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The impact of climate information services on smallholder farmers' livelihood outcomes

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ABSTRACT

A number of strategies are being put in place in many countries to help minimize the negative impacts of climate change on agriculture and related enterprises. One such strategy is the provision of climate forecasts to farmers. This study investigated the impact of access to tailored climate information services on smallholder farmers' livelihood outcome variables such as yield of pearl millet, livestock value and household incomes. A counterfactual framework was used to identify impact, through computation of the Average Treatment effect on the Treated. The study employed the Propensity Score Matching method in estimating the impact. The results revealed that access to tailored climate information services had a positive and significant effect on farmers' incomes. However, impact on yield of pearl-millet was insignificant and impact on livestock value was weakly significant. The study concluded that tailored climate information services have the capacity to enhance farmers' livelihood outcomes such as incomes.

Keywords: Impact evaluation, livelihood outcomes, smallholder farmers, tailored climate forecasts

RÉSUMÉ

Plusieurs stratégies sont en cours de mise en place dans de nombreux pays pour aider à minimiser les effets négatifs du changement climatique sur l'agriculture et les entreprises connexes. L'une de ces stratégies consiste à fournir des prévisions climatiques aux agriculteurs. La présente étude a examiné l'impact de l'accès à des services d'information climatique personnalisés sur les variables de moyens de subsistance des petits exploitants agricoles, telles que le rendement du mil, la valeur du bétail et les revenus des ménages. Un cadre contre-factuel a été utilisé pour identifier l'impact, à travers le calcul de l'effet du traitement moyen sur le traité. L'étude a utilisé la méthode d'appariement des coefficients de propension pour estimer l'impact. Les résultats ont révélé que l'accès à des services d'information climatique personnalisés avait un effet positif significatif sur les revenus des agriculteurs. Cependant, l'impact sur le rendement du mil perlé était insignifiant et l'impact sur la valeur du bétail était faiblement significatif. L'étude a conclu que les services d'information personnalisés sur le climat ont la capacité d'améliorer les moyens de subsistance des agriculteurs, tels que leurs revenus.

Mots clés : évaluation d'impact, moyens de subsistance, petits exploitants agricoles, prévisions climatiques personnalisées

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INTRODUCTION

The majority of the smallholder farmers in Sub-Saharan African countries stay in the communal areas relying on agriculture as their main livelihood source. These farmers are vulnerable to a myriad of external shocks and climate change is one such threat that they have faced in recent years (Fellman, 2012; World Bank, 2019). Smallholder farmers in semi-arid regions of Zimbabwe are often vulnerable to adverse weather conditions including inadequate rainfall; floods and extreme temperatures coupled with pest and disease outbreaks, which normally result in severe crop and livestock losses (Climate Technology Centre and Network, 2017). While these risks are common in the agricultural sector, farmers' lack of access to reliable and area specific climate information hampers their ability to fully prepare for on-coming agricultural seasons (Mapfumo *et al.,* 2013; Oxfam, 2015).

Climate information services (CIS) have thus emerged as a key input for adaptation decision making. In practice, CIS aim to strengthen agricultural livelihoods by managing climatic risks (Singh *et al*., 2016). According to Vaughan and Dessai (2014), the purpose of CIS is to ensure provision of timely and tailored climate forecasts that can be used in managing climate related risks in order to protect farmers' livelihoods and assets. This study adopts Oxfam's definition of a climate service where, 'a climate service is the provision of climate information in a way that assists decision-making locally (tailored) for a particular livelihood system, e.g. mixed crop and livestock system' (Oxfam, 2015). Some of these services include agro-meteorology advice, seasonal forecasts, early warning systems, rainfall recordings and trainings. Climate services offered to smallholder farmers should help them in making their own decisions, diversify their livelihood choices and protect their assets, thus ensuring that they are less vulnerable to climate induced shocks.

Climate information services refer to the provision of one or more weather and/or climate products or advice in such a way that it assists decision-making by individuals or organisations (Mills *et al*., 2016). They involve partnerships among several stakeholders in the provision, dissemination and utilization of the climate information. These stakeholders include the meteorological services departments, government agencies in agriculture, private companies or academia in research and smallholder farmers (Tall *et al*., 2014). If it is untailored, climate information may not be used adequately and may not be integrated effectively into agricultural systems. The climate information (CI) provided to smallholder farmers through forecasts in most cases is too general (untailored), with much use of technical terms which farmers find difficult to understand and act on (Oxfam, 2015). As a result, farmers fail to properly apply the necessary coping strategies meant to reduce the risk of crop failure and deaths of livestock.

For CI to be actionable, communication channels between producers and users need to be accessible, effective, timely and bi-directional. Factors that contribute to effective use of CI by communities include the language, style, the channel through which information is disseminated, packaging of CI, e.g., tailored to specific users' capacities and needs, and the style and visual packaging of translated climate information (Perkins *et al*., 2015). According to Tall *et al*. (2014) there are five challenges that confront efforts to use climate-related information to improve the lives of smallholder farmers. The five challenges are discussed below:

1. Salience - This is about tailoring content, format, scale and lead-time to farm-level decision-making (Tall *et al*., 2013). It entails bridging the gap between providers

of climate information and the users. For the challenge of salience to be successfully addressed, there is need for partnerships among National Meteorological Services departments, stakeholders in agriculture, development, Information Communication Technology providers and farmers.

2. Access - This involves providing timely climate services to remote rural communities with marginal infrastructure (Perkins *et al*., 2015). Scaling up access to climate services will require a combination of communication channels, which include mass media (e.g. radios), electronic media (e.g. text messages/ call-in services), and community channels (e.g., agricultural extension services, farmer organizations, and social networks) (Tall *et al*., 2014). In Africa, the main channels for the dissemination of climate information include televisions, radios, bulletins and emails, and countries like Kenya, Ethiopia and Sudan have developed climate information websites, where they share the information with interested end-users (Wilkinson *et al*., 2015).
3. Legitimacy - Making sure farmers own and have an effective voice in the design, production and delivery of CIS is key to ensuring legitimacy, as are continuous assessments of service quality and delivery (Tall *et al*., 2014). Indeed Tall *et al*. (2014) further note that trust, local relevance and use are fostered when meteorological information is integrated with local indigenous knowledge.
4. Equity - Women generally have less access to information and resources than men, especially in rural Africa (Perkins *et al*., 2015). Equity is about ensuring that women, youth, the poor and other socially marginalized groups are also served in development issues (Tall *et al*., 2013).
5. Integration - This entails providing climate services as a part of a larger package of agricultural support or interventions to enable the effective management of climate related agricultural risks (Tall *et al*., 2013). In order to meet farmers' needs, climate information should be integrated with other forms of agricultural information for example information on agricultural markets (Perkins *et al*., 2015).

Very few studies in the literature of climate information services in agriculture have attempted to assess the impact of climate information services on farmers' welfare/ livelihood outcomes using impact evaluation methods (Patt *et al*., 2005; Maini and Rathore, 2011; Carr *et al*., 2015). The main objective of this study was thus to investigate the impact of access to climate information services on livelihood outcomes of smallholder farmers in Chiredzi and Buhera districts of Zimbabwe. The livelihood outcomes under study included yield of pearl-millet, value of livestock owned and household income.

RESEARCH APPROACH

Study site. The study was carried out in Buhera and Chiredzi districts, of Manicaland and Masvingo provinces of Zimbabwe, respectively. Both Buhera and Chiredzi lie in Natural Regions IV and V of the country, thus representing semi-arid to arid areas which receive a mean annual rainfall of less than 450 mm. The areas are affected by high inter-annual rainfall variability and associated climate risks. The majority of smallholder farmers in these districts depend on rain-fed agriculture making drought the most important production risk that impacts their livelihoods (Unganai *et al*., 2013). Despite this fact, smallholder farmers in Chiredzi and Buhera continue to grow crops and to rear livestock.

The Scaling up Climate Change Adaptation (SCCA) project. In trying to reduce the vulnerability of smallholder farmers in the study area to climate risks, Oxfam in partnership with Plan International, Southern Alliance for Indigenous Resources (SAFIRE) and University of Zimbabwe (UZ), executed a Government of Zimbabwe - United Nations Development Program and Global Environment Facility (GoZ - UNDP/GEF) supported project titled 'Scaling up Climate Change Adaptation (SCCA) in Zimbabwe with a focus on rural livelihoods.' The SCCA project ran from 2014 to 2018 and one of its outcomes was to increase smallholder farmers' knowledge and understanding of climate related issues through provision of climate information services in the study area (Oxfam 2015). The projected targeted smallholder farmers from Buhera, Chiredzi and Chimanimani , and 70% of the targeted farmers were women.

In Buhera, the beneficiaries of the project were selected from three wards (25, 28 and 30) which fall under the Save sub-catchment area in Buhera South (Figure 1). The Save sub-catchment area, being a watershed, was selected as it was highly suitable for the establishment of irrigation infrastructure (Oxfam 2015).

In Chiredzi District, the beneficiaries were selected from nine wards (6, 7, 8, 10, 11, 12, 13, 14 and 15) which represent areas with moderate to high vulnerability to climate change shocks as shown in Figure 2 (Oxfam, 2015).

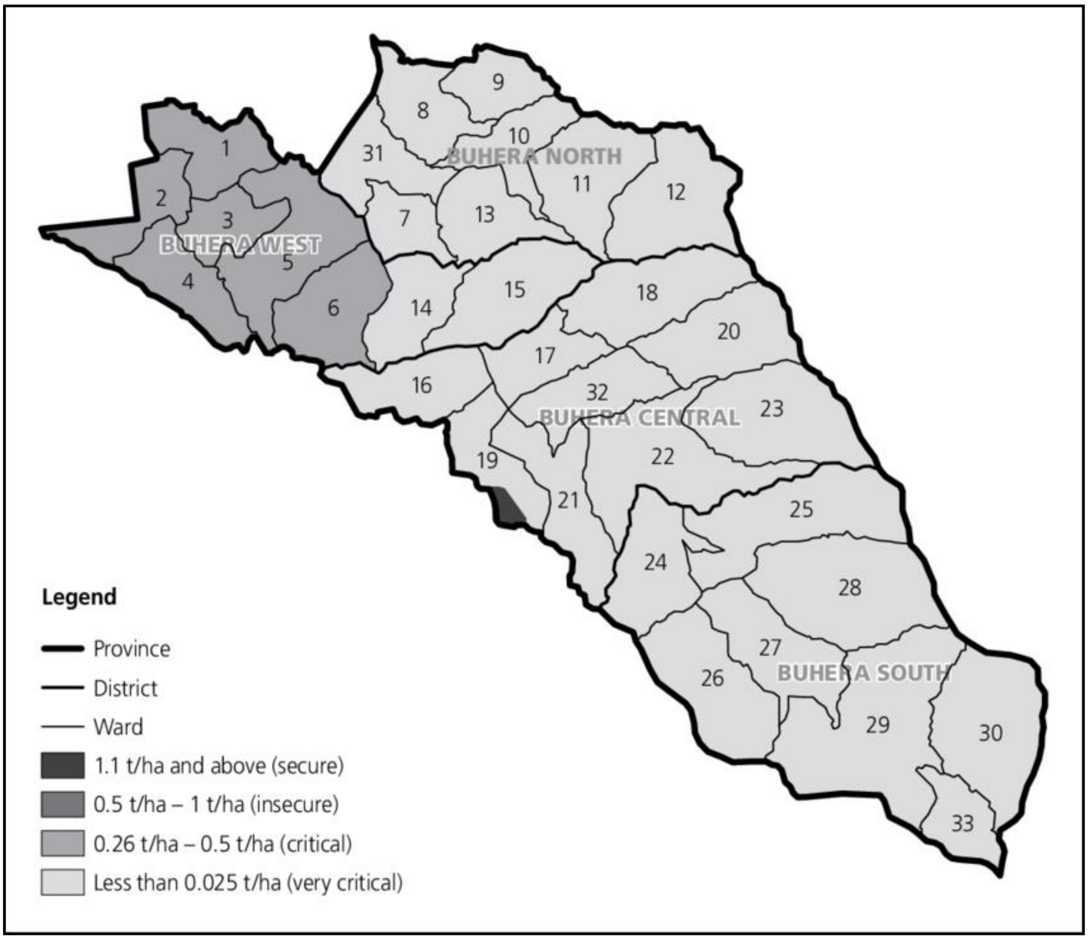

Figure 1. Buhera District ward map for production year 2011/2012
Source: Mupindu (2015)

[1] Chimanimani District was not covered in this study

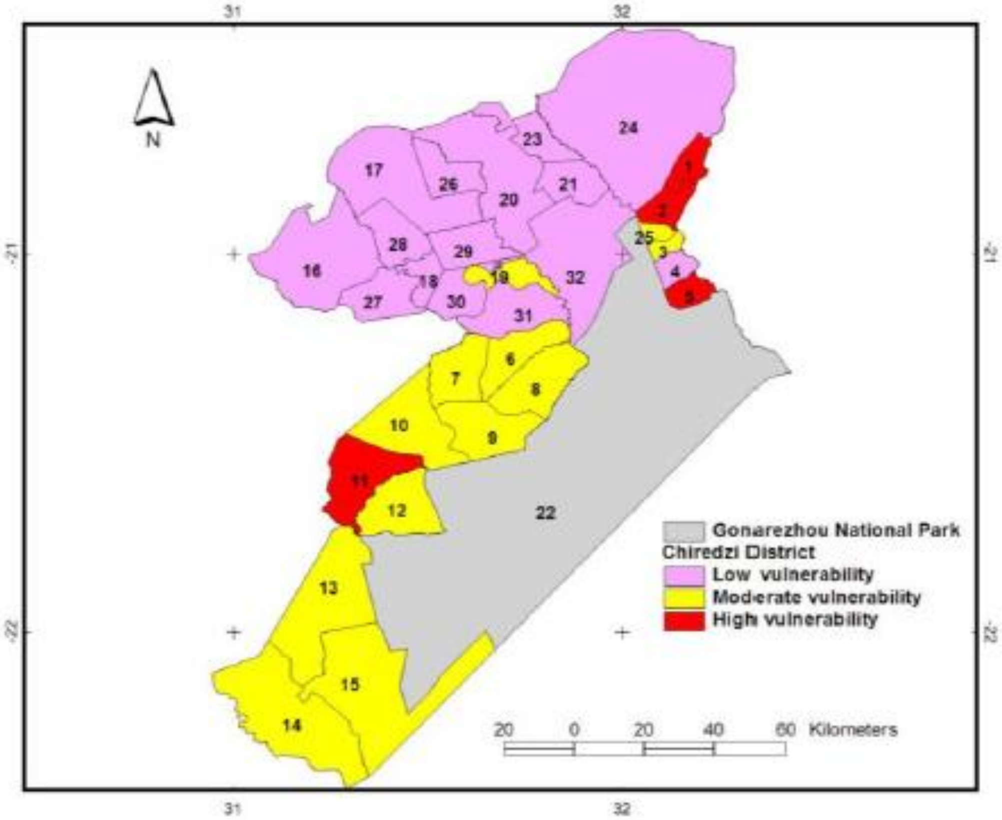

Figure 2. Chiredzi District Wards
Source: (Oxfam, 2015)

The Global Framework on Climate Services (GFCS) was used to split the climate information services value chain into four pillars/ clusters that define the processes by which these services were developed and ultimately delivered to farmers as shown in Figure 1. These pillars include Observation and Monitoring, Prediction and Modelling, Agricultural Advisories and Information Dissemination. A detailed explanation of how these clusters were connected in the climate information services value chain under the SCCA project is given here:

First, to each of these four pillars of the CIS value chain, innovators were assigned with the goal of improving the relevance, quality and reliability of the output of each pillar (Oxfam, 2015) by addressing the challenges faced within that portion of the value-chain as suggested by Tall *et al*. (2014). The innovation process started with the establishment of three Climate User Interface Platforms (CUIPs) in Buhera District (Ward 30), Chiredzi District (Ward 11) and Chimanimani District (Ward 3). The first cluster of the CIS value chain is the Observation and Monitoring cluster. Generally, the aim of this cluster was to close gaps in meteorological data that existed between providers and end users of climate forecasts. Many regions and climatic zones in Africa are poorly observed because the continent has the least developed observation network of all continents (World Meteorological Organization, 2019). Recognizing the need for good quality data is a prerequisite when it comes to provision of climate services (World Meteorological Organization, 2015). To solve the problem of unavailability of data, it was agreed through interaction during CUIPs, that Automatic Weather Stations, Synoptic Weather

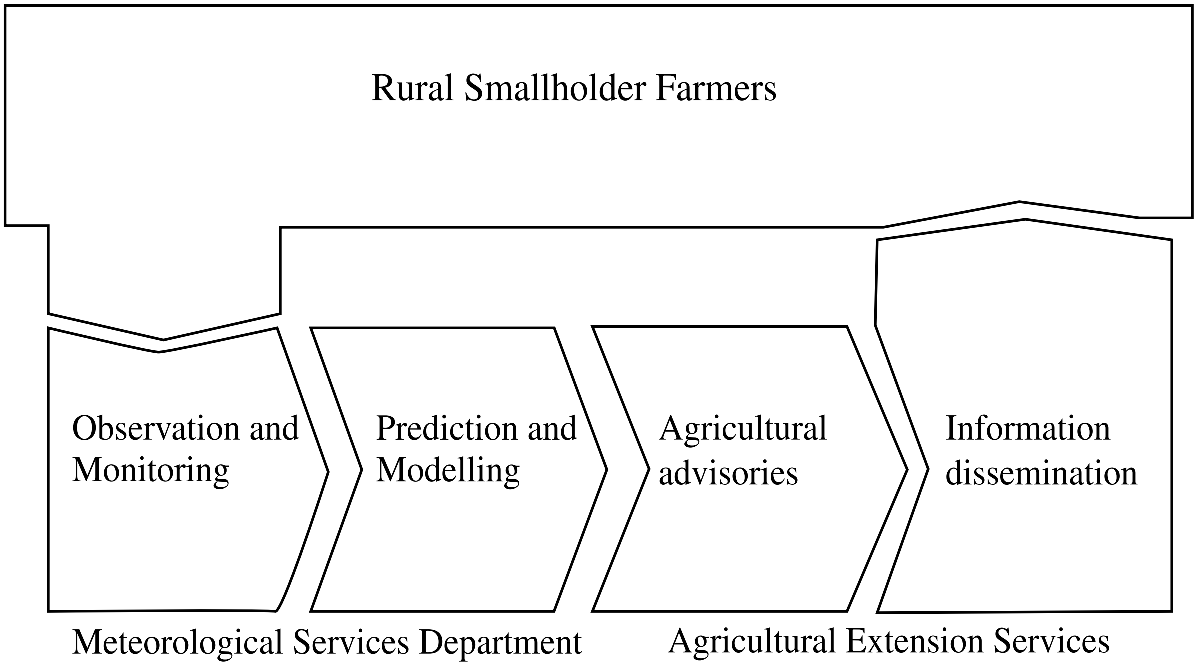

Figure 3. Climate services value chain
Source: (Oxfam 2015)

Stations, Agro-meteorological Weather Stations and Rainfall Stations should be set up in each of the project areas. An Automatic Weather Station (AWS) is an automated version of the traditional weather station which enables measurements from remote areas with limited human input. A Synoptic Weather Station collects meteorological data at synoptic times, and then transmits the data to the World Meteorological Organization (WMO) global database. The data will then be used in global weather forecasts models. The synoptic stations include both Automatic and Manual weather stations.

An Agro-met Weather Station has all attributes of a Manual Weather Station. Data collection in Agro-met Weather Stations was done every 10 days and the data were used for preparing agro-met bulletins. At the rainfall stations, rainfall was measured usually by volunteers and the farmers who were trained to do so.

After the Observation and Monitoring cluster there is the Prediction and Modelling cluster. The aim of this cluster was to produce timely, accurate, usable and localized 10 day weather forecasts using data obtained from the weather stations in the study area. The Prediction and Modelling cluster gave inputs to the Agricultural Advisories cluster, which then translated climate forecasts into actionable climate information. Lastly there is the Information Dissemination cluster. Having its inputs coming from the Agricultural Advisories cluster, the main aim of the Information Dissemination cluster was to disseminate climate information and agro-advisories. In this cluster agricultural extension officers were the critical element in the dissemination and explaining of the climate information (agro-met bulletins) to farmers because they had local knowledge about the areas they were stationed in.

Sampling and Data Collection. The study made use of both primary and secondary data. Primary data were collected between July and August 2017 through use of semi structured questionnaires in the study areas. Multistage sampling was adopted for this study. First in each of the two districts covered by the SCCA project, a ward where the various tailored climate information services were established was identified. Second, for each selected ward in the two districts, a list of farmers who resided in Climate Smart Villages and participated in the project was drawn with the help of project staff and agricultural extension officers. A second list of farmers that did not participate in the project was also obtained with the help of local administration, project staff and extension officers. One main challenge when it comes to the assessment of impact of climate information services is that climate information (just like any other form of information) can be 'leaky' across households and communities (Tall *et al*., 2018). Therefore to avoid contamination of results in this study, the control wards were chosen as far away as possible from the treated wards, while at the same time making sure that the selected villages within the wards were similar enough (geographically, agro-climatically and culturally) for comparisons to be made. Thirdly, the respondents were sampled from the two lists using the simple random sampling method. A total of 90 respondents were interviewed, 43 were beneficiaries/ participants of the SCCA project while the remaining 47 were non-participants.

Data analysis. In order to investigate the impact of an intervention there is need to establish a counterfactual that denotes what would have occurred to the participants, had they not participated in the program (Baker, 2000). However, this poses a challenge because 'the before intervention' situation remains missing. Therefore to ensure proper estimation of the counterfactual, there is need to establish a comparative group that did not participate in the program. This study used the Propensity Score Matching (PSM) method to do so. One of the advantages of PSM method is that it highlights which covariates impact the probability to receive treatment, while this remains unclear in other methods such as the difference-in-difference method (Lobut, 2017). In this study, the Propensity Score Matching method was carried out using the following four steps as suggested by Caliendo and Kopeinig (2008): (1) Justification of Unconfoundedness, (2) Estimation of the propensity scores, (3) Verification of the balancing property, and (4) Selection of the matching algorithm and matching implementation. A detailed outline of these steps is given:

Justification of Unconfoundedness. The data used in this study contained a high number of observations and high quality variables. According to Caliendo and Kopeinig (2008), those two fundamentals permit to assume unconfoundedness.

Estimation of the propensity score. A Logit model was estimated to generate the propensity scores for participation in the SCCA project. As defined by Rosenbaum and Rubin (1983) the selection of the observable variables to be used in the Logit model was based on the following criteria: First, the variable should influence the decision of participation and the outcome variable. Secondly, the choice of variables should be guided by former studies, economic principles/ concepts and the organizational setting within which the treatment and outcomes are measured (Pan, 2014). Therefore, only covariates that fulfilled these requirements were included in the Logit model and they are shown in Table 1.

The SCCA project targeted farmers who were vulnerable to climatic shocks as beneficiaries of the project, and these included the youth, elderly and female-headed households. According to Grundy (2006) the aged have been known to be more vulnerable to poor quality life, disease and death. A family that is headed by an elderly or youth person is more likely to be vulnerable to climatic shocks. Because of this, the age variable was selected to be in the Logit model. The gender of the household head was also included in the model, as a measure of vulnerability. Ligon and Schechter (2003) found out that female headed households are more susceptible to shocks than male headed households. Education was also used in matching. According to some studies, education can affect participation either positively or negatively as it influences wealth and income (Czaja *et al*., 2006; He *et al*., 2007). For example, the negative effect of education on probability of participation may imply that the household head possesses skills that could aid him/her in getting lucrative off-farm employment opportunities (Martey *et al*., 2012). Marital status was included in the model because it determines demand for climate information (Zongo *et al*., 2015). Household size was also used as an observable characteristic to match on because it not only determines the level and source of income but also the wealth of the household as suggested by El-Osta *et al*. (2002). Size of land holding was used in the matching because it is used as a proxy for wealth as postulated by Araral (2009). Savings access and district (Buhera) were also used as observable characteristics to match on.

Table 1. Observable Variables assumed to jointly determine access to tailored Climate Information Services and Outcome Variables

Variable	Type	Measurement	Expected Sign
Treatment	Dummy	1 if head had access to tailored CIS, 0 otherwise	Dependent
Age	Continuous	Age of head in years. Young farmers have more access to information compared to older ones (Diederen et al., 2003). Being better informed, they should have a greater need for CIS (Zongo et al., 2015).	+
Gender of head	Dummy	1 if head is male, 0 otherwise. Chambers et al., (1989) found out that gender, in many African societies, is vital as it affects the use and ownership of resources, how farming operations are undertaken, how new ideas and technologies are perceived and to a large extent how information is disseminated.	-
Education of head	Dummy	1 if head is educated, 0 otherwise.	+/-
Marital status	Dummy	1 if head is married, 0 otherwise. Unlike the unmarried, married farmers are supposed to have a greater need for climate information.	+
Household size	Continuous	Number of people in the household.	+

Size of land	Continuous	Size of land owned by head in hectares. Farmers who have more land sizes are expected to be more interested in the use of CIS in the community.	+
Savings access	Dummy	1 if head has access to savings, 0 otherwise. It is measured in terms of whether the respondents have access to savings interims. It is expected that access to savings will increase the probability of having access to CIS.	+
Buhera	Dummy	1 if head is in Buhera, 0 otherwise	+/-

Source: Author

So, given observed household characteristic (X_i) where the dependent variable (T_i) equals one if the household had access to tailored CIS and zero otherwise, the Logit model was used to estimate the conditional probability of participation (propensity score), i.e.,

$$PR(T\_i=1 \mid X_i)=\beta_0+\beta_1 age+\beta_2 \textit{gender}+\beta_3 mari+\beta_4 hhsize+\beta_5 farmsi+\beta_6 svacc+\beta_7 buhera+\varepsilon i$$

(Equation 1)

Where β0, β1...β7 are coefficients of the observed households characteristics and εi is the error term.

Verification of the balancing property. The pscore command in STATA was used to assess the balancing property. In order for this property to be met, after matching there should be no statistical difference between means of the two groups. The balancing test is usually assessed using two measurements (Rubin's B and Rubin's R) according to Rubin (2001). Rubin's B is the standardized difference of means of the linear index of the propensity score in the treated and control group and should be below 0.25. Rubin's R is the ratio of treated to control variances of the propensity score and should be between 0.5 and 2.0.

Selection of the matching algorithm and matching implementation. Various matching algorithms can be used to match farmers from the control group to those in the treated group. The matching algorithms differ from each other in two ways. First they define different neighbourhoods for the treated individuals and secondly they assign different weights to control units matched with treated ones (Lobut, 2017). In this study, kernel matching, nearest neighbour matching and radius caliper matching were used to give the Average Treatment effect on the Treated (ATT).

Matching was done on the basis of propensity scores (p-scores) of X where X is the set of observable characteristics that determine both outcome variables and participation in the SCCA project. The three outcome variables in this study included average yield of pearl-millet measured in kilograms per hectare, annual income of the respondents measured in United States Dollars (US$) and the value of livestock measured using the Tropical Livestock Unit (TLU). Through matching, the selectivity bias is largely eliminated. The propensity score p(X) is the probability of an individual being in the participant group given the set of characteristics captured by X_i, i.e.,

$$p(X)=Pr(T=1\ X_i)=E(T|X_i) \qquad \text{(Equation 2)}$$

Under given assumptions, individuals with similar propensity scores have been statistically proven to be observationally identical thus, Equation (2) can then be rewritten as:

$ATT=[E\{Y_{1i}-Y_{0i}\ T=1,p(X_i)\ \}]=[E\{Y_{1i}\ T=1,p(X_i)\ \}-E\{Y_{0i}\ T=0,p(X_i)\ \}\ T=1]$ (Equation3)

Where ATT is the Average Treatment effect on the Treated, Y_i is the mean outcome of a target variable, e.g. output and T is a dummy variable, T=1 for participants and T=0 otherwise. Equation (3) shows that the average outcomes on non-participating individuals who are similar to participating individuals based on similar propensity scores, p(X), are a substitute for the counterfactual mean.

RESULTS AND DISCUSSION

Descriptive Statistics. The demographic attributes of the household head presented in Table 2 include age, gender, education level, marital status, household size and size of land owned. The table indicates that of these variables, only household size and level of education of the household head were significant. The mean household size for participants and non-participants was 6.7 and 5.7, respectively, and the difference between the two values was statistically significant (p=0.05).

For smallholder agricultural production systems, household size usually determines availability of family labour and this is an important factor because it influences farm-level crop yields as well as value of livestock (Martey *et al.*, 2013). Table 2 also shows that the education level of the household head was significant. About 54% of the respondents attained primary level education. Education is an important demographic variable because it helps in creating awareness. At least four years of formal education is essential in order to have a significant effect on agricultural production (Weir, 1999). The more educated a farmer is, the better it is for him/her to acquire knowledge and information pertaining to climate change and adaptation strategies which can be used for climate change adaptation.

Table 2. Demographic attributes of household

Variable		Participants n = 43 Mean/ %	Non-participants n = 47 Mean/ %	Pooled n= 90 Mean/ %	t /χ^2 test p–value
Age		49 (2.0)	44.2 (2.7)	46.5(1.7)	0.165
Household size		6.7 (0.4)	5.7 (0.3)	6.2 (0.3)	0.049**
Farm size		3.0 (0.3)	2.7 (0.1)	2.8 (0.2)	0.227
Gender	Male	67.4	74.5	71.1	0.463
	Female	32.6	25.5	28.9	
Marital Status	Married	72.1	74.5	73.3	0.510
	Widowed	23.3	17.0	20.0	
	Divorced	2.3	0	1.1	
	Never married	0	2.1	1.1	
	Single	2.3	6.4	4.4	
Education level	Primary	48.0	59.6	54.4	0.084*
	Secondary	34.9	34.0	34.4	
	High School	11.6	0	5.6	
	Tertiary	4.7	2.1	3.3	
	Vocational	0	4.3	2.2	

Source: Survey Results

Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance.

Figures in brackets are standard deviations.

Table 3 shows the average yields obtained by smallholder farmers for the same crops and agricultural season, but now disaggregated by treatment/ access to tailored CIS. The five main crops grown by the smallholder farmers in the study area during this particular season included maize, pearl-millet, Bambara nuts, groundnuts and cowpeas. Since the study area is relatively dry, it can successfully sustain mainly drought resistant crops such as these. The results reveal that, participants had higher yields of cowpeas and pearl-millet than non-participants. However, the difference in pearl-millet yield for the two groups was not statistically significant. In addition to that, for the same season, the table also shows that non-participants had more maize, Bambara nuts and groundnuts than participants. The differences in yield of these crops were however, not statistically significant.

Table 4 shows the average livestock ownership across treatments in the study area. According to Rukuni *et al.* (2006) livestock rearing is a critical enterprise which forms a dominant component of livelihood strategies of farmers in the semi-arid to arid areas of Zimbabwe. Table 4 shows that generally, participants owned more livestock than non-participants. In particular, the number of cattle, goats and donkeys owned by the participants in the study area was significantly greater than that of non-participants. Table 4 also indicates that small ruminants (goats) were more widely owned than large ruminants (cattle). This result can be attributed to the fact that unlike cattle, goats are not selective browsers and they are well adapted to the annual and seasonal variations in rainfall in the study area. It can also be seen from Table 4 that the average ownership of indigenous chickens is greater than that of turkeys. This is because just like goats, the indigenous chickens are more resilient and more adapted to the climatic conditions in the study area, thus their ownership is more widespread than that of turkeys.

Table 3. Average crop yields in kilograms for the 2016/2017 agricultural season

Crop harvested	Participants Mean	Non-participants Mean	T-test p-value
Maize	364.33 (518.90)	402.77 (520.81)	0.727
Pearl-millet	189.49 (214.79)	106.81 (278.70)	0.121
Bambara-nuts	82.70 (199.46)	117.45 (189.34)	0.399
Groundnuts	73.47 (125.47)	84.04 (149.31)	0.718
Cowpeas	71.86 (204.45)	7.87 (25.62)	0.036**

Source: Survey Results
Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance. Figures in brackets are standard deviations.

Table 4. Average livestock ownership

Type of livestock	Participants Mean	Non-participants Mean	T-test p-value
Cattle	4.93 (4.33)	2.21 (2.58)	0.000***
Goats	8.16 (6.17)	4.38 (4.92)	0.002**
Chickens	13.3 (11.60)	11.5 (11.00)	0.369
Turkeys	0.30 (0.91)	0.23 (1.46)	0.793
Sheep	1.21 (3.11)	0.51 (1.71)	0.184
Donkeys	0.51 (1.39)	0.09 (0.58)	0.006*

Source: Survey Results
Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance. Figures in brackets are standard deviations.

Table 5 shows the household annual incomes in United States Dollars (US$) obtained by the smallholder farmers from particular sources in the study area. From the table it can be seen that dry-land farming constitutes the most in terms of household income for both groups. Results also indicate that participants had more income sources and higher annual income than the non-participants. Participants had access to income from buying and selling, gardening and from Village Savings and Loans Associations (VSLA) which their counterparts did not have. In addition to that, the income that the participants got from sales of large livestock was significantly greater than the income that the non-participants got from the same source. Results also indicate that non-participants got significantly more income from sale of bricks than participants.

Impact evaluation. This section presents results on the impact of access to tailored climate information services on livelihood outcomes of the smallholder farmers. These livelihood outcomes include yield of pearl-millet measured in kilograms per hectare, value of livestock as given by the Tropical Livestock Unit (TLU) and the annual income in US dollars (US$).

Propensity score estimation results. The likelihood ratio statistic of -53.632 shown in Table 6 suggests that the estimated model is statistically significant at the 5% level and the pseudo-R^2 value indicates that the equation explains about 14% of the variance in decision-making about whether to participate in the SCCA project or not. The results also suggest that male farmers were less likely to participate in the project, whereas farmers that had more people in their household had a higher probability of participation. In addition, farmers that owned bigger sizes of land and had more access to savings were more likely to participate in the project.

Table 5. Mean annual household income by source

Source	Participants Mean	Non-participants Mean	T-test p-value
Irrigation farming	34.88 (163.13)	0 (0)	0.146
Dry-land farming	159.88 (243.55)	101.36 (210.35)	0.225
Sale of small livestock	34.84 (83.95)	31.60 (75.59)	0.848
Sale of large livestock	105.00 (181.33)	24.53 (82.01)	0.008**
Sale of bricks	2.32 (7.51)	19.57 (41.28)	0.008**
Buying and Selling	26.09 (87.96)	0 (0)	0.045**
Gardening	43.49 (112.40)	6.38 (13.74)	0.027**
Remittances	71.40 (220.68)	17.87 (28.89)	0.103
Casual labour	47.02 (228.13)	47.66 (59.24)	0.985
VSLA	97.67 (165.73)	0	0.000***

Source: Survey Results

Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance.

Figures in brackets are standard deviations.

Table 6. Logit model predicting probability of participation

Variable	Coefficient	Std Error	Z	P-value
Constant	-3.162	1.198	-2.64	0.008**
Age	0.013	0.016	0.82	0.414
Household size	0.173	0.109	1.58	0.113
Land size	0.154	0.176	0.87	0.383
Gender	-2.257	1.318	-1.71	0.087*
Marital status	1.884	0.482	1.37	0.169
Access to savings	0.991	0.482	2.05	0.040**
Buhera	1.078	0.507	2.13	0.033**
Logistic Regression		Obs = 90		
		LR Chi^2 (7) = 17.33		
		Prob>Chi^2 = 0.0154		
Log likelihood = -53,632		Pseudo R^2 = 0.1391		

Source: Survey Results

Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of

Verification of the Balancing Property

Table 7 displays the means in the treatment and in the control group for the set of covariates selected, before and after matching. After matching, the balancing property was satisfied. The results from the t-test show that there was no statistical difference between means of the two matched groups. For most of the variables, the bias after matching is below 5% as usually recommended, but for some (i.e., age, household size and marital status) it is slightly above 5%. However, for these variables the differences are not statistically significant with t values equal to 0.44; 037 and 0.54, respectively. Table 7 also indicates that the Rubin's B and Rubin's R are 0.36 and 2.31, respectively. After matching, there was a significant reduction in bias and also there were no significant differences in the matched participants *vis-a-vis* non-participants for any of the covariates. Thus, matching substantially reduced the selection bias. In addition to that, the value of Pseudo R^2 of the estimated Logit model became lower after matching, the p-value of the likelihood ratio test became insignificant after matching and this further suggests that after matching there was no significant difference in the distribution of covariates between participants and non-participants.

Results from matching are displayed in Table 8. The results from the three matching methods that were employed (Radius Caliper Matching-RCM, Kernel Based Matching-KBM and Nearest Neighbour Matching-NNM) were almost similar as can be seen from the table. For example, for the treated group, the average yield of pearl-millet in kg/ ha ranged from 218.667 to 224.914 and for the control group it ranged from 151.632 to 164.924. The yield of pearl-millet was measured in kilograms per hectare. The treated households increased their yield by 73.2 kg/ha (p >0.1). This difference was not statistically significant and this could be attributed to a number of reasons. Firstly this could probably be because the farmers used the same variety/ seed of pearl-millet, since they usually make use of recycled seed for crops like pearl-millet, sorghum and finger millet.

Table 7. Balancing Results from Radius Caliper Matching (RCM)

Variable	Unmatched Matched	Mean Treated	Control	% bias	% red. Bias	T	t test p>|t|
Age	U	48.98	44.17	29.8		1.40	0.165
	M	48.31	46.66	10.3	65.6	0.44	0.663
Household size	U	6.72	5.65	42.0		2.00	0.049**
	M	6.22	6.02	8.0	80.9	0.37	0.716
Land size	U	3.04	2.66	25.3		1.22	0.227
	M	2.49	2.77	-18.3	27.8	-0.94	0.352
Gender of head	U	0.67	0.74	-15.3		-0.73	0.468
	M	0.74	0.72	3.5	77.0	0.15	0.880
Marital Status	U	0.72	0.74	-5.3		-0.25	0.802
	M	0.77	0.71	12.7	-138.4	0.54	0.594
Savings Access	U	0.72	0.47	52.7		2.49	0.015**
	M	0.66	0.63	3.6	93.1	0.15	0.881
Buhera	U	0.65	0.46	37.1		1.76	0.082*
	M	0.63	0.64	-2.7	92.8	-0.11	0.910
Sample	PSR²	LRchi²	p>chi²	MnBias	MdBias	B%	R
Unmatched	0.137	0.039	17.04	3.83	0.017	0.799	29.6
Matched	8.4	29.8	8.0	89.9	36.3	1.32	2.31

Source: Survey Results

Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance

Table 8. Matching results

Outcome	Matching Algorithm	Sample	Treated	Control	Difference	Standard Error	T statistic
Pearl-millet yield (kg/ha)	RCM	ATT	224.914	151.632	73.282	74.193	0.99
	KBM		224.914	164.924	59.990	78.051	0.77
	NNM		218.667	153.036	65.631	76.135	0.80
Value of livestock	RCM	ATT	3.129	2.265	0.864	0.692	1.25*
(TLU)	KBM		3.129	2.244	0.884	0.721	1.23*
	NNM		3.144	2.470	0.674	0.701	0.96
Annual income (US$)	RCM	ATT	666.042	372.857	293.186	119.029	2.46**
	KBM		666.043	403.971	262.072	122.084	2.15**
	NNM		654.347	399.240	255.107	119.240	2.14**

Source: Survey Results
Note: *** significant at 1%, ** significant at 5% and * significant at 10% level of significance

Secondly, the reason for this result could be attributed to the fact that the pearl-millet crop is known to perform well in the areas under study, thus the yields of the participants may not be statistically different from those of non-participants. Lastly, the 2016/ 2017 agricultural season was generally good in terms of rainfall amounts in the study area, such that most farmers who planted the crop managed to attain good yields. In Senegal, a study similar to this one was done to assess the proportion of farmers that had access to climate information services (CIS) and the impact of CIS on farmers' decisions and behaviour (Lo and Dieng, 2015). The study concluded that yields on test farms that strictly applied CI were higher than those on farms that did not strictly apply CI (Lo and Dieng, 2015).

In 2008, a project known as the METAGRI project was launched in five West African countries by the World Meteorological Organization and the Spanish State Agency for Meteorology to provide training on climate information to over 1000 farmers (Pye-Smith, 2015). Just like in the SCCA project, farmers who participated in the METAGRI project were also taught how to use agro-meteorological data and rain gauges to determine the best time to plant crops. An interview was conducted with about 100 farmers from some of the villages that benefited from the CIS. According to Pye-Smith (2015) the analyses revealed that about 74% of the farmers believed the project had provided real benefits and influenced their planting times and over 60% of the farmers had doubled their crop yields as a result of the METAGRI project in one year.

The value of livestock for households with access to tailored climate information services was about 0.864 times greater than that of households without access to climate information services (p = 0.10). The low level of significance of this variable can be attributed to the fact that farmers' decisions in a livestock production system do not automatically generate returns, thus, it usually takes time for the impact of a certain intervention to build up and be observed (Tall *et al.,* 2018). Given more time, the impact can probably become more defined and significant. This result however, implies that the participants had more climate change related knowledge concerning rearing of their livestock that non-participants.

Table 8 shows that participating households had an annual income of about US$666.04 and non-participating households had about US$372.86. Participants had about US$293 more income than non-participants (p = 0.05). This result was significant and can be attributed to the fact that participants in the project had more information concerning climate change adaptation strategies and thus, they were more likely to diversify into non-agricultural/ off-farm activities than non-participants. Under smallholder agriculture, one way of diversifying is to venture into production of high value horticultural crops such as vegetables, from production of staple foods like maize (Mango *et al.,* 2017). Apart from gardening and small-scale production of horticultural crops, the other diversification strategies employed by participants of the SCCA project included bee-keeping, panning, buying and selling and participation in Village Savings and Loans Associations.

CONCLUSION

The study concluded that access to tailored climate information services had a positive and significant impact on the annual incomes of the households. However, access to tailored climate information services had a positive but weakly significant impact on the value of livestock of the households. Although not significant, the results also indicated that households which had access to tailored CIS had a slight yield advantage for pearl-millet over the non-participating household. The important finding from this analysis is that access to tailored climate information services provides smallholder farmers with actionable information that they can use in making either on-farm or off-farm decisions. Farmers who had access to tailored CIS were more informed in terms of climate change impacts and possible adaptation strategies. This knowledge enabled them to make better decisions at farm-level than their counterparts and to diversify their livelihoods by venturing into different off-farm activities.

This research focused on assessing the impact of CIS on crop yield, livestock value and household incomes. Further research can be done in the field of CIS in agriculture to establish the impact of CIS on other livelihood outcomes such as food security and nutrition of smallholder farming households.

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STATEMENT OF NO CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest in this paper.

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