What matters in adoption of small-scale rain water harvesting technologies at household level? Evidence from Charco-dam users in Nzega, Tanzania

Shauri Timothy, Razack Lokina, Yohana James Mgale and Provident Dimoso

Abstract: Any effort to improve irrigation water availability has an advantage in the crop production processes. Small-scale rainwater harvesting technologies like Charco-dams (Malambo) in Swahili (the language used by most the Tanzanians) are among the interventions proven to overcome agricultural water shortage. Despite its importance in overcoming water stress in most arid and semi-arid areas of Tanzania, some farmers in the areas are still reluctant to adopt such technology. In this regard, this analyzed and discussed the factors influencing the adoption of the Charco-dam rainwater harvesting technology by smallholder vegetable producers in Nzega district, Tanzania. A survey was used to collect the required information from 528 smallholder vegetable producers in the district. A structured questionnaire was employed to collect data from 220 Charco-dam adopters and 308 non-adopters who were used for the analysis. The data collected was substantiated by six focus group discussions (FGDs); one at council headquarters and five at the village level. The Probit model with instrumental variables was used to identify and analyze factors influencing adoption. The study revealed that socioeconomic, farm level and information sharing factors are all important to improve the adoption of Charco-dam technology. The results suggest that any strategy, innovation or policy aimed at increasing the adoption rate of small-scale rainwater harvesting technologies should be designed or formulated by considering socioeconomic, farm-level, environmental, and information sharing aspects.

Subjects: Technology; Rural Development; Economics and Development

Keywords: small-scale water-harvesting technologies; Charco-dam; adoption; instrumental variable; Nzega-Tanzania

1. Background

1.1. Introduction

Agriculture and specifically crop production is the most water consuming sub-sector across the globe, simply because water is an essential and primary factor that influences crop productivity and hence guarantees high yield which in turn determines small-holder farmers’ wellbeing (Kelemewerk Mekuria et al., 2020; Smith et al., 2011). Apparently, agriculture is inherently sensitive to weather and climate condition, and is among the most vulnerable sectors to the risks and impacts of global climate change and variability (Chartzoulakis & Bertaki, 2015; Kannan &
Anandhi, 2020; Mahoo et al., 2015; Rosa et al., 2016; Tzanakis et al., 2020). It has been agreed that the world is facing a threat from global warming which is causing droughts, flooding, storm damage, long-term shortages of water, worsening soil conditions, desertification, as well as disease and pest outbreaks on crops and livestock (Iizumi & Ramankutty, 2015; Lewis et al., 2018; Rosenzweig et al., 2014, 2002). Consequently, vulnerable areas such as arid and semi-arid areas are experiencing severe losses in agricultural productivity, primarily due to reductions in crop yields (IPCC, 2007; Kang et al., 2009; Ochieng et al., 2016). Therefore, any efforts to improve irrigation water availability have advantages in the crop production processes. According to Gebre and Rahut (2021), East Africa countries experience much higher prevalence of food insecurity due to change in climate and its variabilities as compared to other places in the world. For so many years, small-holder farmers in Tanzania have been facing agricultural water shortage, that directly affecting farm productivity (Jackson et al., 2018). Small-scale rainwater harvesting technologies like Charco-dams (Malambo) in Swahili (the language used by most of Tanzanians) are among the interventions proved to overcome agricultural (for both crops and animals) water shortage. Such technologies observed to have advantages in terms of simplicity in its architectural design, management and control, hence expected to be highly adopted among the arid and semi-arid areas (Awulachew et al., 2005; Mati, 2012; Nissen-Petersen, 2006; Stephens, 2010; Wagner, 2005).

1.2. Statement of the problem
Charco-dam has been used by farmers in several arid and semi-arid areas for domestic use, irrigating the crops as well as for watering the livestock. Hence the use of the water from these dams are differentiated from one area to another based on the water-use, management level, size as well as shapes of the facility, this is mainly due to socio-economic status of the people in particular area (Barron et al., 2009; Hatibu et al., 2000). Unlike other regions in Tanzania (i.e. Shinyanga, Dodoma, Arusha, Tabora, Singida and Mwanza regions), where Charco-dams are owned and managed by community group of people, Charco-dam in Nzega are owned and managed mostly by individuals mainly for crop farming. Due to the challenges brought by the communal managed and controlled water sources (such as public ponds & dams, wet-valleys & catchments), which include limited frequency and amount of water accessed, and to some catchments limitation on the type of crop to cultivate, small holder vegetable farmers in Nzega are expected to highly adopt this technology, so as to enjoy the unique characteristic of this type of dam to overcome water management and control issues, simply because the production decision is purely based on one decision maker (owner of the irrigation facility) and not majority in the community, and hence enables the adopters to increase yields. However, the assumption is not holding true in Nzega District, whereby adoption of such a technology has been very low (30%-40% across the surveyed wards). Therefore this study analyzed and discussed the socio-economic, farm level and information sharing related factors that influencing the adoption of Charco-dam among small holder vegetable farmers in Nzega district.

1.3. Adoption of technology
Adoption can mean different ways depending on the context of its usefulness. It can be choosing, or continued use of recommended idea or practice, not necessarily be new but novel (Baumüller, 2012; Dasgupta, 1989; Hall & Khan, 2002; Rogers, 2003). According to Rogers (1962), adoption is the mental process that starts when an individual first hears or subjected to the information about certain technology and ends to its final adoption or rejection. Rogers (1983) has distinguished the process in five phases: (1) The knowledge phase: the time when an individual becomes aware of a technology after being exposed to it and gains some idea of how it works; (2) the persuasion phase: this is when the individual starts to interpret the technology (favourable or unfavourable); (3) the decision phase: in which person engages in actions that lead to a choice (adopt or reject the technology); (4) the implementation phase: in this stage the individual puts a technology into use; (5) the confirmation phase: this is an evaluation stage where the individual measure the success or failure of the decision made. In all the five stages, flow of information and
particularly how individual perceive the technology has been an important factor for adoption outcomes.

1.4. Measuring adoption of agricultural technologies
Agricultural dynamism due to change in natural conditions, resource availability as well as other socio-cultural issues made adoption of agricultural technologies unavoidable (Cimmyt, 1993). Since the introduction of adoption models in agriculture by work of Griliches (1957), agricultural economists have extensively been using the concept in various studies to analyze adoption of various agricultural technologies and their effects on agricultural performance (Adesina & Baidu-Forson, 1995; Akinola et al., 2010; Kimani et al., 2015; Letaa et al., 2014; Nkegbe et al., 2011). There are many models for measuring processes in which an individual engages in adopting a new innovation (Straub, 2009). Since the adoption is an individual decision-making process, then it is the economic choice decision whereby an individual decides to opt for a certain technology if the chosen technology will provide desired expectations, given socio-economic background of the individual. Knowing that, the stages distinguished by Rogers in 2003 are further manipulated to give the two main paradigms; (1) analysis of the adoption of technology as discrete case, and (2) analysis of adoption as a continuous case. In the first case, dichotomous choice models such as logit and probit models are usually employed to identify and evaluate the determinants of adoption for particular agricultural technologies (Aneani et al., 2012; Ayuya et al., 2012; Kaliba et al., 2000; Kijima et al., n.d.; Letaa et al., 2014). While for the second case, different types of censoring and truncated models such as Tobit and Heckman models are usually employed to explore the extent or effects or impact of the adopted technologies on various aspects in farmers’ livelihood and farming performance (Arsian et al., 2013; Baidu-Forson, 1999; Bokusheva et al., 2012; Hailu et al., 2014; Wang et al., 2012).

2. Methodology
2.1. Study area, research design, sampling and data collection methods
A survey design was used to gather the required information from small-holder vegetable farmers in Nzega District. The district is one of the seven districts of Tabora Region in Central Tanzania, receives annual rainfall between 650 mm and 850 mm, with the annual temperature ranging between 28 to 30 °C; while October and July are the warmest and coolest months, respectively. Such rainfall pattern and temperature extremes make the district one of the hottest and driest districts in the region; which is distinguished as a tropical savanna climate and typically pronounced by a dry season, or mostly referred to as semi-arid.

The survey involved 528 small-holder vegetable farmers, 1 district, 5 wards and 5 villages were purposefully selected. The criteria for selection were based on the presence of CDT and the nature and type of crops cultivated (vegetables for this case). Through respective ward and village extension officers, small-holder vegetable producers in each village were identified, and the lists

| Table 1. Population and sample selected |
|----------------------------------------|
| **Name of Village** | **Total Vegetable Producers** | **Sampled Vegetable Producers** | **Respondents Used for Analysis** |
| | | | **CDT Adopters** | **CDT Non-adopters** |
| Itunda | 102 | 81 | 30 | 46 |
| Ikindwa | 138 | 103 | 39 | 62 |
| Shila | 152 | 110 | 47 | 63 |
| Busondo | 173 | 121 | 44 | 76 |
| Iyombo | 184 | 126 | 60 | 61 |
| **Total** | **749** | **561** | **220** | **308** |
comprised both adopters and non-adopters of the CDT were developed in each village, formula of Yamane (1967) was used to determine required number of farmers in each village (Table 1). Lastly, random selection was done to obtain the number of respondents selected from each village, to get 220 adopters of Charco-dam and 308 non-adopters. Respondents were interviewed using a structured questionnaire, and a total of six focused group discussions (FGDs) were conducted; one at council headquarters and five at village level, to validate and substantiate the information collected during survey.

2.2. Theoretical framework
Adoption of agricultural technology involves a number of characteristics that influence an individual decision option, either to adopt or not to adopt the technology (Adesina & Baidu-Forson, 1995; Misaki et al., 2016; Pierpauli et al., 2013; Rodriguez-Entrena & Arrazia, 2013; Simtowe et al., 2012; Wu et al., 2010). It is noted that for an individual farmer to adopt a certain agricultural related technology, the utility derived from adopting the technology should be higher than the expected utility of not adopting (Afolami et al., 2015). Regarding that, small-holder vegetable farmers in Nzega district are assumed to be rational producers, in the sense that their production choices are in accordance with their preferences, then the equation to model their adoption process is based on utility maximization theory (Adesina & Zinnah, 1993; Sidibé, 2005; Zepeda, 1994). The model assumes that the decision to adopt a particular farm level production technology is based on the maximization of an underlying utility function and a farmer selects his/her production technologies based on his/her expected utility. Therefore a function used to estimate the adoption of Charco-Dam Technology (CDT) can be expressed as:

$$C_i^* = X_i\beta + \mu_i$$  \hspace{1cm} (1)

Where $C_i^*$ is a latent variable denoting the difference between the utility from adopting Charco-Dam technology ($U_{IA}$) and the utility from not adopting the technology ($U_{INA}$). The farmer will adopt the technology if $C_i^* = U_{IA} - U_{INA} >0$. The term $X_i\beta$ provides an estimate of the difference in utility from adopting the technology ($U_{IA} - U_{INA}$). using the household socio-economic, farm-level and information-sharing factors ($X_i$) as explanatory variables—which assumed to be exogenous, and $\mu_i$ is an error term. Basically under this situation, several choice models such as generalized probability models like Linear Probability Model (LPM), Control Function (CF), or Maximum Likelihood (ML) approaches are appropriate to estimate the adoption equation (1; Afolami et al., 2015; Ding et al., 2011; Ojo, 2004).

However, these methods have some drawbacks; for instance, LPM ignores the effect of binary outcome which may easily provide unacceptable predictions resulting to have over or under estimation (Valente et al., 2018); for CF, it is mostly observed to fit continuously distributed endogenous variables and observed to be weak in estimating discrete endogenous variables (Bontemps & Nauges, 2017; Kalisa et al., 2016); while for ML, despite its efficiency in handling discrete endogenous covariates, it requires a complete parametric specification of dependency of each endogenous covariate on error term, failure to have a proper specification may lead to endogeneity problem (Chesher et al., 2013; Greenland, 2000).

2.3. Analyzing adoption of Charco-dam technology
In cross-sectional data, endogeneity problem can arise when there is measurement error or omission of one or more important variables in the model (Koladjo et al., 2018; Lu et al., 2018). One of the solution to the problem is to use instrumental variable (IV) that replace the endogenous variable with a predicted value that has only exogenous information (Becker, 2016; Chesher et al., 2013). Following the works of Heckman et al. (2006), Bollen (2012), and Angrist and Krueger (2001), the adoption equation (1) becomes:

$$C_i^* = I(X_i\beta + \mu_i \geq 0)$$  \hspace{1cm} (2)
Where $C_i$ is the binary decision variable (to-adopt or not-to-adopt CDT), $X_i$ is the vector of explanatory variables (assumed to include at least one endogenous variable), $\beta$ are the parameters to be estimated and $\mu_i$ is the error term, that assumed to have zero mean distribution. $I(\cdot)$ is the indicator function taking the value 1 if the latent variable $X_i + \mu_i \geq 0$ is to adopt CDT and zero otherwise. To overcome the possibility of mis-specify the endogenous variables in vector $X$, an instrument variable $Z$ was introduced in equation (3), which assumed to be uncorrelated with the random shock $\mu_i$, as; $\text{Cov}(Z, \mu) = 0$, but correlated with endogenous variable in $X^i$, i.e. $\text{Cov}(Z, \mu_i) \neq 0$

$$C^*_i = I\left(X_i\beta + Z\gamma + \mu_i \geq 0\right)$$

(3)

From equation (3), the structural binary-choice model is as follows:

$$C^*_i = \begin{cases} 1 & \text{if } X_i\beta + Z\gamma + \mu_i \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

(4)

Therefore, this study analysed the adoption of CDT using instrumental variable (IV) equation (4) whereby $Z'$ is the instrumental variable and $\gamma$ is the parameter to be estimated for instrumental variable, the rest of variables are as in equation (3). For comparison purposes, results from LPM as well as normal probit regressions were also reported (Appendix A). Note, number of labour involved in vegetable production are assumed to be influenced by household-size (for family labour dependants) and the income of household income (for hired labour). Number of labours used in vegetable production assumed to influence adoption of CDT, the number of labours is as well assumed to be influenced by household income (for hired labour) and household-size (for family labour), but the variables household income and household-size are also expected to influence CDT. In such situation, at least one of the explanatory variables can be endogenous, and hence there is a chance of mis-measurement error if otherwise. One of the solutions to overcome this is the use of instrumental variable approach (Lewbel, 2000). Instrumental variables for this case are variables “number of labour used for farm-activities (NoLabourFA)” and “household-income (Hhinc)”, are replacing variable household-size (Hhs) which is assumed to cause endogeneity problem in the discrete choice model. The description of variables used in the adoption model is given in Table 2.

3. Empirical results

3.1. Characteristics of adopters and non-adopters of CDT

The summary statistics of the socio-economic, farm-level and information-sharing factors for adopters and non-adopters of charco-dam technology (CDT) are given in Table 3. It was observed that, 14 out of 22 (64%) of the compared variables were statistically insignificant, this gives an indication that the two groups are likely homogenous and therefore can statistically be compared. However, for the socio-economic variables, it was observed that male household heads occupied a larger share in both overall of the surveyed samples (86.93%), as well as for adopters (90%) and non-adopters (84.74%) categories. The difference of about 5% between the two groups was significant at 10%. No statistical difference observed for the households with formal education between the two groups (adopters and non-adopters of CDT). Mean age for non-adopters of CDT observed to be younger (37.43 years) than that of adopters (39.51%) and the difference is significant at 5% level. Mean household size for CDT-adopters observed to be higher (6.70) than that of non-adopters (3.98), and the difference were significant (at 1%). Further, results show that, the mean annual off-farm incomes for CDT-adopters was 1,361,548TZS while that of non-adopters was 1,172,404TZS, these results were statistically insignificant. For farm-level variables, no statistical difference observed between adopters and non-adopters for the individuals who owns the vegetable cropping land. It is also observed that, 56.36% of CDT adopters are involved in various micro-credit schemes while only 26.30% of non-adopters of CDT are involved with such schemes, the difference is statistically different at 1% level.
Table 2. Description of variables used in adoption model

| Variables                     | Description                                                                 |
|-------------------------------|-----------------------------------------------------------------------------|
| **Dependent Variable**        |                                                                             |
| `Usecdt` (Adoption Model)     | 1 if respondent used charco-dam technology to irrigate his/her crops; 0 otherwise |
| **Independent Variables**     |                                                                             |
| `Malehead`                    | Male household head, 1 if respondent is a male; 0 otherwise                |
| `Agehead`                     | Age of household head in years                                             |
| `Eduhead`                     | Household head’s formal education, 1 if respondent attended formal school; 0 otherwise |
| `Hhsize`                      | Number of people residing in the household                                 |
| `Landown`                     | Land ownership; 1 if farm-land is owned by the respondent; 0 otherwise     |
| `MemberFin`                   | Household head’s membership to micro-finance scheme; 1 if yes; 0 otherwise |
| `UseOSW`                      | Use of other sources of water to irrigate vegetables; 1 if the vegetable former used other RW source of water to irrigate his/her crops; 0 otherwise |
| `Lnlandsize`                  | Log of land-size used to cultivate vegetables in acres                      |
| `SourceLabour`                | Household’s source of labour for the charco-dam related activities, 1 if family 1 only; 0 if otherwise |
| `Tomato`                      | Main vegetable crop cultivated, 1 = if cultivated tomato, 0 if not         |
| `Cabbage`                     | Main vegetable crop cultivated, 1 = if cultivated cabbage, 0 if not       |
| `Sweetpepper`                 | Main vegetable crop cultivated, 1 = if cultivated sweet-pepper, 0 if not  |
| `ScarletEggplant`             | Main vegetable crop cultivated, 1 = if cultivated scarlet-eggplant, 0 if not |
| `LeafVege`                    | Main vegetable crop cultivated, 1 = if cultivated leaf-vegetables, 0 if not |
| `MemberDeve`                  | Household head’s membership to community development groups in the village/ ward; 1 if yes; 0 if no |
| `Extser`                      | Use of extension services, 1 if often; 0 if rarely or not at all           |
| `Radio_listen`                | Household head’s radio listening behaviour; 1 if often; 0 if rarely or not all |

Source: Research Data, 2018
Table 3. Distribution of socio-demographic, socio-economic and farm characteristics of Charco-Dam Technology (CDT) adopters and non-adopters

| Characteristics                           | Pooled (n = 528) | Adopters (n = 220) | Non-adopters (n = 308) | Mean Difference |
|-------------------------------------------|------------------|---------------------|------------------------|-----------------|
| **Socio-Economic Characteristics**        |                  |                     |                        |                 |
| Male household heads                      | 86.93            | 90.00               | 84.74                  | 3.125†*         |
| Households with formal education          | 84.47            | 85.00               | 84.09                  | 0.080†          |
| Mean age of household heads               | 38.30            | 39.51               | 37.43                  | −2.053***       |
| Mean household size                       | 5.11             | 6.70                | 3.98                   | −19.204****     |
| Mean households’ off-farm incomes         | 1251214          | 1361548             | 1172404                | −1.357§         |
| Individual-owned vegetable plot           | 47.54            | 47.27               | 47.73                  | 0.011†          |
| Membership to micro-finance schemes       | 38.83            | 56.36               | 26.30                  | 48.840***       |
| **Farm-Level Characteristics**            |                  |                     |                        |                 |
| Mean vegetable planted land-size          | 2.38             | 2.98                | 1.95                   | −10.313***      |
| Farmers planted tomatoes                  | 24.81            | 24.09               | 25.32                  | 0.105†          |
| Farmers planted cabbage                   | 9.66             | 10.91               | 8.91                   | 0.675†          |
| Farmers planted sweet-pepper             | 27.84            | 35.91               | 22.08                  | 12.220***       |
| Farmers planted scarlet-eggplant         | 17.99            | 20.00               | 16.56                  | 1.030†          |
| Farmers planted leaf-vegetables           | 41.48            | 38.18               | 43.83                  | 1.687†          |
| Use of improved seeds                    | 78.60            | 80.91               | 76.95                  | 1.197†          |
| Use of chemicals                         | 92.99            | 92.73               | 93.18                  | 0.041†          |
| Use of inorganic fertilizers             | 79.73            | 76.82               | 81.82                  | 1.986†          |
| Mean Labour used for farm activities      | 4.98             | 6.16                | 4.13                   | −15.823***      |
| **Information-Sharing Characteristics**   |                  |                     |                        |                 |
| Membership to community development groups| 41.10            | 56.82               | 29.87                  | 38.498***       |
| Access to extension services             | 95.83            | 95.45               | 96.10                  | 0.136†          |
| Access to radio                          | 79.73            | 78.18               | 80.4                   | 0.563†          |
| Access to mobile-phone                   | 77.27            | 75.45               | 78.57                  | 0.710†          |

***, **, and * is significance at 1%; 5%, and; 10% levels; T-test values denoted by §; χ² values denoted by †

Source: Research Data, 2018
Moreover, it was observed that, only three (30%) out of ten variables indicating farm-level characteristics are statistically different (i.e. land-size, those planted sweet-pepper and labour used in farming), the rest (i.e. use of inputs [seeds, chemicals and fertilizer], those planted other vegetables [tomato, cabbage and leafy vegetables]) are not statistically different. In addition, only 1 variable (Membership to community development groups) of the four information sharing characteristics examined was statistically different (at 1% level of significance). Majority of the development groups formulated in the villages or wards level are based on the agriculture, environment and social activities. The attention were given to the groups that were randomly accepting the membership, with the purpose of tracking their influence in improving members knowledge through interactions. No statistical difference observed for the two groups (adopters and non-adopters of CDT) in the; farm production variables, which include: use of improved seed, use of chemicals and use of inorganic fertilizers, as well as for the all information-sharing variables, which include: access to extension service, access to radio behaviour and access to mobile-phone (Table 3).

### 3.2. The diagnostic statistics of the regression models

Generally, Table 4 shows the results of probit model with instrumental variables (IVProbit). This model was having a Wald chi² of 368.62 (significant at 1% level), and Wald test of Exogeneity of 46.63 (Significant at 1% level). The IVProbit model taking the ML assumptions as a normal probit, but assume that the explanatory variables contain exogenous variable and at least one continuous endogenous variable. Using proper instrumental variable—for this case variables (NoLabourFA) and (HHinc), replaced variable (Hhsize)—override the problem of mis-measurement error observed in normal probit model. Both simple check of the Wald test of exogeneity from a “ivprobit regression” by Stock and Yogo (2002) as well as the test of IV strength by Olea and Pfleuger (2013) were applied and found that

| Variables         | Marginal Effects | Std Err | Z-value |
|-------------------|------------------|---------|---------|
| Malehead          | 0.098            | 0.204   | 0.630   |
| Agehead           | −0.008           | 0.006   | 0.192   |
| Eduhead           | −0.038           | 0.169   | 0.824   |
| Hhsize            | 0.815***         | 0.049   | 0.000   |
| Landown           | −0.188           | 0.145   | 0.195   |
| MemberFin         | 0.328**          | 0.150   | 0.029   |
| UseOSW            | −0.647***        | 0.137   | 0.000   |
| Lnlandsize        | 0.116            | 0.176   | 0.510   |
| Labour            | −0.077           | 0.141   | 0.584   |
| Tomato            | 0.453**          | 0.188   | 0.016   |
| Cabbage           | 0.518*           | 0.275   | 0.059   |
| Sweetpepper       | 0.004            | 0.192   | 0.982   |
| Scarleteggplant   | 0.243            | 0.186   | 0.190   |
| Leafvege          | 0.402**          | 0.171   | 0.019   |
| Memberdeve        | 0.296**          | 0.141   | 0.036   |
| Extser            | 0.068            | 0.182   | 0.709   |
| Radio_listen      | 0.306*           | 0.161   | 0.058   |
| Constant          | −4.487           | −7.510  | 0.000   |
| No. Obs           | 528              |         |         |
| Wald chi² (17)    | 368.62***        |         |         |
| Wald test of Exogeneity 46.63*** |            |         |         |
| Lag Pseudolikelihood | −1034.832     |         |         |
the selected instrument were statistically strong. The fact that ivprobit is robust over LPM and normal probit regression, the results for IVProbit model were considered in the discussion.

### 3.3. Determinants of Charco-dam technology adoption decision

Results in Table 4 show that household size was very significant (at 1%) and positively related with the probability of adopting CDT. The results further indicates that, one more increase in household member increases the likelihood of adopting the CDT by 0.815. Literature claims that, farming households with more family members tend to have more labour and have more chances to adopt agricultural technology than household with less family members (Kansiime et al., 2014; Kebede et al., 1990; Lambrecht et al., 2014). Likewise for the charco-dam technology (CDT), the nature of the CDT which is labour-intensive (especially during contraction of the dam, channeling the water to the dam, irrigating the crops, controlling siltation and enlarging the dam size), usually dictates the adopters to have such manpower at household level.

Most of the agricultural technologies especially those related to soil and water have accompanied by initial cost of investment (Atampugre, 2014; Yigezu et al., 2018). Thus, farmers who have substantial and consistent incomes are more likely to adopt these technologies compared to those who have low and/or inconsistent incomes (Alam, 2015). Likewise, farmer with access to credit enables him/her to have enough money to cutter for any initial or operation costs that associated with the agricultural technology opted (Abdallah, 2016; Mekonnen, 2017; Obayelu et al., 2017; Obisesani et al., 2016; Ullah et al., 2018). The findings in Table 4 are also in-line with this allegation, as individual vegetable producers in the study area who accessed micro-finance (tracked through membership to various microfinance schemes for the past three years), observed to have 0.328 likelihood of adopting CDT than those who were not members of any credit scheme, the effect is statistically significant at 5% level.

Basically, small-holder vegetable producers in the study area have two main sources of water to irrigate their vegetables; the first source is community ponds, which include open ponds, dams, wet-valleys and catchment areas that have been established and managed by the community (in this study referred as other sources of water -OSW); the second source of water is from charco-dams (CDT), which is individually established and managed at household level (the major concern of this study). Both adopters and non-adopters of CDT assumed to have an access to OSW upon adhering to the location and existing water use regulations. So, results in Table 4 show that, use of OSW is very significantly (at 1%) and negatively related with the probability of adopting CDT. Given the fact that irrigation investments (both local and improved) are cost effective, in terms of—economic, technical and environmental benefits, among others (Nissen-Petersen, 2006; Rwphemhura, 2007), it was observed that farmers with alternative sources of water for irrigation reduce the chance of adopting CDT by 0.647.

Generally, vegetables are water demanding crops regardless of their agronomic requirements. However, the amount of water required per crop with respect to agronomic specification is varying from one vegetable-crop to another. Farmers with less access to water for irrigation would prefer less water demanding vegetables and the vice-versa holds true. Results in Table 4 shows that cultivating tomato, cabbage and leafy-vegetables increase the chance of adopting CDT. Since all three vegetables are water demanding crops, producing such crops observed to increase the chances of adopting the CDT by 0.453 for tomato (at 5% level of significance), 0.518 for cabbage (at 10% level of significance) and 0.402 for leafy-vegetables (at 5% level of significance).

Essentially there is a close positively relationship between access to information and adoption agricultural technologies. Farmers who have access to agricultural information tend to have a wide knowledge and skills on various agricultural related issues, thus increase the diffusion of the various agricultural technologies and eventually increase adoption of the technologies (Baloch & Thapa, 2016; Chandio & Jiang, 2018; Maffioli et al., 2013; Nakano et al., 2018). This has also been observed, as results in Table 4 show that, access to agricultural-related information has a strong
likelihood and positively influence the adoption of the CDT, as the variables associated with the acquisition and sharing of information at rural setup, i.e. membership to social and community groups is significant at 5% level.

Individuals interaction to various social and development group in the community has been proved to provide social networks, relationships and linkages that enable individuals to cooperate, coordinate, share information and resources, and eventually act collectively, which all together can increase their likelihood to adopt various agricultural related technologies (Ali et al., 2007; Hansen & Roll, 2016; Hunecke et al., 2017; Husen et al., 2017). Likewise, this study has also evaluated the status of respondents’ social capital through membership of vegetable farmers to various social and development groups in the study area and found that, membership to various social and development activities groups in the study area improves the likelihood of adopting CDT by 0.296.

On the other hand, previous studies observed that farmers who are often listening to agricultural radio programs had more chances to adopt various agricultural related interventions than those who are rarely or not listening those programs at all, simply because this behaviour let them grasp more information about agriculture that stimulate their desire to adopt various agricultural technologies (Agwu et al., 2008; Ali et al., 2013; Manda & Wozniak, 2015). The same has been observed in this study, as the results in Table 4 show that frequency of radio listening behaviour can increase the probability of CDT adoption by 0.306, this can be attributed by the fact that, most of the individual small-holder vegetable farmers in the study area who have a desire of improving their wellbeing through improving their vegetable production requires more information regarding vegetable production, this has pushed them to solicit the information to elsewhere possible including radio. The information gathered through focused group discussion reveals that most of the farmers listening to agricultural-related radio programs which focusing on weather forecasting, Rain-Water Harvesting technologies, agricultural productivity (specifically on vegetables) and market information (both input and output markets), most of these individuals have also happened to adopt CDT as well.

4. Conclusion and recommendation
Generally, the results show that household size, access to credit, choice of crop (especially tomato, cabbage and leafy-vegetables) and access to information have positive influence on adoption of CDT, while use of other sources of water for irrigation (as an alternate irrigation-water source) was having a negative relationship with the adoption of CDT. Having these results, it can be concluded that, given the nature of the technology, socio-economic, farm-level and information-sharing factors are all important to enhance the adoption of the technology. Thus it is suggested that, any strategies or innovation or policy geared to improve the adoption rate for such technologies should be designed or developed while considering the three key factors, i.e. socio-economic, farm-level as well as the information sharing aspects. For instance, (i) microfinance institutions should develop special loans to small-holder vegetable farmers to overcome initial investment for such technologies; (ii) Local Government Authorities, Extension Officers and agricultural development partners should use progressive farmers to instill knowledge of such technologies to fellow farmers in their development groups, as well as; (iii) using media campaigns to instill the awareness to farmers on CDT technology and related issues, such media could be local radios and social media groups in ward and village level.

Acknowledgements
This paper benefited from the generous support of individuals, groups, and institutions provided. The authors are grateful to the Environment for Development (EED)-Initiative at Gothenburg University-Sweden and EED-Tanzania at the School of Economics-University of Dar-es-salaam for the financial support in conducting this study. The authors also wish to record sincere appreciation to the smallholder farmers and extension staff who participated in data collections, and we thank “anonymous” reviewers for their so-called insights.

Funding
The authors received no direct funding for this research.

Author details
Shauni Timothy1,2 E-mail: timothy@irdp.ac.tz ORCID ID: http://orcid.org/0000-0001-9743-5761 Razack Lokinaa E-mail: rloki@udsm.ac.tz Yohana James Mgale1,3 E-mail: mgaleyy@gmail.com Provident Dimosoa E-mail: pdimoso@irdp.ac.tz

1 Department of Rural Development and Regional Planning, Institute of Rural Development Planning, Dodoma, Tanzania.

E-mail: timothy@irdp.ac.tz ORCID ID: http://orcid.org/0000-0001-9743-5761 Razack Lokinaa E-mail: rloki@udsm.ac.tz Yohana James Mgale1,3 E-mail: mgaleyy@gmail.com Provident Dimosoa E-mail: pdimoso@irdp.ac.tz

1 Department of Rural Development and Regional Planning, Institute of Rural Development Planning, Dodoma, Tanzania.
2 School of Economics, University of Dar-as-Salaam, Dar-as-Salaam, Tanzania.
3 College of Economics and Management, Jilin Agricultural University, Changchun, Jilin, China.

Authors’ contributions
ST developed the concept, collect data, analyzed data, and draft the manuscript. RL and YM reviewed the literature and write the manuscript. PD edit and proof read the manuscript. All authors read and approved the final manuscript.

Availability of data and materials
All the data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure statement
No potential conflict of interest was reported by the author(s).

Citation information
Cite this article as: What matters in adoption of small-scale rain water harvesting technologies at household level? Evidence from Chorcho-dam users in Nzega, Tanzania, Shua Timotho, Razack Lokia, Yohana James Mgale & Provident Dimoso, Cogent Food & Agriculture (2022), 8: 2112429.

Note
1. www.tabora.go.tz The United Republic of Tanzania President’s Office Regional Administration and Local Government (PORALG), Tabora Regional Administrative Secretary.

References
Abdallah, A.-H. (2016). Does credit market inefficiency affect technology adoption? Evidence from Sub-Saharan Africa. Agricultural Finance Review, 76 (4), 494–511. https://doi.org/10.1108/AFR-05-2016-0052
Adesina, A., & Baidu-Forson, J. (1999). Farmers’ perceptions and adoption of new agricultural technology: Evidence from analysis in Burkina Faso and Guinea, West Africa. Agricultural Economics, 13(1), 1–9. https://doi.org/10.1111/j.1574-0862.1995.tb00366.x
Adesina, A., & Zinnah, M. (1993). Technology characteristics, farmers’ perceptions and adoption decisions: A tabot model application in Sierra Leone. Agricultural Economics, 9(4), 297–311. 10.1016/0169-5150(93)90019-9
Afolami, C. A., Obayelu, A. E., & Vaughan, I. I. (2015). Welfare impact of adoption of improved cassava varieties by rural households in South Western Nigeria. Agricultural and Food Economics, 3(1), 17. https://doi.org/10.1186/s40100-015-0037-2
Agwu, A. E., Ekwueme, J. N., & Anyanwu, A. C. (2008). Adoption of improved agricultural technologies disseminated via radio farmer programme by farmers in Enugu State, Nigeria. African Journal of Biotechnology, 7(9), 1277–1286.
Akinola, A., Alene, A. D., Adeyemo, R., Sanogo, D., Olatunweju, A. S., Nwoke, C., & Nziugbeba, G. (2010). Determinants of adoption and Intensity of use of balance nutrient management systems technologies in the Northern Guinea Savanna of Nigeria. Quarterly Journal of International Agriculture, 49(1), 25–45.
Alam, M. N. (2015). Effect of farmers socio-economic towards adoption level of agricultural technology in Sigi regency Indonesia. Journal of Applied Sciences, 15 (5), 826–830. https://doi.org/10.3923/jas.2015.826.830
Ali, L., Mangheni, N., Sanginga, P., Delve, R., Mastiko, F., & Miro, R. (2007). Social capital and adoption of soil fertility management technologies in Tororo District, Uganda. In A. Batiano, B. Waswa, J. Kihara, & J. Kimetu (Eds.), Advances in integrated soil fertility management in Sub-Saharan Africa: Challenges and opportunities (pp. 947–953). Springer.
Ali, D. Y., Nakelse, T., & Diagne, A. (2013). Rural media, agricultural technology adoption and productivity: Evidences from small rice farmers in Burkina Faso. 14.
Aneani, F., Anchirinah, V. M., Owusu-Ansah, F., & Asamoah, M. (2012). Adoption of some cocoa production technologies by cocoa farmers in Ghana. Sustainable Agriculture Research, 1(1), 103–117. https://doi.org/10.5539/sar.v1n1p103
Angrist, J., & Krueger, A. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. Journal of Economic Perspectives, 15(4), 69–85. https://doi.org/10.1257/jep.15.4.69
Arlstan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2013). Adoption and intensity of adoption of conservation farming practices in Zambia. Agriculture, Ecosystems & Environment, 15, 9. http://doi.org/10.1257/jep.15.4.69
Atampugre, G. (2014). Cost and benefit analysis of the adoption of soil and water conservation methods, Kenya. 4(8), 15. International Journal of Scientific and Research Publications
Avulachew, S. B., Merrey, D. J., Van Koppen, B., Kamara, A. B., Penning de Vries, F., Boelee, E., & Makombe, G. (2005). Experiences and opportunities for promoting small-scale/micro irrigation and rainwater harvesting for food security in Ethiopia
Ayuya, O. I., Kenneth, W. S., & Eric, G. O. (2012). Multinomial logit analysis of small-scale farmers’ choice of organic soil management practices in Bungoma County, Kenya. Current Research Journal of Social Sciences, 4(4), 314–322.
Baidu-Forson, J. (1999). Factors influencing adoption of land-enhancing technology in the Sahel: Lessons from a case study in Niger. Agricultural Economics, 20, 231–239.
Baloch, M. A., & Thapa, G. B. (2016). The effect of agro-cultural extension services: Date farmers’ case in Balochistan, Pakistan. Journal of the Saudi Society of Agricultural Sciences. https://doi.org/10.1016/j.jssas.2016.05.007
Barron, J., Salas, J., Cortesi, L., König, K. W., Malmer, A., Prasad, E., & Sharma, B. (2009). Rainwater harvesting: A lifeline for human well-being. A report prepared for UNEP by Stockholm Environment Institute.
Baumüller, H. (2013). Facilitating agricultural technology adoption among the poor: The role of service delivery through mobile phones. Department of Political and Cultural Change Center for Development Research, University of Bonn.
Becker, S. (2016). Using instrumental variables to establish causality. 12A World of Labor. https://doi.org/10.15185/izawol.250
Bokushewa, R., Finger, R., Berlin, R., Marín, Y., Pérez, F., & Paiz, F. (2012). Factors determining the adoption and impact of a postharvest storage technology. International Association of Agricultural Economists (IAAE) Triennial Conference.
Bollen, K. A. (2012). Instrumental Variables in Sociology and the Social Sciences. Annual Review of Sociology, 38(1), 37–72. https://doi.org/10.1146/annurev-soc-081309-150141
Bontemps, C., & Nauges, C. (2017). Endogenous variables in binary choice models: Some insights for practitioners. Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France, Working Paper (No. 17-855), 32.

Chandio, A. A., & Jiang, Y. (2018). Determinants of adoption of improved rice varieties in Northern Sindh, Pakistan. Rice Science, 25(2), 103–110. https://dx.doi.org/10.1016/j.rsci.2017.10.003

Chartzoulakis, K., & Bertoki, M. (2015). Sustainable water management in agriculture under climate change. Agriculture and Agricultural Science Procedia, 4, 88–98. https://doi.org/10.1016/j.aaspro.2015.03.011

Chesher, A., Rosen, A. M., & Smolinski, K. (2013). An instrumental variable model of multiple discrete choice: IV model of multiple discrete choice. Quantitative Economics, 4(2), 157–196. https://doi.org/10.19082/qe2460

Cimmyt, E. P. (1993). The adoption of agricultural technology: A guide for survey design.

Dasgupta, S. (1989). Diffusion of agricultural innovations in village India. Wiley Eastern Limited.

Ding, S., Menluoto, L., Reed, R. W., Tao, D., & Wu, H. (2011). The impact of agricultural technology adoption on income inequality in rural China: Evidence from Southern Yunnan Province. China Economic Review, 22(3), 344–356. https://doi.org/10.1016/j.chieco.2011.04.003

Gebre, G. G., & Rohut, D. B. (2021). Prevalence of household food insecurity in East Africa: Linking food access with climate vulnerability. Climate Risk Management, 33, 100333. https://doi.org/10.1016/j.crm.2021.100333

Greenland, S. (2000). An introduction to instrumental variables for epidemiologists. International Journal of Epidemiology, 29(4), 722–729. https://doi.org/10.1093/ije/29.4.722

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. Econometrica, 24(4), 501–522. https://doi.org/10.2307/1905380

Hailu, B. K., Abraha, B. K., & Weldegiorgis, K. A. (2014). Adoption and impact of agricultural technologies on farm income: Evidence from Southern Tigray, Northern Ethiopia. International Journal of Food and Agricultural Economics, 2(4), 91–106. https://doi.org/10.22046/ijfae.190816

Hall, B. H., & Khan, B. (2002). Adoption of new technology: The new economy handbook. University of California, Berkeley.

Hansen, M., & Roll, K. (2016). Social capital and adoption of agronomic practices: Theory and findings. SSN Electronic Journal. https://doi.org/10.2139/ssrn.2893610

Hatibu, N., Mahoo, H. F., & Kojiru, G. J. (2000). The role of RWH in agriculture and natural resources management: From mitigating droughts to preventing floods. In N. Hatibu & H. F. Mahoo (Eds.), Rainwater harvesting for natural resources management (pp. 58–83). RELMA in ICRAF/World Agroforestry Centre.

Heckman, J. J., Urzua, S., & Vytlacil, E. (2006). Understanding instrumental variables in models with essential heterogeneity. IZA Discussion Paper, No. 2219, Institute for the Study of Labour (IZA), Bonn, 112.

Hunecke, C., Engler, A., Jora-Rojas, R., & Poortvliet, P. M. (2017). Understanding the role of social capital in adoption decisions: An application to irrigation technology. Agricultural Systems, 153, 221–231. https://doi.org/10.1016/j.agsy.2017.02.002

Husen, N., Loos, T., Siddiq, K., Tiwari, N., Sharma, P., & Zaidi, S. (2017). Social capital and agricultural technology adoption among Ethiopian farmers. American Journal of Rural Development, 5(3), 65–72.

Iizumi, T., & Ramankutty, N. (2015). How do weather and climate influence cropping area and intensity? Global Food Security, 4, 46–50. https://doi.org/10.1016/j.gfs.2014.11.003

IPCC (2007). Climate change 2007: Climate impacts, adaptation and vulnerability. Working group II to the intergovernmental panel on climate change fourth assessment report.

Jackson, S., Claude, G. M., & Godfrey, F. K. (2018). The impacts of climate change and variability on crop farming systems in Semi-Arid Central Tanzania: The case of Manyoni District in Singida Region. African Journal of Environmental Science and Technology, 12(9), 323–334. https://doi.org/10.5897/AJEST2018.2481

Kaliba, A. R. M., Verkuilhi, H., & Mwangi, W. (2000). Factors affecting adoption of improved maize seeds and use of inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. Journal of Agricultural and Applied Economics, 32(1), 35–47. https://doi.org/10.1017/S1074078000027802

Koliso, T., Riddel, M., & Shaw, W. D. (2018). Willingness to pay to avoid arsenic-related risks: A special senior age group. Environmental Economics and Policy Studies, 5(2), 143–162. https://doi.org/10.1007/s10204-015-0787-1

Kong, Y., Khan, S., & Ma, X. (2009). Climate change impacts on crop yield, crop water productivity and food security – A review. Progress in Natural Science, 19(12), 1665–1674. https://doi.org/10.1016/j.pnsns.2009.08.001

Kannan, N., & Anandhi, A. (2020). Water management for sustainable food production. Water, 12(3), 778. https://doi.org/10.3390/w12030778

Kansilme, M. K., Wambuug, S. K., & Shisanya, C. A. (2014). Determinants of farmers’ decisions to adopt adaptation technologies in Eastern Uganda. Journal of Economics and Sustainable Development, 5(3), 189–199. https://www.iste.org/Journals/index.php/JEDS/article/view/11012

Kebede, Y., Gunjal, K., & Coffin, G. (1999). Adoption of new technologies in Ethiopia agriculture: The case of Tegulet-Bulga District, Shoa Province. Agricultural Economics, 4, 27–43. https://doi.org/10.1016/S1045-6089(98)00017-0

Klemewernek Mekuria, Z., Kassegn Amede, A., Endris Mekonnen, E., & Yilma, F. (2020). Adoption of rainwater harvesting technologies in Ethiopia: Evidence from farmer livelihoods in Kutober district, South Wollo Zone, Ethiopia. Cogent Food & Agriculture, 6(1), 1834910. https://doi.org/10.1080/23311932.2020.1834910

Kijima, Y., Otsuka, K., & Sserunkuuma, D. (ind). Determinants of changing behaviors of NERICA adoption: An analysis of panel data from Uganda, 34.

Kimani, M. W., Gitau, A. N., & Ndunge, D. (2015). Rainwater harvesting technologies in Makueni County, Kenya. International Journal of Engineering And Science, 5(2), 39–49. https://doi.org/10.6084/M9.FIGSHARE.1391937.V1

Koladejo, B. F., Escalona, S., & Tubert-Bitter, P. (2018). Instrumental variable analysis in the context of dichotomous outcome and exposure with a numerical experiment in pharmacoepidemiology. BMC Medical Research Methodology, 18(1), 61. https://doi.org/10.1186/s12874-018-0513-y

Lombrocco, J., VonHove, B., Merckx, R., & Maertens, M. (2014). Understanding the process of agricultural technology adoption: Mineral fertilizer in Eastern DR Congo. World Development, 59, 132–146. https://doi.org/10.1016/j.worlddev.2014.01.024
Letao, E., Kabungo, C., Katungi, E., Ojara, M., & Ndunguru, A. Farm level adoption and spatial diffusion of improved common bean varieties in Southern highlands of Tanzania. (2016). Tumour Biology: the Journal of the International Society for Oncodevelopmental Biology and Medicine, 36(2), 1091–1097. International Center for Tropical Agriculture (CIAT), Pan Africa Bean Research Alliance and Agricultural Research Institute-Uyole. https://doi.org/10.1007/s13277-014-2667-5

Lewbel, A. (2000). Semiparametric qualitative response model estimation with unknown heteroscedasticity or instrumental variables. Journal of Econometrics, 97(1), 145–177. https://doi.org/10.1016/S0304-4076(00)00015-4

Lewis, P., Monern, M. A., & Impiglia, A. (2019). Impacts of climate change on farming systems and livelihood in the northeastern and northeastern Africa—special focus on small-scale farming family. FAO.

Lu, G., Ding, X. D., Peng, D. X., & Hao-Chun Chuang, H. (2018). Addressing endogeneity in operations management research: Recent developments, common problems, and directions for future research. Journal of Operations Management, 64(1), 53–64. 10.1016/j. jom.2018.10.001

Maffioli, A., Ufial, D., Vazquez-Bare, G., & Cerdan-Infantes, P. (2013). Improving technology adoption in agriculture through extension services: Evidence from Uruguay. Journal of Development Effectiveness, 5(2), 64–81. https://doi.org/10.1080/19493934.2013.768917

Mahoo, H. F., Simukanga, L., & Koshaga, L. (2015). Water resources management in Tanzania: Identifying research gaps and needs and recommendations for a research agenda. Tanzania Journal of Agricultural Science, 14(1), 57–77.

Manda, L. Z., & Wozniak, J. (2015). Farmer participation in radio campaigns for technology adoption: Lessons from AFFRI’s hybrid maize campaign in Mangochi, Malawi. Journal of Development and Communication Studies, 4(1), 2. http://dx.doi.org/10.4314/jdcs.v4i1.1

Matí, B. (2012). Best practices for water harvesting and storage within valleys. Training Manual 3. 46. [Training Manual]. NBU/ NELSAP - Regional Agricultural and Trade Programme (RATP).

Mekonnen, T. (2017). Impact of agricultural technology adoption on market participation in the rural social network system –. Maastricht Economic and Social Research Institute on Innovation and Technology, 43.

Misiko, E., Apio, M., & Gaijina, S. (2016). Technology for small-scale farmers in Tanzania: A design science research approach. The Electronic Journal of Information Systems in Development Countries, 4(74), 1–15. https://onlinelibrary.wiley.com/doi/pdf/10.2002/j.1811-4835.2016eb00538.x

Nakano, Y., Tsuzoka, T. W., Aida, T., & Pede, V. O. (2018). Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. World Development, 105, 336–351. https://doi.org/10.1016/j.worlddev.2017.12.013

Nissen-Petersen, E. (2006). Water from Small Dams: A handbook for technicians, farmers and others on site investigations, design, cost estimates, construction and maintenance of small earth dams (E. Biarmoh, A. Verjee, & S. Larsen, Eds.). ASAL Consultants/ DANIDA. http://www.waterforafricaand.com/Books/Book4water%20from%20small% 20dams.pdf

Nkenge, P. K., Shankar, B., & Ceddio, G. M. 2011. Smallholder adoption of soil and water conservation practices in Northern Ghana. Congress Change and Uncertainty: Challenges for Agriculture, Food and Natural Resources.

Obayelu, E. A., Ajioy, O. D., & Oggunmola, O. O. (2017). What does literature say about the determinants of adoption of agricultural technologies by smallholder farmers? Agricultural Research & Technology: Open Journal Access, 6(1), 5. https://doi.org/10.19080/ARTOJA.2017.06.555576

Obisesan, A., Amos, T., & Akinlade, R. (2016). Causal effect of credit and technology adoption on farm output and income: The case of cassava farmers in Southwest Nigeria. Transforming smallholder agriculture in Africa: The role of policy and governance, Addis Ababa.

Ochieng, J., Kimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small scale farmers in Kenya. NIAS: Wageningen Journal of Life Sciences, 77(1), 21–28. https://doi.org/10.17632/03K903.4

Ojo, S. O. (2004). Improving labour productivity and technical efficiency in food crop production: A panacea for poverty reduction in Nigeria. Food, Agriculture & Environment, 2(2), 227–231.

Olea, J. L. M., & Pflueger, C. E. (2013). A robust test for weak instruments. Journal of Business and Economic Statistics, 31(3), 358–369. https://doi.org/10.1080/ 00400756.2013.806694

Pierpola, E., Carli, G., Pignatti, E., & Canovari, M. (2013). Drivers of precision agriculture technologies adoption: A literature review. Procedia Technology, 8, 61–69. https://doi.org/10.1016/j.protcy.2013.11.010

Rodriguez-Entrena, M., & Arrizo, M. (2013). Adoption of conservation agriculture in olive groves: Evidences from Southern Spain. Land Use Policy, 34, 294–300. https://doi.org/10.1016/j.landusepol.2013.04.002

Rogers, E. M. (1962). Diffusion of innovations. Free Press.

Rogers, E. M. (1983). Diffusion of innovations (3rd ed.). Free Press.

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Rosa, L., Chiarelli, D. D., Rulli, M. C., Dell’Angelo, J., & D’Olorico, P. (2016). Global agricultural economic water scarcity. Science Advances, 6(18), 10. 101126/sciadv.aax0631

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Göttert, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., & Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences, 111(9), 3268–3273. https://doi.org/10.1073/pnas. 1222463110

Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Tol, J. S. (2002). Increased crop damage in the US from excess precipitation under climate change. Global Environmental Change, 12(3), 197–202. https://doi.org/10.1016/S0959-3780(02)00008-0

Rwehumbizo, F. B. (2007). Best practices for water harvesting and irrigation [Efficient Water Use for Agricultural Production (EWUAP) project]. Nile Basin Initiative.

Sidibe, A. (2005). Farm-level adoption of soil and water conservation techniques in Northern Burkina Faso. Agricultural Water Management, 71(3), 211–224. https://doi.org/10.1016/j.agwat.2004.09.002

Simtowe, F., Kassie, M., Asfaw, S., Shiferaw, B., Monya, E., & Siambi, M. (2012). Welfare effects of agricultural technology adoption: the case of improved groundnut varieties in rural Malawi. International
Association of Agricultural Economists (IAAE) Triennial Conference, Foz Do Iguaçu (pp. 37).

Smith, R. B. W., Hildreth, L. A., & Savadago, K. (2011). Evaluating the economic impacts of water harvesting in Burkina Faso. Ecosystem Services Economics (ESE), Division of Environmental Policy Implementation, UNEP, Nairobi, Kenya, Paper No. 6, 17.

Stephens, T. (2010). Manual on small earth and dams: A guide to siting, design and construction (Irrigation and Drainage Paper No. 64). FAO.

Stock, J., & Yogo, M. (2002). Testing for Weak Instruments in Linear IV Regression. No. 284. 73.

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. Review of Educational Research, 79(2), 625–649. https://doi.org/10.3102/0034654309325896

Tzanakakis, V. A., Paranychianakis, N. V., & Angelakis, A. N. (2020). Water supply and water scarcity. Water, 12(9), 2347. https://doi.org/10.3390/w12092347

Ullah, A., Khan, D., Zheng, S., & Ali, U. (2018). Factors influencing the adoption of improved cultivars: A case of peach farmers in Pakistan. Ciência Rural, Santa Maria, 48(11), 1–11. https://doi.org/10.1590/0103-8478cr20180342

Valente, J., Murteiro, J., & Augusto, M. (2018). Endogeneity issues in the empirical assessment of the determinants of loan renegotiation. Center for Business and Economics Research, University of Coimbra, Working Paper No 15, 31.

Wagner, B. (Ed.). (2003). Water from ponds, pans and dams: A manual on planning, design, construction and maintenance. RELMA in ICRWF World Agroforestry Centre. http://www.worldagroforestry.org/downloads/Publications/PDFS/MN13546.pdf

Wang, H., Pandey, S., & Velarde, O. (2012). Pattern of adoption of improved rice varieties and its determinants in Cambodia. Procedia Economics and Finance, 2, 335–343. https://doi.org/10.1016/S2212-5671(12)00095-0

Wu, H., Ding, S., Pandey, S., & Tao, D. (2010). Assessing the impact of agricultural technology adoption on farmers’ well-being using propensity-score matching analysis in rural China. Asian Economic Journal, 24(2), 141–160. https://doi.org/10.1111/j.1467-8381.2010.02033.x

Yamane, T. (1966). Statistics: An Introductory Analysis (2nd ed.). New York: Harper and Row.

Yigezu, Y. A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., & Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. Technological Forecasting and Social Change, 134, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006

Zepeda, L. (1994). Simultaneity of technology adoption and productivity. Journal of Agricultural and Resource Economics, 19(1), 46. https://doi.org/10.22004/ag.econ.31232
Appendix A

General Information of the Used Models

Three models were considered to analyze the determinants of CDT adoption. Generally, the results in Appendix B show that, model (1) and model (2) have related findings in terms of sign, they only differ in terms of the magnitudes. While results for model (3) were different from the rest.

Model (1)—is Linear Probability Model (LPM), taking the assumptions of Ordinary Least Square (OLS), the model found to have R-square of 0.5891, which indicates that the independent variables were able to explain the adoption effect by only 58.9%.

Model (2)—is normal probit regression taking the assumptions of Maximum Likelihood (ML) while assuming no-endogeneity explanatory variables. This model was having a Waldi chi² of 185.52 (significant at 1% level), and a Pseudo R² of 0.5811, again indicating that only 58% of the variation in dependent variable are explained by independent variables. Since, this model assumed all of the explanatory variables are exogenous, hence there is a chance of mis-measurement error if otherwise (Lewbel, 2000).

Model (3) shows the results of probit model with instrumental variables (IVProbit). This model was having a Waldi chi² of 368.62 (significant at 1% level), and Wald test of Exogeneity of 46.63 (Significant at 1% level). The IVProbit model taking the ML assumptions as a normal probit, but assume that the explanatory variables contains exogenous variable and at least one continuous endogenous variable. Using proper instrumental variable—for this case variables (NoLabourFA) and (HHinc), replaced variable (Hhsise)—override the problem of mis-measurement error observed in normal probit model.

Appendix B

Regression Results for; Logit Probability Mode (Model 1); Normal Probit (model 2), and; Probit with IV (Model3)

| Variables  | Model (1) LPM | Model (2) Normal Probit | Model (3) IVProbit |
|------------|---------------|-------------------------|--------------------|
|            | Coefficient   | Std Err                 | Coefficient        | Std Err             | Coefficient | Std Err |
| MaleHead   | 0.0653        | 0.0422                  | 0.018              | 0.040              | 0.098       | 0.204   |
| AgeHead    | −0.0011       | 0.0013                  | 0.000              | 0.001              | −0.008      | 0.006   |
| Eduhead    | −0.0221       | 0.0397                  | −0.018             | 0.034              | −0.038      | 0.169   |
| Hsize      | 0.1013***     | 0.0084                  | 0.089***           | 0.007              | 0.815***    | 0.049   |
| Landown    | −0.0280       | 0.0319                  | −0.037             | 0.029              | −0.188      | 0.145   |
| MemberFin  | 0.1109***     | 0.0314                  | 0.081***           | 0.026              | 0.328**     | 0.150   |
| UseOSW     | −0.1650***    | 0.0300                  | −0.137***          | 0.026              | −0.647***   | 0.137   |
| Lnlandsizye| 0.0946***     | 0.0318                  | 0.092***           | 0.028              | 0.116       | 0.176   |
| Labour     | −0.0306       | 0.0298                  | −0.034             | 0.027              | −0.077      | 0.141   |
| Tomato     | 0.0784*       | 0.0406                  | 0.069**            | 0.041              | 0.453**     | 0.188   |
| Cabbage    | 0.0658        | 0.0559                  | 0.038              | 0.056              | 0.518*      | 0.275   |

(Continued)
(Continued)

| Variables          | Model (1) LPM |            | Model (2) Normal Probit |            | Model (3) IVProbit |            |
|--------------------|--------------|------------|-------------------------|------------|-------------------|------------|
|                    | Coefficient  | Std Err    | Coefficient             | Std Err    | Coefficient       | Std Err    |
| Sweetpepper        | 0.0294       | 0.0424     | 0.000                   | 0.036      | 0.004             | 0.192      |
| Scarleteggplant    | 0.0397       | 0.0449     | 0.028                   | 0.038      | 0.243             | 0.186      |
| Leafvege           | 0.0391       | 0.0385     | 0.043                   | 0.034      | 0.402**           | 0.171      |
| Memberdeve         | 0.0765**     | 0.0317     | 0.069***                | 0.026      | 0.296**           | 0.141      |
| Extser             | 0.2731       | 0.0364     | 0.155***                | 0.026      | 0.068             | 0.182      |
| Radio_listen       | 0.0670**     | 0.0310     | 0.069                   | 0.030      | 0.306*            | 0.161      |
| No. Obs            | 528          | No. Obs    | 528                     | No. Obs    | 528               |            |
| F(17, 510)         | 43.00***     |            | Wald chi2 (17)          | 185.51***  | Wald chi2 (17)    | 368.68***  |
| R-Square           | 0.5891       |            | Pseudo R2               | 0.5811     | Wald test of Exogeneity (/athrho = 0) | 46.63***  |

***Significant at 1%; **Significant at 5% and *Significant at 10% levels.
Source: Research Data, 2018
