & editing, Funding acquisition. **Mercy Gloria Ashepet:** Methodology, Investigation. **Grace Kagoro-Rugunda:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Matthieu Kervyn:** Writing – review & editing, Funding acquisition, Conceptualization. **Liesbet Vranken:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Disclosure statement

The authors reported no potential conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

We did not use generative AI assisted technologies during the research/writing process of this manuscript.

Funding

We acknowledge the funding from the Flemish Interuniversity Council (VLIR-OUS) through the TEAM project (grant number: UG2019TEA492A105): Digital citizen Science for community-based Resilience on Environmental management (D-SiRe). The project was implemented in a collaboration between Vrije Universiteit Brussels, and KU Leuven in Belgium and Mountains of the Moon University, and Mbarara University of Science and Technology in Uganda.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

Acknowledgments

It would have been difficult to conduct this study without these key people. Special thanks to our research assistants: Taddeo Kyomuhendo, Godfrey Kyomuhendo, Stephan Thembo, Annet Arora, and Daniel Musinguzi. We also acknowledge the dedicated and resilient team of Citizen Scientists (called geo-observers) in the Rwenzori and the Ankole sub-regions who not only showed the videos to farmers but also worked as field guides. Finally yet importantly, we specially thank Engineer Kaganda Akiiki for accepting that we use Mugamba Organic Coffee Farm in Kabarole District to prepare the videos.

Appendices.

Table A.1
Results of tests for systematic attrition (households who dropped out)

	Midline Survey		Endline survey		
	Attrition dummy (1)	Attrition dummy (2)	Attrition dummy (3)	Attrition dummy (4)	Attrition dummy (5)
Control one (1)			0.000 (Base category)	0.000 (Base category)	0.000 (Base category)
Control two (2)			−0.009 (0.009)	−0.006 (0.009)	−0.025 (0.022)
Treatment one (T1)	0.000 (Base category)	0.000 (Base category)	0.001 (0.013)	0.005 (0.014)	0.012 (0.035)
Treatment two (T2)	0.016 (0.055)	0.525* (0.294)	−0.001 (0.013)	−0.000 (0.013)	−0.085 (0.073)
Treatment three (T3)	0.020 (0.050)	0.007 (0.372)	−0.000 (0.012)	0.001 (0.013)	−0.035 (0.029)
Gender (male HH Head) (1/0)	−0.175* (0.096)			0.008 (0.005)	
Group membership (Household) (1/0)	−0.039 (0.037)			−0.007 (0.011)	
Access to credit by the household (1/0)	0.050 (0.036)			0.008 (0.011)	

(*continued on next page*)

Table A.1 (*continued*)

	Midline Survey		Endline survey		
	Attrition dummy (1)	Attrition dummy (2)	Attrition dummy (3)	Attrition dummy (4)	Attrition dummy (5)
Extension visit to the household (1/0)	0.032 (0.043)			−0.005 (0.007)	
NGO support for the household (1/0)	0.145 (0.092)			0.024 (0.032)	
Extended family in the village (1/0)	−0.120* (0.065)			−0.008 (0.012)	
HH head's educ. (≤primary level) (1/0)	0.001 (0.036)			−0.004 (0.008)	
House type (permanent) (1/0)	−0.010 (0.050)			−0.014** (0.007)	
Leadership position (HH head) (1/0)	−0.056 (0.035)			0.009 (0.008)	
Phone ownership (HH head) (1/0)	0.088 (0.056)			0.006 (0.004)	
Training attended (HH head) (1/0)	−0.032 (0.033)			0.002 (0.009)	
Age (household head(years))	−0.000 (0.001)	−0.000 (0.003)		0.000 (0.000)	−0.000 (0.000)
Family size (number of persons)	−0.010 (0.009)	0.002 (0.017)		0.000 (0.002)	0.001 (0.001)
Constant	0.371** (0.143)	0.167 (0.269)	0.009 (0.009)	0.006 (0.023)	0.025 (0.022)
			F-test (p-values) of:		
			a. Baseline controls		0.975
F-test (p-values) of:			b. Interaction terms with C2	0.001***	
a. Baseline controls		0.001***	c. Interaction terms with T1	0.322	
b. Interaction terms with T2	0.009***		d. Interaction terms with T2	0.947	
c. Interaction terms with T3	0.125		e. Interaction terms with T3	0.976	
N	333	333		553	553

Note: Standard errors clustered at the parish level are reported in parentheses; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A.2
Correction for multiple hypothesis testing using False Discovery Rate (C1 is the base category)

Treatments	Tree planting (1)		Diversion channels (2)	
	p-values	q-values	p-values	q-values
Control two (C2)	0.551	0.381	0.849	0.717
Treatment one (T1)	0.028	0.092	0.313	0.378
Treatment two (T2)	0.042	0.092	0.039	0.185
Treatment three (T3)	0.440	0.381	0.137	0.259

Table A.3
Knowledge about tree planting and diversion channels included in the video

Questions	Percentage of correct responses			
	Full sample	T1	T2	T3
Tie bands help to prevent water from accumulating on one side of the diversion channel (True)	0.866(0.341)	0.892(0.311)	0.865(0.344)	0.853 (0.356)
The main role of grass strips is source of income (False)	0.911(0.285)	0.851(0.358)	0.948(0.223)	0.931 (0.254)
The width of a diversion channel should be more than 5 m (False)	0.710(0.455)	0.638(0.483)	0.729(0.447)	0.755 (0.432)
Silt accumulated in the diversion channel should be removed only during the dry season (False)	0.887(0.317)	0.862(0.347)	0.906(0.293)	0.892 (0.312)
After planting, trees can be left to grow on their own without any further care (False)	0.959(0.199)	0.968(0.177)	0.969(0.175)	0.941 (0.236)
Two hundred trees can be planted in one acre in agroforestry (False)	0.799(0.402)	0.766(0.426)	0.792(0.408)	0.833 (0.375)
A tree that is good for reducing landslide risk should have deep roots (True)	0.840(0.368)	0.787(0.411)	0.948(0.223)	0.784(0.413

Note: Standard deviations are in parentheses.

Table A.4
ITT effects on adoption of tree planting and diversion channels: Actual number at baseline and endline survey (C2 as the base category and with control variables)

Treatments	Tree planting	Diversion channels
ANCOVA results		
Control two (C1)	−6.655(11.088)	0.097(0.512)
Treatment one (T1)	64.581**(24.766)	−0.301(0.447)
Treatment two (T2)	32.528**(13.218)	0.886*(0.468)
Treatment three (T3)	3.364(11.923)	0.708(0.468)
Baseline control means (Control two)	48.222(7.130)	4.245 (0.354)
N	366	353
***p*-values of two-sided tests**		
T1 ≠ C1	**0.027****	0.312
T1 ≠ T2	0.232	**0.001*****
T1 ≠ T3	0.050	**0.007*****
T2 ≠ C1	**0.042****	0.039
T2 ≠ T3	0.042	0.642
T3 ≠ C1	0.440	0.137

Note: ITT is Intention to Treat; Standard errors in parentheses are clustered at the parish level Sig. levels: **P $<$ 0.05, and ***P $<$ 0.01; N is number of plots.

Table A.5
ITT effects on adoption of tree planting and diversion channels: Actual number at baseline and endline survey (C1 as base category and without control variables)

Treatments	Tree planting	Diversion channels
ANCOVA results		
Control two (C2)	−7.532(5.242)	0.187(0.466)
Treatment one (T1)	57.807**(26.212)	−0.138(0.323)
Treatment two (T2)	39.449(25.430)	1.021**(0.398)
Treatment three (T3)	0.057(4.127)	0.609(0.418)
Baseline control means (Control one)	43.166(7.299)	4.160(0.283)
N	366	353
***p*-values of two-sided tests**		
T1 ≠ C2	**0.016****	0.493
T1 ≠ T2	0.628	**0.006*****
T1 ≠ T3	**0.033****	0.079
T2 ≠ C2	0.082	0.113
T2 ≠ T3	0.123	0.382
T3 ≠ C2	0.197	0.430

Note: **ITT** is Intention to Treat; Standard errors in parentheses are clustered at the parish level; Sig. levels: **P $<$ 0.05, and ***P $<$ 0.01; N is number of plots.

Table A.6
DiD estimates of the ITT information effect on the adoption of tree planting and diversion channels (C1 as base category and with control variables)

Treatments	Tree planting	Diversion channels
DiD estimates		
Control two (C2)	−5.168(9.133)	0.133(0.451)
Treatment one (T1)	66.260**(29.529)	−0.013(0.289)
Treatment two (T2)	23.983(26.439)	0.914**(0.411)
Treatment three (T3)	3.907(7.390)	0.494(0.413)
Base level mean (Control one)	47.089(3.994)	4.249(0.209)
N	366	353
***p*-values of two-sided tests**		
T1 ≠ T2	0.267	0.045**
T1 ≠ T3	0.037**	0.276
T2 ≠ T3	0.461	0.431
T1 ≠ C2	0.020**	0.765
T2 ≠ C2	0.271	0.172
T3 ≠ C2	0.195	0.533

Note: **DiD** is Difference in Differences (in equation (2)); **ITT** is Intention to Treat; Standard errors (in parentheses) are clustered at the parish level; Sig. levels: *P $<$ 0.1, **P $<$ 0.05; control two produces the same results as control two when used as base category.

Table A.7
DiD estimates of the ITT information effect on the adoption of tree planting and diversion channels (C1 as base category and without control variables)

Treatments	Tree planting	Diversion channels
DiD estimates		
Control two (C2)	−3.639(7.515)	0.181(0.448)
Treatment one (T1)	64.423**(28.634)	−0.055(0.286)
Treatment two (T2)	27.389(28.926)	0.932**(0.385)
Treatment three (T3)	6.248(6.972)	0.515(0.421)
Base level mean (Control one)	47.089(3.994)	4.249(0.209)
N	366	353
***p*-values of two-sided tests**		
T1 $\neq$ T2	0.357	0.024**
T1 $\neq$ T3	0.044**	0.220
T2 $\neq$ T3	0.462	0.433
T1 $\neq$ C2	0.020**	0.627
T2 $\neq$ C2	0.283	0.177
T3 $\neq$ C2	0.086	0.564

Note: **DiD** is Difference in Differences (in equation (2)); **ITT** is Intention to Treat; Standard errors (in parentheses) are clustered at the parish level; Sig. levels: *P $<$ 0.1, **P $<$ 0.05.

Data availability

Data will be made available on request.

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