Rwanda Climate Services for Agriculture: Farmers willingness to pay for improved climate services

Working Paper No. 314

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

This willingness-to-pay (WTP) study aims to understand how Rwandan farmers value the improved characteristics of agricultural climate services introduced to them in a choice experiment (CE) setting; estimate how Participatory Integrated Climate Services for Agriculture (PICSA) and Radio Listener Clubs (RLC) influenced perceived value; and provide insights into how the products and services can be improved. Data were collected in November 2019 from 1525 households in each intervention category (PICSA only (*n*=395)), RLC only (*n*=321), PICSA + RLC (*n*=182)), and a control group from sectors where the interventions were not implemented (*n*=627). A random parameters logit model was used to analyse the data. The estimation was conducted by disaggregating the data into the three treatment groups and the control group that was set-up by the Rwandan Climate Services for Agriculture (RCSA) project to evaluate the effectiveness of PICSA and RLCs in improving farmers' awareness, access, use and value of climate services. For all the treatment and control groups, results suggest that Rwandan farmers value forecast accuracy; dissemination through a combination of extension agents and the PICSA process; and bundling with market price information. PICSA participation was associated with higher WTP for all of the improved characteristics of climate services introduced as a package, as indicated by the WTP values attached to the different characteristics of these services. Accuracy of information scored the highest WTP value, particularly in the PICSA treatment group. This study suggests that to improve agricultural management planning and food security of farmers through the provision of climate services, these services need to be accurate, user-tailored, and accessible. In addition, setting up a reliable market information system and bundling with climate services may help farmers make informed decisions. Results suggest that project communication interventions increased the perceived value of climate information to farmers.

Keywords

Climate services, choice experiment, random parameters logit model, willingness to pay, agriculture, Rwanda.

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Contents

Acronyms

CE	Choice experiment
CS	Climate services
GDP	Gross domestic product
ML	Mixed logit model
MNL	Multinomial logit model
MWTP	Marginal willingness to pay
PICSA	Participatory Integrated Climate Services for Agriculture
RLC	Radio Listener Club
SMS	Short messaging service
WTP	Willingness to pay

Introduction

Agriculture is the backbone of the Rwandan economy, accounting for about 63% of the export earning, 31% of the gross domestic product (GDP) and employing 75% of the labour force (CIA 2019). Agriculture is also Rwanda's most vulnerable sector to climatic change as most of agricultural production depends on rainfall (Gasheja and Gatemberezi 2017, Republic of Rwanda 2018). Irregular rainfall and interruption of rainy seasons lead to late planting with negative effects on agricultural production in the country (Mikova et al. 2015). The Stockholm Environment Institute (2009) reported that Rwanda was not adequately adapted to the prevailing climate risks, and hence, climate change could cause economic losses of at least 1% GDP annually by 2030.

Climate services, which involve the production, translation, transfer, and use of climate knowledge and information in relevant decision-making, policy and planning, aim to enable decision-makers, from national to local levels to better manage the risks of climate variability and change at all levels (Vogel et al. 2019). Climate services are a critical component of an enabling environment for climate change adaptation (Hansen et al. 2019). Empirical evidence suggests that African smallholder farmers are receiving and using climate services to make changes in farming practices, and livelihood decisions that enhance their resilience to climate shocks (e.g. Gbetibouo et al. 2017, Tiitmamer and Mayai 2018, McKune et al. 2018, Hansen et al. 2018, Nkiaka et al. 2019, Muasa and Matsuda 2019, Vaughan et al. 2019).

In most African countries, climate services are disseminated free of charge mainly through radio broadcasts (Hampson et al. 2014, World Bank 2016, Muema et al. 2018. Tesfaye et al. 2019), mobile phone and extension agents (Churi et al. 2012, Etwire et al. 2017, Tesfaye et al. 2019). Provision of these services free of charge shows the public good nature of these services (Freebairn and Zillman 2002). The two defining characteristics of public goods are:

non-excludability[1] and non-rivalrous[2] (Rollins and Shaykewich 2003, Gunasekera 2010). Given these features, the provision of climate services as a public good makes it difficult to limit its supply only to those who are willing to contribute to the costs of supplying them (Gunasekera 2002, Freebairn and Zillman 2002). However, a significant economic feature of information is that it is expensive to produce, but relatively cheap to reproduce. This property suggests that economic efficiency is served by making climate services freely available as a public good (Freebairn and Zillman 2002). Although the actual and potential benefits to the community from climate services are substantial, when provided freely, these benefits are inadequately recognized and insufficiently exploited (Gunasekera 2004). Understanding how climate services help the various sectors of society to make informed decisions and reduce risks as well as to outline what changes would be needed to improve decision making is crucial (World Bank 2008). Similarly, identifying the value of the services can motivate users to be willing to pay for the existing or improved services. It can also help justify funding and guide priorities to invest in managing the impacts of weather and climate across economic sectors (Zillman 2007).

This study was part of a bigger survey implemented to support an ex-post evaluation of the RCSA project funded by USAID. The project was implemented from 2016 to 2019. Through the project, climate services were disseminated directly to more than 111,000 farmers in four provinces across Rwanda through PICSA, RLCs and cell phones; as well as broadcast by a radio network accessible to about 70% of the population. This study aims to assess how Rwandan farmers value the general features of improved climate services; investigate their WTP to provide insights into how the products and services can be improved; and estimate how project interventions influenced perceived value of climate services. The specific objectives of the study are: (i) identify the preferred package of improved agricultural climate services; (ii) assess preference heterogeneity[3]; and (iii) estimate WTP values among

[1] Non-excludability refers to a situation where there is no easy way of preventing someone from having access to and benefiting from a good or service.
[2] Non-rivalrous refers to a condition in which consumption by one agent does not diminish the availability of the good's benefit for others.

[3] Preference heterogeneity refers to a situation where a group of respondents likes or dislikes different alternatives in a systematic and quantifiable way.

Rwandan farmers – as influenced by participation in PICSA and RLCs. This study adds to the set of recent studies conducted in Africa (Amegnaglo et al. 2017, Donkoh et al. 2019, Ouedraogo et al. 2018, Tesfaye et al. 2019, Zongo et al. 2016) that report the value smallholder farmers attach to the different characteristics of climate services.

The remainder of the paper is organized as follows. The next Section explains the methodology. Section 3 presents the results and discussion and Section 4 concludes with relevant policy implications.

Methodology

Random utility model

Individuals' preferences are modelled in terms of McFadden's (1974) random utility model. The random utility model can be approximated by the multinomial logit model (MNL). In MNL, the utility to individual *N* (*n*=1, 2, … 1525) from choosing alternative improved climate services *J* (*j*= 0,1,2) on choice situation *T* (*t*=1,2, …12) is represented by a utility expression of the general form in Equation (1) (Train 2003).

$$U_{njt} = \beta x_{njt} + \varepsilon_{njt} \qquad (1)$$

The component observed by the analyst, X_{njt} is a vector of independent variables including attributes of the improved climate service alternatives, socio-demographic characteristics of the individual, and descriptors of the decision context and choice task. The components β and ε_{njt} are not observed by the analyst, and are treated as stochastic influences (Hensher and Greene 2003). β is a corresponding vector of utility weights that are homogeneous across individuals and ε_{njt} ~ i.i.d. extreme value –I is the individual specific error component (Kanninen 2007).

Individuals are expected to differ in terms of the weather and climate events they face and the bundle of improved climate services they prefer. To account for such preference heterogeneity, the taste parameters for the attributes are allowed to differ across individuals, applying different mixing distributions. The mixed logit (ML) is a highly flexible model that can approximate any random utility model (McFadden and Train 2000). It obviates the three limitations of standard logit by allowing for random taste variation, and correlation in unobserved factors over time (McFadden and Train 2000). In the ML model, the utility to individual *n* from choosing alternative improved climate services *j* on choice situation *t* is presented as Equation 2.

$$U_{njt} = \beta_n x_{njt} + \varepsilon_{njt} \qquad (2)$$

β_n is a corresponding vector of utility coefficients that vary randomly over individuals, and ε_{njt} is a random term that represents the unobserved component of utility. The vector of observed attributes, X_{njt} can include binary (0/1) terms to allow for alternative specific constants and for individual attribute levels as well as continuous attributes. The unobserved term ε_{njt} is assumed to be i.i.d. extreme value. In this assumption, the probability that individual *n* chooses alternative *i* in choice situation *t*, conditional on β_n is the logit formula in Equation (3) (Hess and Train 2017).

$$L_{nit}(\beta_n) = \frac{e^{\beta_n x_{nit}}}{\sum_j e^{\beta_n x_{njt}}} \tag{3}$$

The researcher does not observe the utility coefficients of each individual and knows that the coefficients differ over individual. The cumulative distribution function of β_n in the population is F ($\beta | \theta$) which depends on parameters θ. The distribution can be continuous or discrete, and the elements of β may be correlated with each other. With continuous *F*, the choice probability for the individual's sequence of choices, given the researcher's information, is:

$$P_{nit} = \int L_{nit}(\beta) f(\beta/\theta) d\beta \tag{4}$$

Here *f* is the density associated with *F*. If *F* is discrete, then the ML model formula is

$$P_{nit} = \sum_{r \in S} L_{nit}(\beta_r) \Pi_r(\beta_r / \theta) \tag{5}$$

Π is the probability mass function associated with *F* and *S* is its support set with elements indexed by *r*. The goal here is to specify *F* and estimate its parameters θ. The main feature of the ML model is its ability to account for the unobserved heterogeneity, however, the model fails to explain the sources of heterogeneity (Hynes et al. 2008). Due to this drawback, interactions of individual specific characteristics can be included with choice-specific attributes in the utility function to improve the model fit (Revelt and Train 1998).

Experimental design

Choice experiments are based on the idea that a good or service can be described in terms of its attributes and the levels that these attributes take (Bateman et al. 2002). The CE approach allows estimating a monetary value for an existing good or service that may have no market or limited market (Champ et al. 2003). In addition, the approach can also be used to assess the value of potential goods or services that are yet to be introduced into the market (Bateman et al. 2002, Louviere et al. 2010). In this study, attributes of improved climate services are assessed to examine the value farmers put on the different packages of these services. The experimental design in this study contains attributes such as type of climate information received, accuracy of the information received, dissemination channel of the information and relevant market information. The different characteristics of improved climate services are traded off against the monthly telephone bill which is relatively higher than they currently pay. The different attributes and their levels were selected based on a literature review, focus group discussions, key informant interviews and pretesting.

To test farmers' preference for improved climate information, they were presented with three different types of information: daily weather forecasts, seasonal forecasts of onset and cessation of rain, and agro-met advisories. Daily weather forecasts were the baseline, while seasonal weather forecasts on onset and cessation of rain and agro-met advisories were presented as improved suites of information. A farmer who receives seasonal forecasts of onset and cessation of rain is more likely to increase her/his average agricultural income because such forecast gives opportunity to adjust additional decisions related to crop and variety selection and timing of planting (e.g. Bryan et al. 2009, Gunda et al. 2017). The use of agro-met advisories is the other improved form of information suggested. Agro-met advisory services translate weather and climate information into farm management advisories such as sowing, transplantation of crops, fertilizer application; and can be directly applied to improve and protect the livelihood of farmers (Roy 2018, Chattopadhyay and Chandras 2018).

The importance of accurate climate information for farm decision-making is underscored in the literature (e.g. Clements et al. 2013, Vaughan et al. 2019). In this CE design, accuracy[4] of climate information services was described in three different levels, not accurate being the status quo, average accuracy and accurate were considered the improved situations. The preference for communication channel to access climate services was tested by taking the

[4] To maintain a more uniform understanding of the word accurate among respondents, other synonyms of the word such as correct and precise were interchangeably used while explaining the attribute and their levels.

radio-based dissemination as the status quo. One of the improvements introduced was face to face communication of farmers with extension agents. The second improvement introduced was the PICSA approach, which trains and facilitates farmers to make informed decisions based on accurate, location specific, climate and weather information (Dorward et al. 2015). In Rwanda, the RCSA project trained 1823 agricultural professionals, volunteer farmer extension agents and cooperative leaders in the PICSA process, who in turn trained and facilitated 111,835 farmers to use climate information in their planning (Birachi et al. 2020). Empirical evidence in Rwanda and elsewhere (Clarkson et al. 2017, Clarkson et al. 2019, Stats4SD 2017, Dayamba et al. 2018, Birachi et al. 2020) demonstrated that the PICSA training approach empowered farmers to adapt a range of farm and livelihood management decisions to their local climate. Farmers also described positive effects including on income and food security and importantly on wellbeing, and confidence in their abilities to address climate change and variability. The third improvement over the dominant radio-based dissemination considered was mobile phone text message (SMS). An assessment of mobile phone-based dissemination of weather and market information in the upper west region of Ghana reported that farmers generally rate mobile phone-based weather and market information as very useful (Etwire et al. 2017). Similarly, Tesfaye et al. (2019) reported that farmers prefer receiving weather information services through SMS compared to radio due to the handy nature of mobile phones and its ability to retain and retrieve messages received.

The availability of reliable market information can assist farmers to compare the prices they are offered with market prices, to inform decisions on whether to sell or store produce (FAO 2011). Bundling climate services with market information can increase the value for farmer decision making, as Haile et al. (2015) found in the case of rural Ethiopia. Given the importance of market information in assisting farmers’ decision-making, this study tested farmers preference for market information by presenting them with two improved levels: (i) information on selling price, and (ii) information on market location to sell their produce, and assuming no market information as the status quo (baseline). To understand the trade-off farmers would make among the different attributes of improved climate services, a monetary amount with different levels was introduced. This amount is a monthly telephone bill of farmers ranging from 400 to 1000 RWF[5]. These monetary values were based on literature review (e.g. World Bank 2013, RIA 2017). Table 1 presents the different attributes and their levels.

Table 1. List of attributes and their levels

No.	Attributes	Levels
1	Type of information received	Daily weather forecast (status quo) Seasonal weather forecasts on the onset and cessation of rain Weather forecast information translated to agro-met advisories
2	Accuracy of information	Weather forecast information received is not accurate (status quo) Weather forecast information received has average accuracy level Weather forecast information received is accurate
3	Dissemination channel	Radio (status quo) Face to face communication with extension agents PICSA training SMS
4	Market information	No market information (status quo) Receive information on selling price Receive information on market location
5	WTP value (RWF)	400 - 600 - 800 - 1000

[5] RWF is Rwandan franc. One USD is equivalent to 924.17 RWF.

Sampling design and survey implementation

The study was conducted in four provinces of Rwanda: Southern, Western, Northern and Eastern (Figure 1[6]).

Figure 1. Study locations

Data were collected from 1525 household heads, sampled from 15 of Rwanda's 30 districts, as part of a bigger survey implemented to support an ex-post evaluation of the RCSA project (Birachi et al. 2020). The sampling design aimed to provide representative samples of participants in each intervention (PICSA only (*n*=395)), RLC only (*n*=321), and PICSA + RLC (*n*=182)), and a control sample of farmers from sectors where the interventions were not implemented (*n*=627). Districts were clustered on the basis of where each of the interventions was implemented. In the case where more than one district was involved in an intervention, the sampled district was randomly selected. A multistage sampling procedure was used, where in each district, two sectors were randomly selected for a given treatment; and in each sector, cells and villages were randomly selected. In each village, proportional sampling was used to achieve the target sample size of 1525 households.

[6] For a detailed description of study locations, readers are referred to Birachi et al. (2020).

The data collection was carried out in November 2019 using a farm household survey and trained enumerators who speak the local language. Enumerators were trained on the two alternatives of improved climate services that were described in terms of two improved alternatives together with the opt-out option that gave respondents the chance to choose none of the two options. In cases where respondents chose the opt-out option 12 times, they were asked in a follow-up question, why they chose the opt-out option 12 times. Enumerators were given an introductory text to memorize that explains the contents of the attributes and their levels. In order to make sure farmers had a clear understanding of the choice task, they were first asked to make their choice using an example card, allowing them to ask questions about the choice cards before the experiment started. While shown the example card, respondents were informed that the different cards were not linked to each other and the card that was presented to them each time was independent from the previous card. The choice cards were generated using Ngene[7] software version 1. To help respondents understand the choice task more consistently, attributes and their levels were presented using pictograms. Figure 2 shows an example card that was presented to respondents.

The data used for this specific analysis consisted of six components. The first component was about respondents' socio-economic characteristics. The second component focused on agricultural and non-agricultural enterprise equipment and agricultural input use. The third component focused on communication assets including, mobile phone use, access road to market, extension office etc. The fourth component was related to crop production and sales. In the fifth component questions related to awareness, access and perceived impacts of climate information services were asked. And lastly, the CE was introduced in the sixth component.

[7] Ngene is software for generating experimental designs that are used in stated CE for the purpose of estimating choice models, particularly of the logit type.

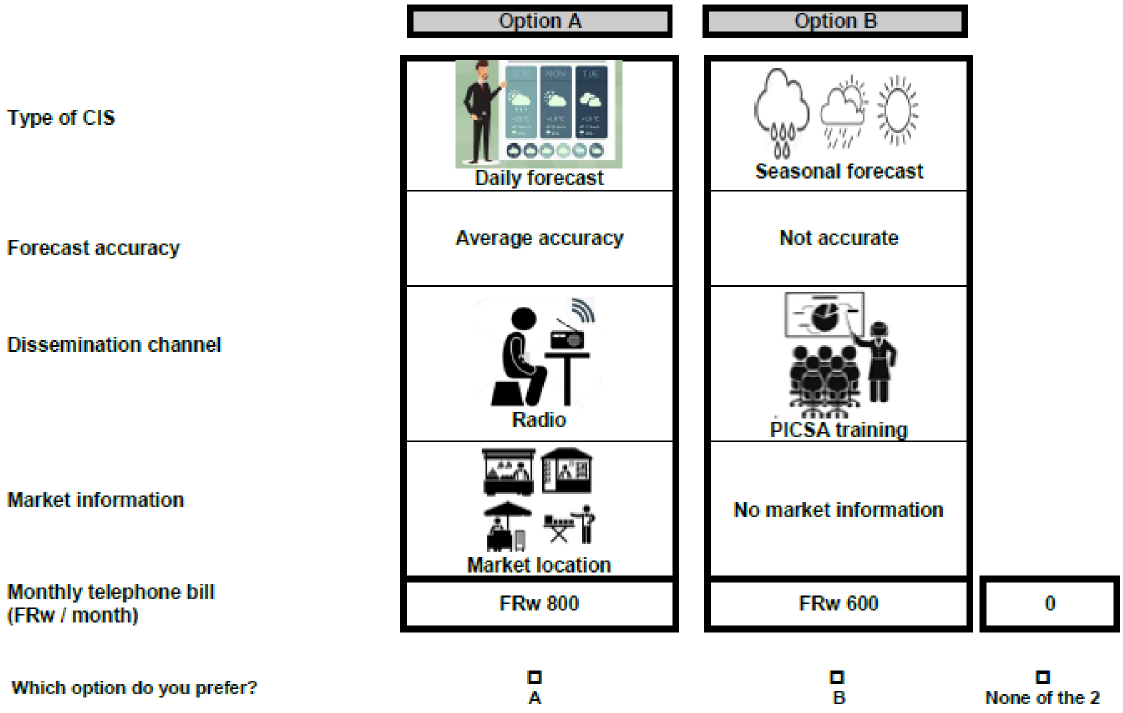

Figure 2. Example choice card

Results and discussion

Household characteristics

Table 2 presents the general household characteristics across the four provinces. In this study, the majority of the sample respondents were female, with 77% of them being married. The average age of respondents was 46. The average household had five members. About a third of the respondents had formal education of up to 6 years while 21% did not go to school. The remaining respondents had different levels of higher education. Crop farming was the primary livelihood activity for the majority of the respondents, and 33% were engaged both in crop and livestock production. Other livelihood activities included wage labour, trade, salaried work and pensions. Almost all the households (94%) owned land. Major crops grown included beans, maize, cassava and banana. The main agricultural inputs used in crop production were diammonium phosphate (DAP), urea, manure, pesticides and nitrogen, phosphorus, and potassium (NPK) fertilizer. All the sampled farmers reported that hoes, cutlasses and machetes were the key agricultural equipment for cultivation of cropland.

Examining the food security status and coping mechanism, 66% of respondents stated that in the past 12 months they did not have enough food to eat. Common coping mechanisms included substituting commonly bought food with cheaper food, reducing the number of meals, modifying cooking method and participating in food-for-work programs. For the vast majority of respondents, agricultural extension services were disseminated an average of once per month in the last 12 months. For almost all the respondents, walking was the most regular means of transport to the nearest market for crop produce and livestock. Similarly, almost all the respondents stated that they walked to the nearest farm input and fertilizer markets. The majority of respondents (71%) were members of farmer associations or cooperatives. Among those, some belonged to the agriculture-livestock producer group, others joined the saving group, and the remaining were part of the radio listener group and civic group. Chargeable batteries and bulbs were the main sources of lighting their houses, while some households used the electrical grid or solar power. Other sources of lighting houses included candle, oil lamp, firewood, kerosene and biogas.

Table 2. General household characteristics across the four provinces

Household characteristics	Southern	Western	Northern	Eastern	Whole sample
Average age (years)	47	46	47	46	46
Share female (%)	60	60	42	43	51
Education level (%)					
No education	21	20	23	22	21
1-5 years	8	7	9	10	33
6 years	36	30	29	27	30
7-18 years	4	4	3	4	16
Average household size	5	5	5	5	5
Land ownership (%)	91	95	95	95	94
Livelihood activity (%)					
Crop farming	62	39	60	79	61
Livestock farming	0	0.6	0.3	0	0.2
Crop and livestock farming	32	55	34	15	33
Other (casual wage labour, traders, salaried, pensioners)	2	1	2	2	6
Food shortage in the household (%)	64	61	67	71	66
Climate risk coping mechanism					
Buying cheaper food	28	25	17	24	23
Reducing the number of meals	24	12	18	18	19
Modifying cooking method	30	21	15	21	22
Involving in food for work	17	12	15	16	15
Access to extension services	87	79	79	88	84
Group membership					
Farmer association/cooperatives	57	50	31	29	41
Agricultural/livestock producer group	45	64	69	64	60
Saving group	17	26	18	4	15
Radio listener group	8	9	3	20	11
Civic group	0.3	0.5	0.8	1.2	3
Sources of lighting houses					
Chargeable battery and bulbs	25	37	42	23	31
Electricity	26	30	24	31	28
Solar	32	15	19	28	24
Other (firewood, kerosene, oil lamp, candle, biogas etc)	5	4	4	5	17

Media, awareness and frequency of accessing climate services

Half of the respondents reported that they owned radios. Respondents who did not own a radio accessed information from their neighbours, community shops, children and spouses. Some mentioned that they did not have access at all. Television was owned by very few respondents. About 76% of the respondents owned one or two mobile phones. Most of these were basic phones, and only a few were smart phones. Those who did not own mobile phones got access from their spouse and neighbours. Fifty-nine percent of respondents identified radio as their main means of accessing weather and climate information. Radio Rwanda and Radio Huguka (105.9FM) were the main sources of forecast information. The morning was the most preferred time to listen to the radio broadcast, while some respondents reported that they followed the afternoon and night broadcasts. Debates were the most popular climate service radio programming format, identified by half of the respondents. Farmer Promoters[8], PICSA, and mobile phones were also identified as important channels for accessing climate information. Television did not play any role in accessing these services. Table 3 presents the share of respondents using different dissemination channels across the four provinces.

Table 3. Dissemination channel for climate services

Proportion of respondents (%)	**Southern**	**Western**	**Northern**	**Eastern**	**Whole sample**
Media of climate services					
Does the household own a radio?	48	51	47	57	50
Does the household own a television?	5	3	3	11	6
How many mobile phones does the household have?					
One	38	48	44	48	44
Two	34	29	27	35	32
Media of accessing climate services					
Radio	56	65	50	65	59
Farmer promotor	45	39	30	61	44
PICSA training	10	24	30	47	29
Mobile phone	23	28	30	39	30

When respondents were asked if they were aware of forecasts for today, and with 2-3-day and 10-day lead times, 70% confirmed that they are aware and access such information. A similar proportion of respondents was aware of seasonal forecasts of total rain, and 66% were aware of seasonal forecasts of the timing of the onset of the rainy season. Only 28% of the respondents were aware of historical information about seasonal rainfall. When we

[8] Farmer Promoters serve as village-level agricultural extension agents on a volunteer basis. Although PICSA is implemented primarily by trained Farmer Promoters, Farmer Promoters may communicate weather and climate information outside PICSA.

looked at the frequency of accessing weather forecasts (i.e., today and with 2-3 day, and 10-day lead times), 31% of respondents reported accessing them daily, 49% once per week, 13% monthly, and 7% once per agricultural season. More than half of the respondents reported accessing seasonal forecasts of rainfall once per agricultural season, while it was once per month for 26%, once per week for 15% and daily for 4% of respondents. The majority of respondents (68%) accessed seasonal forecasts of the timing of the onset of the rain once per agricultural season, and 20%, 10% and 3% of respondents reported accessing it with a frequency of once per month, once per week and once per day respectively. A third of the respondents accessed historical information about seasonal rainfall once per agricultural season, and 28% accessed it once per year. The frequency was once per month for 19% and once per week for another 19%, a few reported to have accessed it daily. The share of respondents on awareness and frequency of accessing the forecasts across the four provinces is depicted in Table 4.

Table 4. Awareness and frequency of accessing climate services

Proportion of respondents (%)	Southern	Western	Northern	Eastern	Whole sample
Awareness about climate services					
Today and with 2-3 day, and 10-day lead times weather forecast	62	72	58	91	71
Seasonal forecast of total rain	64	69	67	76	69
Seasonal forecast on onset of the rain	58	69	66	74	66
Historical seasonal rainfall information	27	32	32	24	28
Frequency of accessing climate services					
Today and with 2-3 day, and 10-day lead times weather forecast					
Once per day	31	36	54	14	31
Once per week	41	50	32	65	49
Once per month	13	10	13	15	13
Once per agricultural season	15	4	1.5	6	7
Once per year	0	0.9	0	0	0.2
Seasonal forecast of total rain					
Once per day	4	4	6	1	4
Once per week	17	30	8	9	15
Once per month	17	41	20	30	26
Once per agricultural season	62	25	65	60	55
Once per year	0	1	1	0	1
Frequency of accessing climate services					
Forecast on onset of the rain					
Once per day	4	3	5	0	3
Once per week	14	16	8	5	10
Once per month	9	37	16	20	20
Once per agricultural season	72	45	70	75	67
Once per year	0	1	1	0	1
Historical information about seasonal rainfall					
Once per day	9	7	2	0	4
Once per week	27	31	5	13	19
Once per month	12	36	15	17	19
Once per agricultural season	37	23	17	44	30
Once per year	16	3	62	26	28

Use of climate services

Rainfall was the main information included in the daily weather forecast, seasonal forecast of total rainfall, seasonal forecast of timing of onset of rain and historical information on seasonal rainfall. In addition, information on wind, temperature and storm and other extreme events was provided in the forecast. Distribution of rain through the season and risk of maximum/minimum rainfall (precipitation extremes) were the most important climate information respondents were satisfied with. Weather forecast for today and with 2-3-day, and 10-day lead times was used by respondents to make decisions on fertilizer application (33%), weeding (31%), timing of planting (28%), timing of harvesting (26%) and timing of land preparation (22%). A large share of the respondents (44%) indicated that they did not use the information for any decision making. Seasonal forecasts of the total amount of rainfall was used by 40% of respondents to inform decisions on type of crop to grow, while another 26% used the information to help decide how to prepare the land and the type of crop variety to grow. Some 32% of respondents mentioned that the information was important to decide the timing of planting and 30% used it for deciding the timing of land preparation. This forecast information was important to inform decisions on the use of organic fertilizer by 24% of the respondents, application of chemical fertilizer (21%), land allocation for crop (20%) and timing of weeding (18%). In contrast, close to half of the respondents (45%) did not use seasonal forecasts of the total amount of rainfall to inform any farming decision. Seasonal forecasts of the onset of rain was used by 49% of respondents to decide the timing of planting. The same forecast information was important for 45% of respondents to decide on timing of land preparation. How to prepare land and the type of crops to grow were based on such information for 30% and 31% of respondents, respectively. There were respondents (32%) who reported not using the forecast information for any decision making. Timing of planting and land preparation were also based on forecasts through the season for 32% and 30% of respondents, respectively. Seasonal forecasts of cessation of rain were not important information for 72% of the respondents. Only 19% used it for choosing the crop type to grow. Historical climate information was used to inform decisions on planting, fertilizer application, weeding, timing of land preparation and harvesting. More than half of the respondents reported that they did not use historical climate information for farming decisions. Figures 3-5 present the different types of forecasts farmers used in major agricultural activities across the four provinces.

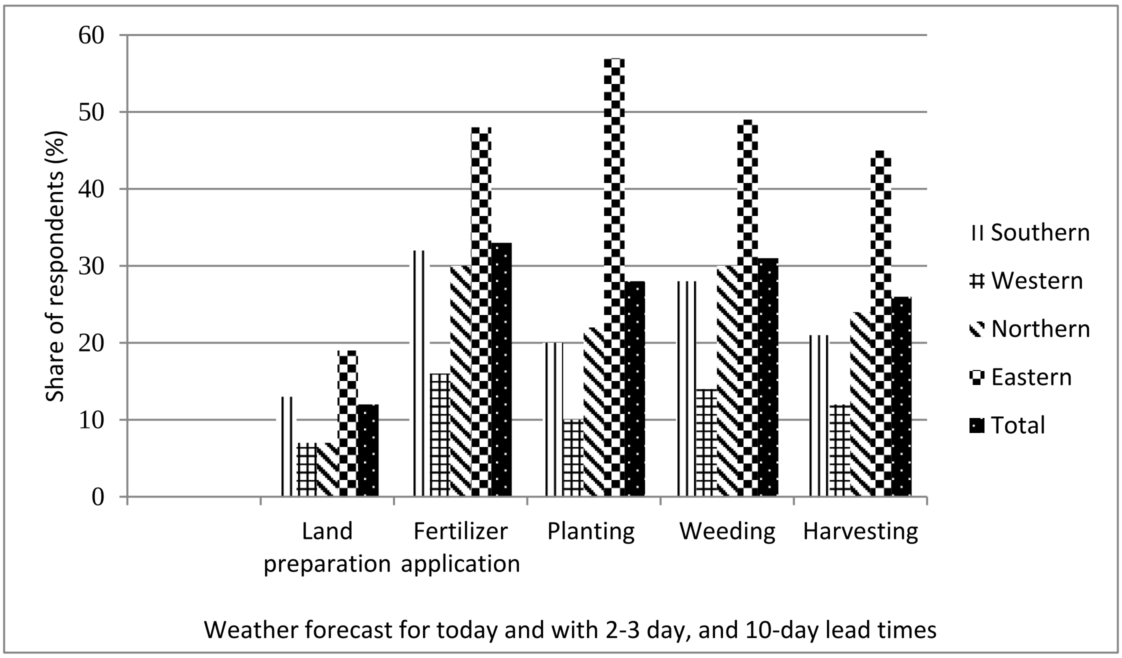

Figure 3. Share of respondents using weather forecast for today and with 2-3 day, and 10-day lead times

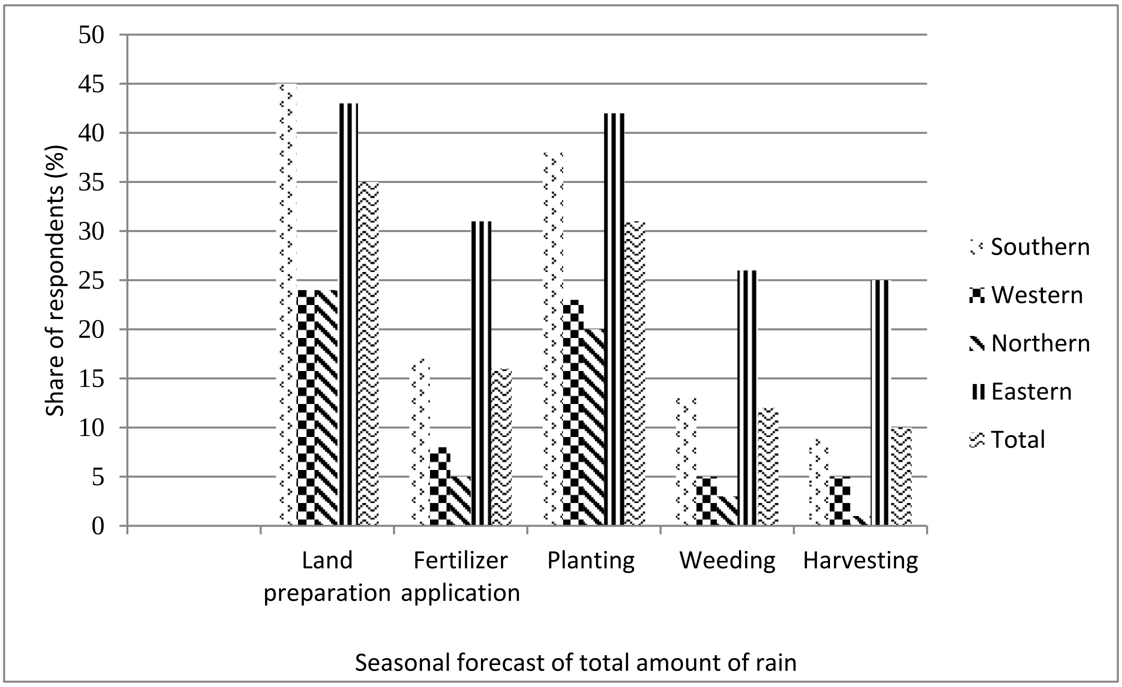

Figure 4. Share of respondent who are using seasonal forecast of total amount of rain

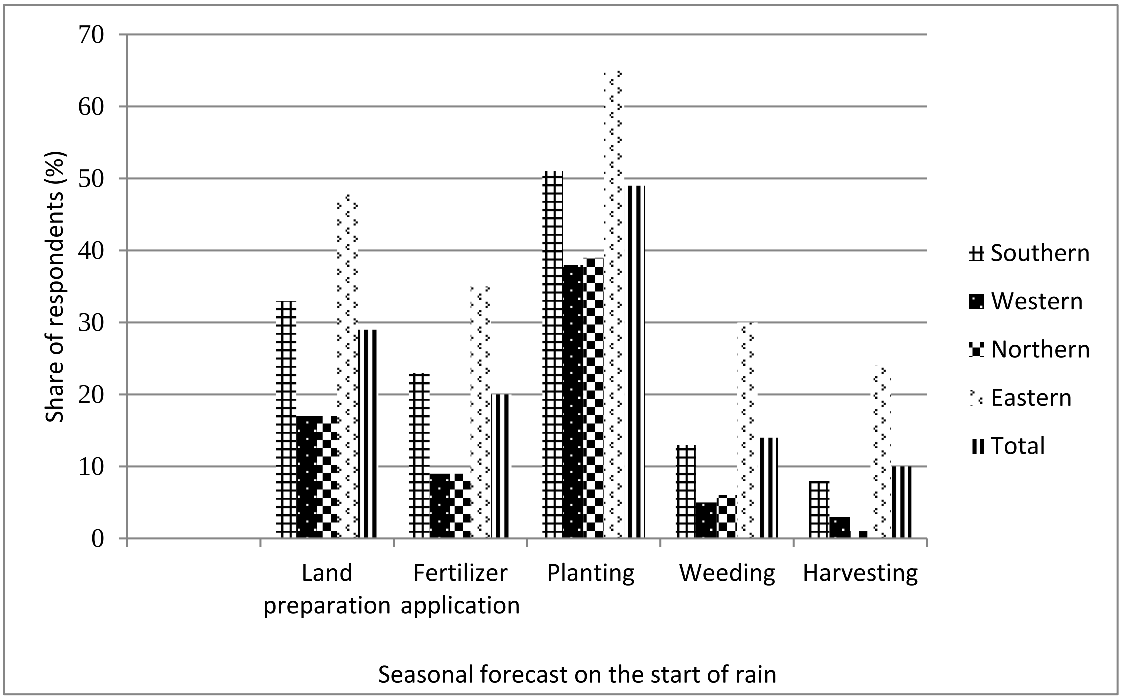

Figure 5. Share of respondents who are using seasonal forecast of onset of rain

Regarding the changes made by using the different forecast information, many respondents reported to have made a change on crop production. These changes included incorporating new crop enterprise, increasing the scale of crop enterprise and changing crop management practices. Few changes were reported for livestock production because of forecast information and these included increasing the scale of livestock enterprise, trying to change the way they managed livestock, and incorporating new livestock enterprise. The change in livelihood because of changes made in crop and livestock production was not substantial. Less than a third were successful in making livelihood change. Table 5 shows changes made using forecast information.

Table 5. Changes made by using climate information services across the four provinces

Proportion of respondents (%)	Southern	Western	Northern	Eastern	Whole sample
Change in crop production					
Yes	66	70	54	71	65
New crop enterprise	23	30	28	24	26
Increase the scale of crop enterprise	21	54	35	33	35
Change the way of managing crops	58	42	75	84	65
Change in livestock production					
Yes	26	41	28	29	30
Increase the scale of livestock enterprise	35	55	15	15	31
Change the way of managing livestock	42	33	65	75	53
New livestock enterprise	25	14	10	31	20
Change in livelihood	25	44	27	19	28

Choice model results

The choice share across the three alternatives (the two improved situations and the opt-out option) indicated the positive attitude of respondents toward the proposed improvement in climate services. The first improved alternative was chosen in 36% of the cases and the second was chosen in 47% of the cases. Most of those who chose none of the two explained that they could not afford to pay extra for improved climate services, while a few more suggested that they were not interested in the proposed improvement. Nearly half of the respondents (49%) said that both alternatives presented to them were very credible (believable), 35% reported they were somewhat credible, and the rest were divided between those who mentioned that it is not credible and those who said, 'I don't know.' Almost all (95%) stated that they understood the content of the choice cards. More than 40% reported that the accuracy of climate information was the most important characteristic of the improvement that influenced their decision. About 25% stated that market information influenced their decision, and one fifth mentioned the dissemination channel as an important characteristic. For about 12%, the type of climate information was the reason for their choice. The CE data was analysed using NLOGIT software version 4. Estimates of marginal WTP and standard errors were calculated using the Wald procedure. All model attributes were treated as random variables with normal distribution and estimated using Halton sequence of 100 random draws.

The CE data was disaggregated into four groups while estimating attributes of improved climate services, preference heterogeneity and WTP values. Four models (Table 6.1-6.4) were run representing three treatments and a control group that the RCSA project implemented for ex-post evaluation. The three treatment groups were the PICSA training group, the RLC, and those who were involved in both groups (PICSA + RLC), and the control group represented respondents who neither received PICSA training nor were members of the RLC. All the four models produced consistent results for attribute levels such as seasonal forecasts, average and accurate forecast information, face to face communication, PICSA training and market price information. In the three models, the value of the monetary attribute was negative and significant as expected, allowing for estimating WTP values. In the RLC model, however, the monetary value turned positive (and insignificant) implying that respondents enjoy paying more, which is inconsistent with the intuitive understanding of rational economic behaviour (Tandon 2015). This is also contrary to the CE approach, which predicts that an increase in monetary value of an alternative decreases the probability that this alternative is chosen if all levels of non-monetary attributes are equal across alternatives (Hanley et al. 2002).

In all four models, respondents preferred daily weather forecasts over the seasonal forecast. This finding was contrary to recent studies that reported the benefits of seasonal forecasts in increasing agricultural income of African farmers and their WTP for these services (e.g. Gunda et al. 2017, Amegnaglo et al. 2017, Ouédraogo et al. 2018). Unlike studies that argue for the benefits of agro-met advisories (e.g. Ramachandrappa et al. 2018, Chattopadhyay and Chandras 2018), no significant relationship could be detected between farmers choice behaviour and agro-met advisories in this study. The importance of accuracy of climate information was reflected in the significant positive value respondents attached to average level of accuracy and even highly significant positive value to receiving accurate climate information. This result was consistent in all four models. This may imply how valuable precise climate information could be in informing farmers in their livelihood decision. This is also highlighted in the literature (e.g. Hansen et al. 2019, Vaughan et al. 2019) where providing farmers with accurate climate information services helps them to make informed decisions that improve agricultural production and enhance agricultural income and food security. The other interesting finding was the significant positive value respondents attached to the climate information communication channels. In all four models, face to face communication with extension agents and the PICSA approach were both highly valued by respondents compared to radio-based dissemination. SMS text message was significantly valued in the PICSA and control models. Despite the failure of extension workers to achieve their extension roles in many African countries (Msuya et al. 2017), Rwandan farmers preference for face-to-face communication of climate information through agricultural extension workers may indicate how well these development agents are performing in carrying out their duties and are therefore trusted by farmers. Respondents' interest in the PICSA training approach in the dissemination of climate information may shed light on the importance of the approach in enabling farmers to make informed decisions by taking advantage of the participatory tools. Similarly, farmers preference for SMS text messages compared to radio is consistent with studies such as Tesfaye et al. (2019) who reported the result of a similar study conducted among Ethiopian farmers, and Churi et al. (2012) who examined farmers information communication approaches for handling climate risks in rural semi-arid areas in Tanzania.

Table 6.1. Choice model results for PICSA treatment group

	Model parameters		Standard deviation	
Variable	**Coefficient**	**St. error**	**Coefficient**	**St. error**
Choice attributes				
Type of CIS				
Seasonal forecasts	-0.61***	0.13	1.01***	0.11
Agro-met advisories	-0.54	0.52	1.06***	0.21
Accuracy of CIS				
Average accuracy	0.61***	0.25	0.54***	0.14
Accurate	3.78***	0.39	2.02***	0.20
Dissemination channel				
Face to face with ext. agents	1.95***	0.31	0.29	0.18
PICSA training	2.48***	0.44	1.73***	0.15
SMS text message	2.50***	0.74	1.52***	0.30
Market information				
Selling price	1.09***	0.15	1.66***	0.13
Market location	1.43***	0.44	0.98***	0.24
Monthly telephone bill	-1.26***	0.44	4.54***	0.31
ASC	0.01	0.32		
Covariates				
Age*SMS text message	-0.03***	0.01		
Gender*PICSA training	-0.49**	0.21		
Northern province*Average accuracy	0.40*	0.22		
Southern province*Accuracy	-2.33***	0.30		
Model summary statistics				
Log likelihood function	-2526.07			
Chi-square (21 d.o.f.)	3332.45			
McFadden Pseudo R-squared	0.39			
No. of observation	3816			

Notes: Significance levels: ***, 1%; **, 5%; *10%.

All models consistently produced results that showed that access to market price information was very important to inform farming decisions. This could be an innovative approach that gives Rwandan farmers a chance to plan when to sell their produce. This finding supports studies conducted in other African countries, such as Magesa et al. (2014) who reported the importance of access to agricultural market information to farmers in rural Tanzania, and Arinloye et al. (2016) who assessed the role market prices play in decreasing transaction costs among Ghanaian farmers and the positive WTP for market price information among Beninese farmers. Information on market location was preferred as an important package for improved climate services only in the PICSA model.

Looking at preference heterogeneity, only those interactions that turned significant were presented. Important covariates that resulted in sources of preference heterogeneity among respondents in the choice of attributes of improved climate services included: age, gender, education level, size of land holding and province. There was significant negative relationship between age of the respondent and SMS text message in the PICSA and control groups. The implication of this may be that older respondents were not interested in receiving climate services through SMS text message as elderly populations, particularly across Sub-Saharan Africa, have higher illiteracy rates (UIS 2016). When the attribute, the PICSA approach, was interacted with gender of the respondents, the result showed a significant inverse relationship, and this was consistent in both the PICSA and PICSA + RLC treatment models. This might indicate that the PICSA training approach was not the preferred means of disseminating climate services among female respondents. One possible explanation could be that these training sessions are usually not gender inclusive, taking place when women are engaged in family care work and unable to attend. This highlights the importance of organizing meetings and trainings that are inclusive of both men and women. Similarly, in the PICSA + RLC group, respondents with bigger land size were not interested in the PICSA approach as a means of communicating the information. In the control group, educated respondents were in favour of accurate climate information considering the potential benefits from correct climate information. Similarly, the preference for accurate information was detected in the eastern province among respondents who were involved in the PICSA + RLC group and average accuracy was preferred in the northern province among the PICSA group. Contrary to expectation, respondents in the southern province who were involved in the PICSA group were not interested in accurate information. No preference was observed for access to market price information among respondents in the PICSA + RLC and control groups in the western and southern provinces, respectively. These results are contrary to expectation and may need further investigation.

Table 6.2. Choice model results for RLC treatment group

	Model parameters		Standard deviation	
Variable	**Coefficient**	**St. error**	**Coefficient**	**St. error**
Choice attributes				
Type of CIS				
Seasonal forecasts	-3.98**	0.13	0.43***	0.15
Agro-met advisories	0.25	0.58	1.08***	0.36
Accuracy of CIS				
Average accuracy	1.02***	0.27	0.73***	0.25
Accurate	2.47***	0.43	1.74***	0.20
Dissemination channel				
Face to face with ext. agents	1.02***	0.34	0.38*	0.21
PICSA training	1.71***	0.56	2.14***	0.20
SMS text message	0.00	0.66	0.12	0.28
Market information				
Selling price	0.89***	0.20	1.65***	0.15
Market location	0.02	0.50	2.25***	0.28
Monthly telephone bill	0.15	0.46	2.76***	0.25
ASC	0.32	0.35		
Covariates				
Age*SMS text message	-0.01	0.01		
Gender*PICSA training	-0.19	0.27		
Northern province*Average accuracy	0.00	0.26		
Southern province*Selling price	-0.06	0.25		
Southern province*Accuracy	-0.27	0.36		
Model summary statistics				
Log likelihood function	-1993.99			
Chi-square (21 d.o.f.)	2155.44			
McFadden Pseudo R-squared	0.35			
No. of observation	2796			

Notes: Significance levels: ***, 1%; **, 5%; *10%.

Table 6.3. Choice model results for PICSA plus RLC treatment group

	Model parameters		Standard deviation	
Variable	**Coefficient**	**St. error**	**Coefficient**	**St. error**
Choice attributes				
Type of CIS				
Seasonal forecasts	-0.62***	0.15	1.04***	0.15
Agro-met advisories	0.94	0.59	0.58	0.71
Accuracy of CIS				
Average accuracy	1.20***	0.25	0.00	0.42
Accurate	1.41***	0.55	2.10***	0.22
Dissemination channel				
Face to face with ext. agents	1.16**	0.51	0.62***	0.24
PICSA training	1.97***	0.55	1.08***	0.16
SMS text message	0.36	0.80	0.93***	0.32
Market information				
Selling price	1.32***	0.20	1.70***	0.13
Market location	0.39	0.49	1.97***	0.32
Monthly telephone bill	-1.17**	0.52	3.11***	0.29
ASC	0.14	0.61		
Covariates				
Gender*PICSA training	-0.86***	0.26		
Eastern province*Accuracy	2.29***	0.46		
Western province*Selling price	-0.50**	0.24		
Size of land holding*PICSA	-0.00***	0.00		
Model summary statistics				
Log likelihood function	-2067.79			
Chi-square (21 d.o.f.)	2456.08			
McFadden Pseudo R-squared	0.37			
No. of observation	3000			

Notes: Significance levels: ***, 1%; **, 5%; *10%.

Table 6.4. Choice model results for Control group

	Model parameters		Standard deviation	
Variable	**Coefficient**	**St. error**	**Coefficient**	**St. error**
Choice attributes				
Type of CIS				
Seasonal forecasts	-0.57***	0.09	0.62***	0.11
Agro-met advisories	0.52	0.37	0.24	0.31
Accuracy of CIS				
Average accuracy	1.18***	0.16	0.62***	0.26
Accurate	1.58***	0.31	2.35***	0.18
Dissemination channel				
Face to face with ext. agents	0.81***	0.22	0.72	0.11
PICSA training	1.25***	0.32	1.35***	0.11
SMS text message	1.26***	0.44	0.81***	0.30
Market information				
Selling price	0.92***	0.10	1.50***	0.10
Market location	0.30	0.31	1.29***	0.14
Monthly telephone bill	-0.96**	0.42	4.51***	0.33
ASC	0.29	0.23		
Covariates				
Age*SMS text message	-0.01**	0.00		
Education*Accuracy	0.17***	0.03		
Southern province*Selling price	-0.42***	0.16		
Model summary statistics				
Log likelihood function	-4568.62			
Chi-square (21 d.o.f.)	5549.00			
McFadden Pseudo R-squared	0.37			
No. of observation	6684			

Notes: Significance levels: ***, 1%; **, 5%; *10%.

Marginal willingness to pay (MWTP)

Table 7 shows MWTP of respondents for improved climate services across the two treatment groups and the control group. The RLC group is not in the MWTP estimation Table since respondents' behaviour was not consistent with rational economic behaviour, not allowing estimation of MWTP values. Respondents in the PICSA group are willing to pay on average USD 3 per month for receiving accurate climate information. This is the highest average amount when comparing the three groups. The second highest amount was USD 1.98 per month that was attached to SMS by the same group. Respondents in the PICSA, PICSA + RLC and control groups were willing to pay USD 1.96, USD 1.68 and USD 1.29, respectively, to get climate information through the PICSA training approach. Those respondents in the PICSA group were also willing to pay USD 1.54 per month for communicating face to face with extension agents to receive climate information. If climate services are provided together with market price and location information, respondents in the PICSA + RLC group were willing to pay USD 1.2 for accessing market price information and those in the PICSA group were willing to pay USD 1.1 per month to receive information on market location.

Table 7. Estimated MWTP values across the two treatments and the control group

Attributes	PICSA treatment		PICSA + RLC treatment		Control	
	USD/ month	St. error	USD/ month	St. error	USD/ month	St. error
Accuracy of climate information						
Average accuracy	0.49	0.31	1.02	0.57*	1.21	0.60**
Accurate	3.00	0.98***	1.20	0.50***	1.63	0.72**
Dissemination channel						
Face to face with ext. agents	1.54	0.49***	0.99	0.49**	0.84	0.36**
PICSA training	1.96	0.71***	1.68	0.72***	1.29	0.58**
SMS text message	1.98	0.84***	0.30	0.67	1.30	0.60**
Market information						
Selling price	0.86	0.34***	1.12	0.50**	0.95	0.44**
Market location	1.13	0.34***	0.34	0.37	0.31	0.30

Notes: Significance levels: ***, 1%; **, 5%; *10%.

Conclusions

This study analysed the preferred package of improved climate services, assessed preference heterogeneity and estimated WTP values among Rwandan farmers using data from 1525 randomly selected household heads across four provinces in November 2019. A random parameters logit model was used to analyse the data. The estimation was conducted by breaking down the data into three treatment groups and a control group that was set-up by the RCSA project to evaluate the effectiveness of PICSA and RLCs in improving farmers' awareness and access of climate services in informing farmers' decision-making.

The results in all four models suggest that Rwandan farmers would value: accurate weather forecasts; disseminated through a combination of extension agents and the PICSA training approach; bundled with market price information, as a way to improve their farming and livelihood decisions. Comparing the four treatment groups, respondents in the PICSA group significantly value all the improved characteristics of climate services introduced as a package with the exception of agro-met advisories. The importance of the preferred package of improved climate services was reflected in the WTP values respondents attached to the different characteristics of these services. Particularly in the PICSA group, receiving accurate climate information scored the highest WTP value. Household characteristics such as age, gender, education level, land holding and location (province) were significant covariates that influenced preference for improved climate services among respondents in the three groups.

This study suggests that to improve agricultural management planning and food security of farmers through the provision of climate services, these services need to be accurate, user-tailored and accessible. To improve the accuracy of climate information, development of modern infrastructure could facilitate the generation of timely and accurate climate information. Capacity building of experts involved in the generation, translation and dissemination of these services would enhance their ability to communicate user tailored climate services. As shown in this study, age and gender were detected as significant sources of taste heterogeneity where older respondents were not interested in receiving climate information services in SMS text messages, and female respondents were not interested in the PICSA training approach as a means of obtaining climate services. Hence, the use of suitable and gender inclusive communication channels may benefit the different end users. By providing farmers with market information, it is likely to increase their bargaining power with traders and reduce negotiation failure. Hence, setting up a reliable market information system bundled with climate services may help farmers make informed decisions. Integrating climate services into the policy and resource allocation process may help promote farmers livelihood and food security.

References

Amegnaglo CJ, Anaman KA, Mensah-Bonsu A, Onumah EE, Gero FA. 2017. Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa. *Climate Services* 6: 1–11.

Arinloye DDAA, Linnemann AR, Hagelaar G, Omta SWF, Coulibaly ON, van Boekel MAJS. 2016. Willingness to pay for market information received by mobile phone among smallholder pineapple farmers in Benin. In: Bijman J, Bitzer V, eds. *Quality and innovation in food chains: lessons and insights from Africa*. Wageningen Academic Publisher.

Bateman IJ, Carson RT, Day B, Hanemann WM, Hanley N, Hett T, Jones-Lee M, Loomes G, Mourato S, Ozdemiro˘glu E, Pearce DW, Sugden R, Swanson J. 2002. *Economic Valuation with Stated Preference Techniques: A Manual*. Cheltenham: Edward Elgar Publishing.

Birachi E, Hansen J, Radeny M, Mutua M, Mbugua MW, Munyangeri Y, Rose A, Chiputwa B, Solomon D, Zebiak SE, Kagabo DM. 2020. Rwanda Climate Services for Agriculture: Evaluation of farmers' awareness, use and impacts. CCAFS Working Paper 304. Wageningen: CCAFS. p 1-63.

Bryan E, Deressa TT, Gbetibouo GA, Ringler C. 2009. Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental science and Policy* 12: 413-426.

Clements J, Ray A, Anderson G. 2013. The Value of Climate Services across Economic and Public Sectors: A Review of Relevant Literature. Washington, DC.: USAID. p 1-26.

Champ PA, Boyel KJ, Brown TC. 2003. *A Primer on Nonmarket Valuation*. New York: Springer Science+Bussines Media.

Chattopadhyay N, Chandras S. 2018. Agrometeorological advisory services for sustainable development in Indian agriculture. *Biodiversity International Journal* 2:12–18.

Churi AJ, Mlozi MRS, Tumbo SD, Casmir R. 2012. Understanding farmers information communication strategies for managing climate risks in rural semi-arid areas, Tanzania. *International Journal of Information and Communication Technology Research* 2: 838–845.

CIA. 2019. The World Fact Book. (Available from https://www.cia.gov/library/publications/the-world-factbook/geos/rw.html) (Accessed on 9 March 2020).

Clarkson G, Dorward P, Kagabo DM, Nsengiyumva G. 2017. Climate services for agriculture in Rwanda: Initial findings from PICSA monitoring and evaluation. CCAFS Info Note.

Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). p 1-4.

Clarkson G, Dorward P, Osbahr H, Torgbor F, Kankam-Boadu I. 2019. An investigation of the effects of PICSA on smallholder farmers' decision making and livelihoods when implemented at large scale – The case of Northern Ghana. *Climate Services* 14:1–14.

Dayambaa DS, Ky-Dembelea C, Bayalaa J, Dorward P, Clarkson G, Sanogo D, Mamadoud LD, Traorée I, Diakitéa A, Nenkam A, Binama JN, Ouedraogog M, Zougmoreg R. 2018. Assessment of the use of participatory integrated climate services for agriculture (PICSA) approach by farmers to manage climate risk in Mali and Senegal. *Climate services* 12: 27-35.

Donkoh SA. 2019. Farmers' willingness-to-pay for weather information through mobile phones in northern Ghana. *Ghana Journal of Science*, *Technology and Development* 6: 19-36.

Dorward P, Clarkson G, Stern R. 2015. Participatory integrated climate services for agriculture (PICSA) field manual. A step-by-step guide to using PICSA with farmers. University of Reading. Walker Institute.

Etwire PM, Buah S, Ouedraogo M, Zougmor R, Partey ST, Martey E, Dayamba SD, Bayala J. 2017. An assessment of mobile phone-based dissemination of weather and market information in the upper west region of Ghana. *Agriculture and Food Security* 6: 1–9.

FAO. 2011. Understanding and using market information. Marketing Extension Guide. FAO, Rome.

Freebairn JW, Zillman JW. 2002. Economic benefits of meteorological services. *Meteorological Applications* 9:33-44.

Gasheja F, Gatemberezi P. 2017. An assessment of Rwanda's agricultural production, climate change, agricultural trade and food security. The Kenyan institute for public policy research and analysis and United Nations Economic Commission for Africa. Working Paper 23. Nairobi: ECA. p 1-70.

Gbetibouo G, Hill C, Joseph A, Mills A, Snyman D, Huyser O. 2017. *Impact assessment on climate information services for community-based adaptation to climate change*. Ghana Country Report.

Gunasekera D. 2002. *Economic issues relating to meteorological service provision*. BMRC Research Report 102. Australia: Australian Bureau of Meteorology.

Gunasekera D. 2004. Economic value of meteorological services: a survey of recent studies. A background paper for the World Meteorological Organization. In: Gunasekera D, eds. *Economic Issues Relating to Meteorological Provision*. Bureau of Meteorology Research Centre Report 102.Australia: Australian Bureau of Meteorology.

Gunasekera D. 2010. Use of climate information for socio-economic benefits. *Procedia Environmental Science* 1: 384–386.

Gunda T, Bazuin JT, Nay J, Yeung KY. 2017. Impact of seasonal forecast use on agricultural income in a system with varying crop costs and returns: an empirically grounded simulation. *Environmental Research Letter* 12:1-14.

Hampson KJ, Chapota R, Emmanuel J, Tall A, Huggins-Rao S, Leclair M, Perkins K, Kaur H, Hansen J. 2014. Delivering climate services for farmers and pastoralists through interactive radio: scoping report for the GFCS Adaptation Programme in Africa. CCAFS Working Paper 111. Copenhagen: CCAFS. p 1-53.

Hansen J, Fara K, Milliken K, Boyce C, Chang'a L, Allis E. 2018. Strengthening climate services for the food security sector. In: WMO eds. *Climate Change: science and solutions.* Geneva: WMO Vol. 67.

Hansen J, Furlow J, Goddard L., Nissan H, Vaughan C, Rose A, Fiondella F, Braun M, Steynor A, Jack C, Chinowsky P, Thomson M, Baethgen W, Dinku T, Yirgu, A, Do S, Phuong M, Huq S, Ndiaye O. 2019. Scaling climate services to enable effective adaptation action. Background Paper. Rotterdam: p 1-23.

Hensher DA, Greene WH. 2003. The Mixed Logit model: The state of practice. *Transportation* 30: 133–176.

Hess S, Train K. 2017. Correlation and scale in mixed logit models. *Journal of Choice modelling* 23: 1-8.

Haile MG, Kalkuhl M, Usman MA. 2015. Market information and smallholder farmer price expectations. *African Journal of Agricultural Resource Economics* 10: 297-311.

Hanley N, Wright RE, Koop G. 2002. Modelling recreation demand using choice experiments: climbing in Scotland. *Environment and Resource Economics* 22: 449-466.

Hynes S, Hanley N, Scarpa R. 2008. Effects on welfare measures of alternative means of accounting for preference heterogeneity in recreational demand models. *American Journal of Agricultural Economics* 90: 1011–1027.

Louviere JJ, Hensher DA, Swait JD. 2010. *Stated Choice Methods: Analysis and Applications*. Cambridge: Cambridge University Press.

Kanninen BJ. 2007. *Valuing Environmental Amenities Using Stated Choice Studies*. Dordrecht: Springer.

Magesa MM, Michael K, Ko J. 2014. Access to agricultural market information by rural farmers in Tanzania. *International Journal of Information and Communication Technology Research* 264-273.

McFadden D. 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka P, eds. *Frontiers of Econometrics*. New York: Academic Press.

McFadden D, Train K. 2000. Mixed MNL models for discrete response. *Journal of Applied Econometrics* 15: 447-470.

McKune S, Poulsen L, Russo S, Devereux T, Faas S, McOmber C, Ryley T. 2018. Reaching the end goal: do interventions to improve climate information services lead to greater food security? *Climate Risk Management* 22: 22-41.

Mikova K, Makupa E, Kayumba J. 2015. Effect of climate change on crop production in Rwanda. *Earth Sciences* 4:120-128.

Msuya CP, Annor-Frempong FK, Magheni MN, Agunga R, Igodan C, Ladele AA, Huhela K, Tselaesele NM, Msatilomo H, Chowa C, Zwane E, Miiro R, Bukeyn C, Kima LA, Meliko M, Ndiaye A. (2017). The role of agricultural extension in Africa's development, the importance of extension workers and the need for change. *International Journal of Agricultural Extension* 5:59-70.

Muasa L, Matsuda H. 2019. Mobile based agriculture and climate services impact on farming households in rural Kenya. *Journal of Sustainable Development* 12: 1-12.

Muema E, Mburu J, Coulibaly J, Mutune J. 2018. Determinants of access and utilization of seasonal climate information services among smallholder farmers in Makueni County, Kenya. *Heliyon* 4: 1-19.

Nkiaka E, Taylor A, Dougill AJ, Antwi-Agyei P, Fournier N, Bosire EN, Konte O, Lawal KA, Mutai B, Mwangi E, Ticehurst H, Toure A, Warnaars T. 2019. Identifying user needs for weather and climate services to enhance resilience to climate shocks in sub-Saharan Africa. *Environmental Research Letters* 14: 1-14.

Ouédraogo M, Barry S, Zougmore RB, Partey ST, Some L, Baki G. 2018. Farmers' willingness to pay for climate information services: evidence from cowpea and sesame producers in northern Burkina Faso. *Sustainability* 10: 1–16.

Republic of Rwanda. 2018. *Third National Communication: Report to the United Nations Framework Convention on Climate Change*. Kigali.

Ramachandrappa BK, Thimmegowda MN, Krishnamurthy R, Srikanth-Babu PN, Savitha MS, Srinivasarao Ch, Gopinath KA, Ravindra-Chary G. 2018. Usefulness and impact of agro-met advisory services in eastern dry zone of Karnataka. *Indian Journal of Agricultural Research and Development* 33: 32-36.

Revelt D, Train K. 1998. Mixed logit with repeated choices: households' choice of appliance efficiency level. *Review of Economics and Statistics* 53: 647–657.

RIA. 2017. Research ICT Africa: beyond access study. Rwanda Summary Report.

Rollins KS, Shaykewich J. 2003. Using willingness-to-pay to assess the economic value of weather forecasts for multiple commercial sectors. *Metrological Application* 10:31–38.

Roy P. 2018. Agromet advisory for empowering farmers to mitigate climate change. (Available from https://www.researchgate.net/publication/325593652).

SEI. 2009. Economics of Climate Change in Rwanda. Final Report to DFID. UK.

Stats4SD. 2017. Evaluation of climate services interventions in the GFCS adaptation programme for Africa: beneficiary assessment final evaluation summary report. Report prepared by Statistics for Sustainable Development and Cramer-Njihia Consultants for the World Food Programme and CGIAR Research Programme on Climate Change, Agriculture and Food Security (CCAFS).

Tandon P. 2015. *A Textbook of Microeconomic Theory*. Boston: SAGE Publications Pvt. Ltd.

Tesfaye A, Hansen J, Kassie GT, Radeny M, Solomon D. 2019. Estimating the economic value of climate services for strengthening resilience of smallholder farmers to climate risks in Ethiopia: a choice experiment approach. *Ecological Economics* 162: 157-168.

Tiitmamer N, Mayai AT. 2018. Climate services model for South Sudan's rural farmers and agro-pastoralists. Special Report. Juba: The Sudd Institute.

Train K. 2003. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.

UIS. 2016. 50th anniversary of international literacy day: literacy rates are on the rise but millions remain illiterate. UIS Fact Sheet 38.

Vaughan C, Hansen J, Roudier P, Watkiss P, Carr E. 2019. Evaluating agricultural weather and climate services in Africa: evidence, methods, and a learning agenda. *WIREs Climate Change*. doi.org/10.1002/wcc.586.

Vogel C, Steynor A, Manyuchi A. 2019. Climate services in Africa: re-imagining inclusive, robust and sustainable services. *Climate Services* 15: 1-9.

World Bank. 2008. Weather and climate services in Europe and Central Asia: a regional review. Working Paper 151. Washington, D.C.: The World Bank.

World Bank. 2013. Rwanda economic update. Maintaining momentum with a special focus on Rwanda's pathway out of poverty. Kigali: The World Bank.

World Bank. 2016. Climate information services providers in Kenya. Agriculture global practice technical assistance paper. World Bank Group Report 103186-KE. Washington, DC.: The World Bank.

Zillman JW. 2007. Economic aspects of meteorological services. WMO workshop on public weather services. Melbourne.

Zongo B, Diarra A, Barbier B, Zorom M, Yacouba H, Dogot T. 2016. Farmers' perception and willingness to pay for climate information in Burkina Faso. *Journal of Agricultural Science* 8:175-187.

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