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Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa

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ABSTRACT

This study aims to assess the economic benefits of seasonal climate forecasts in West Africa based on a random survey of 354 maize farmers and to use the contingent valuation method. Results indicate that farmers need accurate seasonal climate forecasts between 1 and 2 months before the onset of rains. The most desirable dissemination channels are radio, local elders, local farmer meetings and extension agents. The most likely used farming strategies are change of: planting date, crop acreage, crop variety, and production intensification. The vast majority of farmers are willing to pay for seasonal climate forecasts, and the average annual economic value of seasonal climate forecasts are about USD 5492 for the 354 sampled farmers and USD 66.5 million dollar at the national level. Furthermore, benefits of seasonal climate forecasts are likely to increase with better access to farmer based organisation, to extension services, to financial services, to modern communication tools, intensity of use of fertilizer and with larger farm sizes. Seasonal climate forecasts are a source of improvement of farmers' performance and the service should be integrated in extension programmes and in national agricultural development agenda.

Practical Implications

Our study analyses the economic benefits of seasonal climate forecasts for small farmers in the Republic of Benin in West Africa and shows a clearly expressed need of these farmers for seasonal climate forecasts from public and community-based agencies to improve their production and increase their incomes. We also show that available seasonal climate forecasts can lead to improved benefits for farmers. The most important forecasts requested by farmers are those related to the onset, distribution and amount of rainfall preferably forecasts that are available one to two months before the onset of rains. Many farmers would like to receive these seasonal climate forecasts through radio dissemination and also through meeting with extension and other local farmers. This suggests that national and local government authorities need to prioritise the establishment of public radio stations that can reach local farming areas with information on farming including weather and climate forecasts.

We also show that the majority of farmers respond to the availability of seasonal climate forecasts by adopting various strategies such as change of planting date, change of crop acreage, change of crop variety, change of crops planted and increase of fertilizer. Uncertainty in getting the information on time and continuously, and difficulties in understanding the information, are the main factors that influence the usefulness of forecasts. Access to extension services increases the likelihood of using seasonal climate forecasts significantly. Membership of a farmer based-organisation, access to credit, access to extension services, the intensity of

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fertilizer and the ownership of a mobile phone, help in the more effective utilisation of seasonal climate forecasts ensuring that overall benefits are increased to farmers.

We conclude by noting the key areas that need to be emphasised by government include improved extension services that have components of seasonal climate forecasts in their programmes, the need for national meteorological agency to produce locality-specific seasonal climate forecasts which are relevant to various farming communities with respect to the major crop and farming activities undertaken. Staff of national meteorological agencies need to be more proactive in seeking information from farmers in specific localities with regards to their needs of climate and weather forecasts. Lastly, it is important to note that farmers do not expect perfect seasonal forecasts and would be happy with an accuracy of around 80% that is eight seasonal forecasts out of ten seasonal forecasts issued that are useful.

1. Introduction

Over the last decades meteorological scientists have improved forecast technologies and models based on an improved understanding of the interaction between atmosphere and oceans and their link with certain climatic patterns (Ingram et al., 2002; Mjelde et al., 1998; PytlikZillig et al., 2010; WMO, 2015). Meteorologists can currently provide enhanced data and information on past, present and future states of the atmosphere. Climate forecasts are characterized to last for periods greater than two weeks (Mjelde et al., 1998; WMO, 2015). In this study, seasonal climate forecasts refer in this study to the provision of improved seasonal forecasts to farmers before the starting of the farming season.

Seasonal climate forecasts are assumed to speed up the adoption rate of high yielding and climatic risks reducing technologies and activities (Kenkel and Norris, 1995; Mjelde et al., 1998; Shankar et al., 2011; WMO, 2015). These forecasts are assumed to alleviate poverty. Seasonal climate forecasts are also assumed to help farmers (to) adjust their daily decisions (input timing and use, sowing period, marketing decisions), take advantage of favourable conditions and better choose which crop(s) to produce and in addition efficiently manage inputs such as land, labour, fertilizers, financial assets devoted to each crop (Hammer et al., 2001; Hansen et al., 2011; Kenkel and Norris, 1995; Mjelde and Hill, 1999; Phillips et al., 2002; WMO, 2015). The benefits of seasonal climate forecasts are likely to be higher in developing countries, like Benin, because of the large difference between current agricultural performance and the optimal potential agricultural performance and of the high-climate dependency nature of the agricultural sector in these countries (Vogel, 2000; World Bank, 2015).

In spite of the improvements of the climate predictions and their potential benefits to farmers in developing countries like Benin, the use of seasonal climate forecasts by farmers remains low (Clements et al., 2013; Ingram et al., 2002; O'Brien et al., 2000; PytlikZillig et al., 2010). Studies suggest that the National Meteorological Services (NMSs) in charge of the production of enhanced climate data and information and their dissemination in developing countries like Benin, lack both financial and human capacity to fully meet the international obligations and growing national needs and requirements for production of forecasts data and services (Clements et al., 2013; Lazo, 2015; WMO, 2015).

The building and sustaining of the capacity of NMSs, in order to ensure qualitative and continuous delivery of seasonal climate forecasts, require a scientific demonstration, through rigorous studies, of the economic benefits of the use of seasonal climate forecasts (Clements et al., 2013; Freebairn and Zillman, 2002; Rollins and Shaykewich, 2003; WMO, 2015). The evaluation of the benefits is necessary because it will offer quantitative arguments which can help to put the use of seasonal climate forecasts on the agenda of debates of development institutions (national and international) (WMO, 2015). It can also help to get the technical and financial support of these institutions (WMO, 2015). The lack of awareness of the benefits of seasonal climate forecasts is another major reason limiting the adoption and use of seasonal climate forecasts by farmers (Clements et al., 2013). Researchers call for studies related to the economic valuation of seasonal climate forecasts, especially in developing countries (Clements et al., 2013; WMO, 2015).

Two broad methods are used to value seasonal climate forecasts. Some studies use evaluation of field or project experiments and state a preferred approach (Anaman and Lellyett, 1996; Di Vecchia et al., 2006; Hammer et al., 2001; Kenkel and Norris, 1995; O'Brien et al., 2000; Patt et al., 2005; Phillips et al., 2002) whereas other studies use simulation experiments or on *ex-ante* approach (Meza et al., 2008; Roudier et al., 2012; Sultan et al., 2010; Ziervogel et al., 2005; Zinyengere et al., 2011). This work analyses the economic benefits of seasonal climate forecasts for farmers in Benin. The study has chosen to use a stated preference approach, the contingent valuation method (CVM), to value the economic benefits of the seasonal climate forecasts.

2. Theoretical framework for contingent valuation of seasonal climate forecasts

CVM is widely recognised as one of the major tool used by researchers to assess the total value of non-market goods (Bett et al., 2013; Carlsson et al., 2005). The objective of the CVM is to measure an individual's monetary value for non-market goods by creating a hypothetical market where individuals are asked to express their Willingness to Pay (WTP) or their compensation for having or not having a well-defined product. We assume that the individual has a utility function $U(Z)$ (measured in terms welfare or total income), where Z is a vector of n goods consumed by that individual.

Following Zapata and Carpio (2014), it is assumed that an individual derives one part of his/her income from agricultural production (FY) and the other part from non-agricultural activities (NFY). The indirect utility function for user j can be specified as:

$$\mathrm{V}[FY, NFY, P_Z] \tag{1}$$

where P_Z is the vector price of n goods consumed (food, clothing and composite goods excluding the price of leisure). The agricultural income is a share of the profit of agricultural production and can be expressed as:

$$FY = n(\pi(P_y, Q_y, r, q)) \tag{2}$$

where P_Y is the price of the produced output, Q_y is the quantity of output produced, q is the good being valued (seasonal climate forecasts), $\pi(.)$ is a profit function, r is a vector of input costs and $n \in [0, 1]$.

The indirect utility function can be rewritten as:

$$V[n(\pi(P_y, Q_y, r, q)), NFY, P_Z] \tag{3}$$

The act of valuation implies a contrast between two situations: a situation in which the goods are valued (seasonal climate forecasts) and one in which the goods are not valued. Specifically, if q changes from q^0 to q^1; with $q^0 < q^1$; the agent utility will change from $u_0 \equiv V[n(\pi(P_y, Q_y, r, q^0)), NFY, P_Z]$ to $u_1 \equiv V[n(\pi(P_y, Q_y, r, q^1)), NFY, P_Z]$.

The producer's WTP is the amount of money that makes the following condition to hold:

$$V[n(\pi(P_y, Q_y, r, q^0)), NFY, P_Z] = V[(n(\pi(P_y, Q_y, r, q^1)) - WTP), NFY, P_Z] \quad (4)$$

The producer's WTP can be simplified to:

$$WTP = \pi(P_Y, Q_y, r, q^1) - \pi(P_Y, Q_y, r, q^0) \quad (5)$$

Therefore, the maximum amount of money a producer is willing to pay for (the) improvement in the quality of the seasonal climate forecasts is equal to the difference in profit between the profit that prevails when the farmer uses the new seasonal climate information and the profit that prevails when the farmer uses pre-existing forecasts.

The reliability and robustness of the result of the CVM depend to a high degree on the respondents' understanding of the goods in question (here seasonal climate forecasts) because the misunderstanding of the hypothetical or artificial market leads to measurement errors and to unreliable results (Mitchell and Carson, 1989). Bett et al. (2013) point out that another common criticism of the CVM is on the question of style or format which can be misunderstood by the interviewees. This technique is also assumed to be subject to starting point bias.

There are several ways of requesting a farmer to reveal his/her willingness to pay (WTP): Open-ended questions, closed-ended questions (payment cards), double dichotomous choices and iterative bidding formats. An iterative bidding technique consists in the variation of the amount of money (initial bid) that the respondents are prepared to pay until the highest amount respondents are ready to pay for (final bid) is ascertained (Randall et al., 1974). This highest amount then becomes the individual's final WTP for seasonal climate forecasts. An iterative bidding technique is preferred because of the difficulty of elicitation of the initial bidding and the nature of the African market situations where agents are used to bargaining before a final price has been settled on. The final WTP can then be totalled by the number of maize farmers for an estimate of the aggregate value of the seasonal climate forecasts. Regression analysis can be used to find the factors that explain the value of seasonal climate forecasts.

3. Methods of analysis and materials

3.1. Descriptive statistics

Descriptive statistics were used to analyse the type of information needed by farmers: the desirable characteristics (optimal lead-time and accuracy level) of seasonal climate forecasts that make them acceptable for farmers, the dissemination channels of seasonal climate forecasts as well as the potential strategies used by farmers after they have received the seasonal climate information. The elicitation of the type of seasonal climatic information needed by farmers was done by proposing to farmers the kind of information scientists (meteorologists) can provide and farmers were in turn to indicate by using a simple 1–5 Likert scale (5 = Very Highly Needed, 4 = Highly Needed, 3 = Moderately Needed, 2 = Lowly Needed, 1 = Very Lowly Needed) their degree of need of each type of seasonal climatic information. The medium score of each type of climate information was estimated and Mann-Whitney *U* test was undertaken to evaluate significant regional differences in medium values.

The determination of the optimal lead-time was done by asking farmers to elicit the optimal lead time for the seasonal climate forecasts. But before the farmers could determine their optimal lead-time, the negative relationship between forecasts' lead-time and the forecasts' accuracy was explained to the farmers and a time range of up to 180 days was set. The level of accuracy of seasonal climate forecasts was determined by asking farmers to indicate the number of right predictions they were ready to accept over 10 predictions and still have confidence in seasonal climate forecasts. Resources and management options required to respond to seasonal climate forecasts were also analysed. A mean difference test was undertaken to evaluate significant differences in the mean of the variables across the three climatic zones.

The economic value of seasonal climate forecasts was determined by aggregating the values proposed by individual farmers as their WTP amount. A mean difference test was undertaken to evaluate significant differences in the mean of the variables across the three climatic zones. A two-step Heckman selection model was also used to determine the factors that explain the value of seasonal climate forecasts.

3.2. Econometric approach: the two step Heckman selection model

In this study, the two-step Heckman selection model approach was chosen because of its ability to explain both the decision to pay or not to pay, as well as the size of the WTP amount. The two-step Heckman selection model is based on the main hypothesis that the process that determines the producer decision to pay or not to pay for seasonal climate forecasts is different from the process that determines the amount paid by the producer (Heckman, 1979). Also, this approach is adopted because researchers (Amare et al., 2016; Birol et al., 2006; Liu et al., 2012; Strazzera et al., 2003) think that the WTP model is subject to sample selection bias and they therefore suggest the use of the two-step Heckman selection model rather than the classical probit and Ordinary Least Squares (OLS) models.

The model consists of two steps: Firstly, each producer is asked whether he/she is willing to pay for having access to the new seasonal climate forecasts or whether he/she wishes to continue using pre-existing seasonal climate forecasts. The respondent was expected to answer 'Yes' or 'No'. Therefore, the WTP decision can take the following values: $WTP = 1$ if the farmer answers 'Yes' and $WTP = 0$ if the farmer answers 'No'.

The probability of responding 'Yes' or 'No' given a set of independent variables X_i is stated as follows:

$$P_i = A_0 + \sum_{j=1}^{k} A_j X_{ij} + u_i \quad (6)$$

where

A_j is the coefficient of the *jth* socio-economic characteristic;
X_{ij} is the *jth* socio-economic characteristic of the *ith* producer;
U_i is the error term;

The error term u_i is independently and identically distributed with a normal probability distribution function.

The empirical model used for this study is described in Eq. (7).

$$\begin{aligned} \mathrm{SCF} = {} & \beta_0 + \beta_1\mathrm{SEX} + \beta_2\mathrm{EXPE} + \beta_3\mathrm{EDUC} + \beta_4\mathrm{LAND} + \beta_5\mathrm{RADIO} \\ & + \beta_6\mathrm{MPHONE} + \beta_7\mathrm{FERTI} + \beta_8\mathrm{MARKET} + \beta_9\mathrm{EXTEN} \\ & + \beta_{10}\mathrm{CREDIT} + \beta_{11}\mathrm{FBO} + \beta_{12}\mathrm{OFFARM} + \beta_{13}\mathrm{RELI} \\ & + \beta_{14}\mathrm{REGION1} + \beta_{15}\mathrm{REGION2} + \beta_{16}\mathrm{INDIMET} + V_1 \end{aligned} \quad (7)$$

where *SCF* is a dummy variable with 1 representing farmers who are willing to pay for having access to seasonal climate forecasts and zero otherwise and where V_1 is the equation error term. The independent variables used are listed in Table 1.

The probit model was estimated in order to obtain the Inverse Mill's Ratio (IMR). Heckman (1979) shows that the IMR is a proxy variable for the probability of using seasonal climate forecasts and when it is added to the outcome (amount spent to have access to seasonal climate forecasts) equation as an additional independent variable, it measures the sample selection effect due to the lack of observations on the value of seasonal climate forecasts for the non-adopters. The IMR' inclusion, as an additional independent variable, results in the consistent estimation of the remaining coefficients of the outcome equation. If the IMR is significant in the second stage, it means that a selection problem is apparent in this model, and as a result it is incorrect to estimate the Eq. (8) using OLS.

Secondly, if the producer is willing to pay, a second question is asked about the amount of money the producer is willing to sacrifice in order to have access to seasonal climate forecasts. The second stage Ordinary Least Squares (OLSs) equation will then be as follows:

$$\ln WTP = \alpha + \beta' x_i + \gamma IMR + v_i \tag{8}$$

where $\ln WTP$ is the logarithm of the amount a farmer is willing to pay for having access to seasonal climate forecasts, β is a $k \times 1$ vector of unknown parameters; x_i is a $k \times 1$ vector of known constants; and v_i are independently and normally distributed $(0, \sigma^2)$.

The empirical OLS model used for this study is described in Eq. (9).

$$\begin{aligned}\ln WTP = {} & \beta_0 + \beta_1 SEX + \beta_2 EXPE + \beta_3 LAND + \beta_5 RADIO \\ & + \beta_6 MPHONE + \beta_7 FERTI + \beta_8 MARKET + \beta_9 EXTEN \\ & + \beta_{10} CREDIT + \beta_{11} FBO + \beta_{12} OFFARM + \beta_{13} RELI \\ & + \beta_{14} REGION1 + \beta_{15} REGION2 + INDIMET + \gamma IMR \\ & + V_2 \end{aligned} \tag{9}$$

where V_2 is the equation error term.

3.3. Materials including survey procedures and administration

Benin is located in the zone of the so-called Dahomey Gap that receives less rainfall than the surrounding regions at the same latitude (Saha and Saha, 2001). Furthermore, Benin is prone to high rainfall variability when drought years are followed by floods years (Hountondji et al., 2011). The country is characterized by three main climatic zones (Fig. 1). Maize is produced in all of the three main climatic zones. Each climatic zone has its own use of inputs such as water, fertilizer, herbicides for the production of maize.

A multi-stage cluster-based random sampling approach was used as the design to select the respondents of the study. The first stage of the design consisted of the random selection of municipalities from the three climatic zones. The names of the municipalities were written on pieces of paper and one municipality was randomly picked for each climatic zone leading to the selection of three municipalities for the study: Kandi, Glazoué and Zè.

Kandi is located in the Sudanian zone with sorghum, millet, cotton, maize, rice, and groundnut as the main crops (INSAE, 2012). Kandi is one of the major (second largest) cotton producing basins in Benin (Djohy et al., 2015). The production of cotton, which is the main cash crop in Benin, gives access to subsidized inputs (fertilizers, weedicides, herbicides) and cotton specific services such as extension services and credit. Cotton farmers tend to re-allocate part of these subsidized inputs and cotton specific services to maize production. Farmers living in cotton producing areas have generally higher use of external inputs and thereby achieve higher agricultural performance. Furthermore, Kandi is one of the main centres of livestock production in Benin. Due to low population density, estimated at an average of 55 inhabitants per km^2 in 2013 (INSAE, 2013), Kandi is also characterized by large farm sizes The proportion of poor in Kandi is lower than the national average. In 2015, 40.1% of the population of Benin were living under the monetary poverty threshold while 36.9% of Kandi population felt under the poverty line (INSAE, 2015).

Table 1
Variables description for the two-step Heckman model.

Variables	Description	Measurement
SEX	Sex	Dummy (male = 1, female = 0)
EXPE	Maize Farming Experience	Years
EDUC	Education	Number of years of Schooling
LAND	Farm Size	Hectares
RADIO	Radio Ownership	Dummy (Yes = 1, No = 0)
MPHONE	Mobile Phone Ownership	Dummy (Yes = 1, No = 0)
FERTI	Quantity of Fertilizer Used	kg used per hectare
MARKET	Access to Market	Dummy (Yes = 1, No = 0)
EXTEN	Access to Extension Services	Dummy (Yes = 1, No = 0)
CREDIT	Access to Credit	Dummy (Yes = 1, No = 0)
FBO	FBO Membership	Dummy (Yes = 1, No = 0)
OFFARM	Off-Farm Participation	Dummy (Yes = 1, No = 0)
RELI	Traditional Religions	Dummy (Yes = 1, No = 0)
REGION1	Kandi	Dummy (Kandi = 1, Zè and Glazoué = 0)
REGION2	Glazoué	Dummy (Glazoué = 1, Zè and Kandi = 0)
INDIMET	Use of Indigenous Forecasting Knowledge within production system	Dummy (Yes = 1, No = 0)

Zè is located in the sub-humid Guinean zone (INSAE, 2012). The main crops cultivated are maize, cassava, potatoes, pineapple, tomato, pepper and legume. Zè does not produce cotton, and farmers in this area do not have access to subsidized external inputs (Djohy et al., 2015). The production system in this area is characterized by small farm sizes due to high land fragmentation and the high population density (197 inhabitants per km^2 in 2013). The proximity of Zè to the economic capital of Benin, Cotonou, tends to exacerbate the pressure on arable land for construction associated with urban spread. Zè is one of the poorest municipality in Benin. In 2015, 64.8% of the population living in Zè lived under the monetary poverty threshold (INSAE, 2015).

Glazoué is located in the Sudan-Guinean zone and most of its population are engaged in agriculture and the main crops cultivated are maize, yams, cassava, rice, groundnut, cotton, bean, soybean and cashew (INSAE, 2012). Compared to Kandi, Glazoué has only a small community of cotton producers who benefit from the subsidized external inputs programme (Djohy et al., 2015). The production systems in Glazoué are characterized by higher farm sizes, compared to Zè, and lower, compared to Kandi. The population density in Glazoué was about 70 inhabitants per km^2 in 2013 (INSAE, 2013). The rate of poverty in Glazoué in 2015 was 52.8%, which is higher than the national average of 40.1% (INSAE, 2015).

In Benin, a municipality consists of several local government areas or districts. The second stage of the selection process, therefore, consisted of the random selection of three districts per selected municipality.[1] The third stage of the selection process consisted of the selection of villages in each district. Two villages were

[1] From the municipality of Kandi, the three districts, Sonsoro, Kassakou and Donwari, were randomly selected out of a total of 10 districts. From the municipality of Glazoué, the randomly-selected districts were Aklampa, Asanté and Zaffé out of a total of 10 districts. Tangbo-Djevie, Sedje-Denou and Djigbé were randomly selected from the 11 districts from the municipality of Zè.

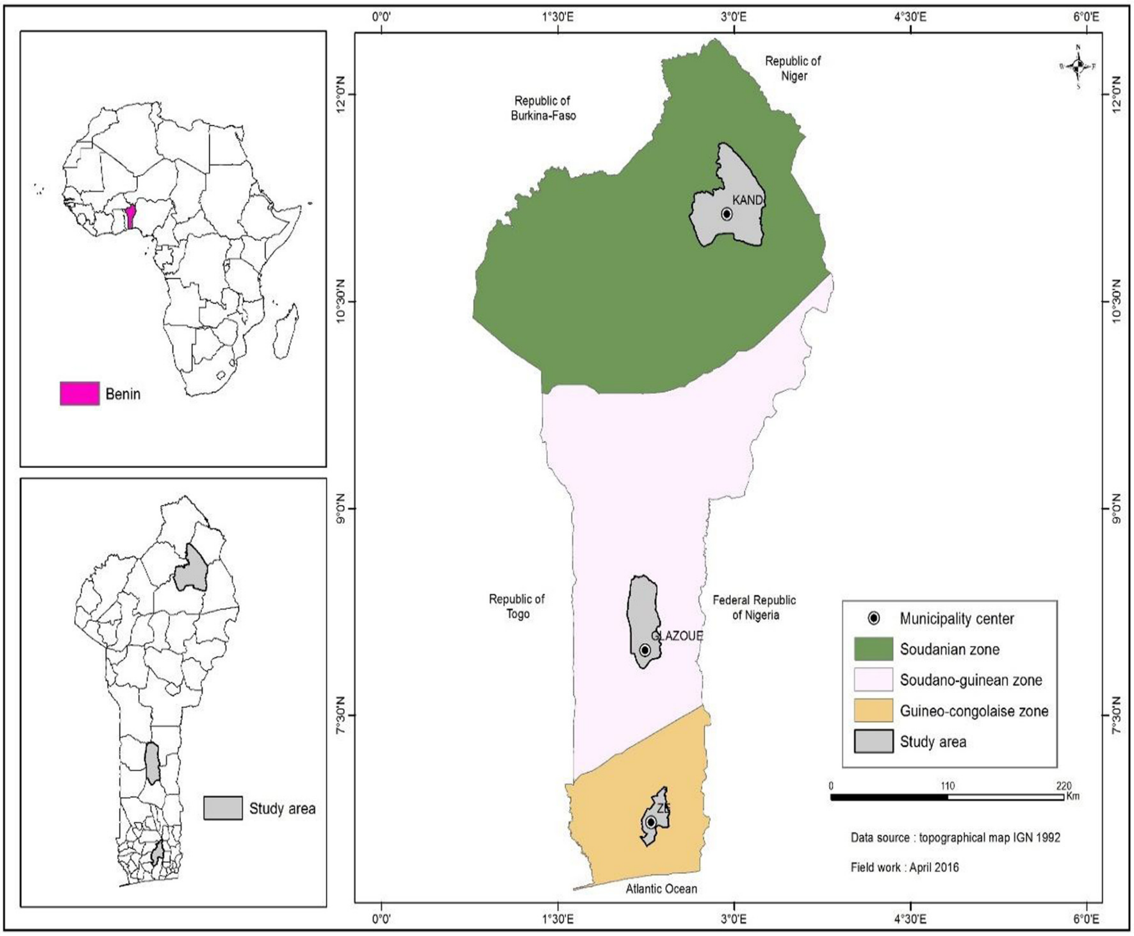

Fig. 1. Location of the study areas and climatic Zones in Benin.

randomly selected from each district, making up 18 villages for the nine districts and the three municipalities. The fourth and final stage was the actual selection of farmers to be interviewed with a structured questionnaire in the randomly selected villages. The optimal sample size for the number of farmers selected for the whole study was 323.[2]

In the practical setting of Benin, each village has a large number of farmers. For each village, the approximate number of farmers was provided by the Chief of the Village. The farmers selected were those known to be available in the village at the time of the study. Twenty-two (22) farmers were randomly selected from each village based on identifiable clusters of houses and huts in the different geographical areas of the village.

The identifiable number of clusters of houses and huts varied among each of the 18 randomly selected villages. However, the principle used to randomly select the maize farmers was the same. This principle was based on the number of identified farmers in each cluster of houses and huts as a proportion of the total number of farmers for all the houses and huts in the entire village. The actual number of randomly-selected farmers in each cluster in a village corresponded to the relative proportion of farmers living in each cluster relative to all the farmers living in the entire village.

[2] The determination of the optimal sample size is based works of Babbie (2016) dealing with the sampling from very large population sizes. Based on the formula the optimal sample size was derived to be 323. Oversampling was used and hence 396 farmers were chosen for the study indicating an oversampling of about 22.6%. This oversampling was done due to the possibility of some farmers refusing to participate in the study.

The farmers were basically identified and sampled through the numbering of houses and huts that were known to have people living in them for every village. In total, 396 farmers were interviewed, but data on 354 farmers were used for the analysis due to some missing data for 43 farmers.

4. Results and discussion

4.1. Socio-economic characteristics of farmers

About 38% of farmers interviewed came from Kandi, 32% from Zè and 30% from Glazoué. About 73% of the respondents were male and one third of the farmers were young (18–35 years). The mean age of sampled farmers was 41.7 years, with the youngest being 18 and the oldest 85 years. Potential users of seasonal climate forecasts were slightly older than potential non-users (Table 2).

Respondents with no schooling constituted the largest group based on educational attainment (61.6%), while primary school leavers were the second most prominent class of respondents (28.5%). The mean household size is 11 (Table 2). The mean size of farm for the whole group was about 3.9 ha, with the smallest being 0.28 and the largest 35 ha.

The mean farming experience on maize production is 22 years. For the majority of farmers (73%), maize is their main crop and the majority of the farmers (57.3%) declared agriculture as their sole source of income. Also, only 12.7% of farmers belonged to a Farmer Based Organisation (FBO). Only one third of farmers interviewed have interacted with extension services during the last three

Table 2
Summary of socio-economic characteristics of survey respondents and profile analysis between potential users and non-users of seasonal climate forecasts based on averages and frequencies analysis.

Items	All farmers (354)		Users (293)		Non-Users (61)		Prob (*t*-test)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Educational attainment level (%)							
No education at all	61.6	48.7	63.5	48.2	52.4	50.3	0.1080
Primary School	28.5	45.2	25.2	43.5	44.3	50.0	0.0027
Post Primary School	9.9	29.9	11.3	18.5	3.3	17.9	0.0576
Sex (% male)	73.1	44.4	72.3	44.8	77.0	42.4	0.4530
Age (Years)	41.7	12.6	41.0	12.0	44.8	15.2	0.0345
Maize farming experience (years)	22.2	1.7	21.4	10.8	25.6	15.0	0.0127
Household size (persons)	10.9	7.1	11.1	7.0	9.9	7.8	0.2456
Farm size (ha)	3.9	4.4	4.0	4.3	3.5	4.8	0.3631
Access to extension services (%)	33.9	47.4	39.6	49.0	6.6	25.0	0.0000
Farmer Based Organisation membership (%)	12.7	33.3	13.6	34.4	8.2	27.6	0.2458
Off-farm activity' Participation (%)	42.7	49.5	43.0	49.6	41.0	49.6	0.7724
Use of fertilizer (%)	56.8	49.6	59.7	49.1	42.6	49.9	0.0141
Quantity of fertilizer used (kg/Ha)	94.7	104.5	104.6	106.4	49.4	78.0	0.0001
Radio Ownership (%)	81.4	39.0	83.9	36.7	68.8	46.7	0.0058
Mobile Phone Ownership (%)	80.5	39.7	82.9	37.7	68.8	46.7	0.0115
Access to credit (%)	52.2	50.0	57.0	49.6	29.5	46.0	0.0001
Access to market (%)	89.8	30.3	91.5	28.0	82.0	38.8	0.0255
Profit per hectare (US dollar)	156.2	150.9	155.0	145.1	162.1	177.6	0.7375

farming seasons (2012–2014), with a higher proportion among potential users of seasonal climate forecasts (Table 2). The analysis of the profile of potential users and non-users of seasonal climate forecasts showed that the potential users have better access to credit, market, extension services, modern telecommunications tools (mobile phone), compared to the non-users (Table 2).

About 57% of farmers had applied fertilizer during the last cropping season. Potential users of seasonal climate forecasts use more fertilizer compared to potential non-users. On average, a farmer gets USD156.2 as profit per hectare for maize production and the profit per hectare does not differ across users and non-users of seasonal climate forecasts.

4.2. Seasonal climate information needed by farmers

All the farmers interviewed practice a rain-fed maize farming system, and the success of the agricultural season depends to a larger extent on the nature of the rainy season. The central role played by rainfall in the success of the agricultural venture justifies the high interest of farmers in receiving forecasts related to rainfall (onset, distribution and amount) (Table 3). Farmers across the three climatic zones indicated a need for seasonal climate forecasts relative to onset of rains. Forecasts related to the onset of rains got the highest ranking among the six meteorological variables, using a scoring scale from 1 to 5, with the higher figure indicating higher need of the information about this climatic variable (Table 3). Farmers' high interest for information about the onset of the rainy season can be explained by the fact that maize is a weather sensitive crop, especially during the germination (Ingram et al., 2002; MEPN, 2008; Phillips et al., 2002). Information about the onset of the rainy season can help farmers choose the crop cultivars that are more suited with the season. Farmers can choose late or early maturing cultivars in order to mitigate climatic risks.

Two other climatic variables (rainfall distribution and amount) are also highly needed by farmers. These two variables give information about water stress and deficits and extreme climatic events during the rainy season. Farmers also need information about the end of rains to better plan their post-harvest activities. Similar results were obtained by Ingram et al. (2002) in Burkina-Faso. In Lesotho, Ziervogel and Calder (2003) found that information of primary importance for decisions related to crop production was the distribution of rainfall followed by the onset of the rainy season and the maximum amount of expected rainfall.

Table 3
Type, lead time and accuracy of seasonal climate forecasts needed by farmers.

Items	All farmers	Kandi	Glazoué	Zè
Type of seasonal climate forecasts needed by farmers based on a scale of 1–5				
Onset of rains	4	$4^{A,B}$	5	5
End of rains	4	$4^{A,B}$	5^{C}	3
Amounts of rain during the rainy season	4	$3^{A,B}$	5^{C}	4
Distribution of rain during the rainy season	4	$3^{A,B}$	5^{C}	4
Intensity of the dry season	3	$3^{A,B}$	5^{C}	3
Speed of winds during the rainy season	3	3^{A}	5^{C}	3
Optimal lead time (in days) needed by farmers to receive seasonal climate forecasts about:				
Onset of rains	39	40	42	38
End of rains	45	$54^{A,B}$	44^{C}	35
Amounts of rain during the rainy season	37	35^{B}	41^{C}	35
Distribution of rain during the rainy season	39	41	42^{C}	35
Intensity of the dry season	42	48	42^{C}	34
Speed of winds during the rainy season	38	38	42^{C}	34
Optimal forecasts' Accuracy (%)				
Accuracy	2.3	$2.3^{A,B}$	1.8^{C}	2.8

A, B and C denote statistical significance at 5% between Kandi and Glazoué, Kandi and Zè and Glazoué and Zè respectively.

Table 4
Channels through which farmers want to receive seasonal climate forecasts.

Channels	All farmers	Kandi (%)	Glazoué (%)	Zè (%)
Radio	75.1	91.9[B]	95.9[C]	36.6
Locals elders	50.3	22.0[A,B]	79.6[C]	58.9
General meetings	26.3	8.0[A,B]	26.5	48.2
Extension agents	24.3	33.8[B]	8.1[C]	26.8
Mobile Phone	18.2	46.3[A,B]	0.0	0.0
Farmers Based Organisation	17.6	11.7[B]	36.7[C]	8.0
Friends	16.8	19.9	17.3	12.5
Research institutes	12.7	27.9[A,B]	0.0[C]	5.3
Traditional professional forecasters	2.6	1.5	4.1	2.7

A, B and C denote statistical significance at 5% between Kandi and Glazoué, Kandi and Zè and Glazoué and Zè respectively.

The two last climatic variables (intensity of the dry season and the speed of winds during the rainy season) are moderately needed by farmers and this can be explained by the general low speed of winds in Benin. Another explanation can be the farmers' inability to use information relative to wind speeds. Some farmers are interested in seasonal climate forecast relative to the intensity of the dry season because they think that the intensity of the dry season influences the intensity of the following rainy season (Table 3). Overall, farmers in Glazoué expressed stronger interest in receiving seasonal climate forecasts and this can be explained by the more unstable nature of climate in this area (Table 3).

The provision of seasonal climate forecasts is not sufficient to ensure a successful agricultural venture, the timing of delivery of seasonal climate forecasts is also important to allow farmers to respond adequately to whatever the predictions suggest. A range of time up to 180 days was proposed to farmers to elicit the optimal lead time for the seasonal climate forecasts. But before the farmers could determine their optimal lead-time, the negative relationship between forecasts' lead-time and forecasts' accuracy is explained to farmers. Based on this information, the farmers determined the optimal lead time to be between 1 and 2 months before the onset of rains. This suggests that the optimal lead time is similar to the results obtained by Sultan et al. (2010), Makaudze (2005) and Ingram et al. (2002). The difference in the optimal lead time declared by farmers across the different climatic zones is due to the number and the length of the rainy seasons. In the south (Zè) where the climate offers two rainy seasons, farmers indicated shorter lead-time, around one month, compared to the two other climatic zones characterized by one rainy season and where the optimal lead time was one and a half month.

The results of the analysis showed that farmers generally are looking for accurate information. The mean accuracy level of climate forecasts is about 77% and this implies that farmers can accept eight (8) correct seasonal climate forecasts over ten (10) forecasts released and still trust the information provider (Table 3). Ziervogel et al. (2005) established that a 60–70% accuracy of seasonal climate information is necessary for the climate information to be worthwhile. If the accuracy of information is less than 60% then the use of climate information may induce loss of production outcome (Ziervogel et al., 2005).

4.3. Seasonal climate forecasts' dissemination channels

The communication channels used to deliver seasonal climate forecasts to end-users are important because it can influence the use or non-use of the information and significantly reduce the verification costs (Goddard et al., 2010; Roncoli et al., 2009). The results from this study suggest that the majority of farmers would like to receive the seasonal climate forecasts through radio (75.1%) and local elders (50.3%). Other channels through which farmers would like to receive seasonal climate forecasts are local farmers meetings (26.3%), extension agents (24.3%), mobile phone (18.2%), FBOs (17.6%), friends (16.8%) and research institutes (12.7%) (Table 4). Regional differences are observed in channels through which farmers want to receive seasonal climate information.

In the northern zone (Kandi), farmers would like to receive seasonal climate forecasts primarily through radio, mobile phone and extension agents (Table 4). In the north, where the population density is low, farmers would like to use communication channels that can allow them to get information at any place and at least cost. The large preference for radio can be explained by the low literacy rate in this area (two thirds of farmers in this zone never attended school) and the widespread and timely coverage of radio. Consultation with elders and participation in meetings can generate important transaction costs and that may prevent some farmers from getting the seasonal climate information, especially in low density areas such as Kandi. In the transition zone (Glazoué), farmers prefer to receive seasonal climate information through radio, local elders and FBOs, while in the southern zone (Zè) they prefer local elders, local farmers meetings, radio and extension agents. This could be due to the high population density in these two zones that can favour the consultation of local elders or participation in local farmers meetings. This can also be seen as a strategy for farmers to discuss and analyse the seasonal climate forecasts in groups.

Across the three climatic zone farmers place extension agents among the favourite desirable (fourth place in the ranking) communication channels (Table 4). This would be due to the additional explanation that the agents can bring (Roncoli et al., 2009; Shankar et al., 2011). Analysts suggest that extension services can serve as bridge between farmers and forecasters on one the hand by helping forecasters to focus on the development of type and characteristics of seasonal climate forecasts needed by farmers and by providing feedback to forecasters about the performance and utility of the seasonal climate forecasts (Shankar et al., 2011). On the other hand, extension services can help farmers interpret seasonal climate forecasts correctly and make appropriate decisions, such as the time of planting, choice of crops and crop varieties, application of fertilizers, herbicides, pesticides and irrigation water at the appropriate time (Shankar et al., 2011).

4.4. Farmers' response system to seasonal climate forecasts

Seasonal climate forecasts generate benefits only when the producers change their decisions with regards to farming strategies. The change of farming strategy is assumed to better fit with the climate conditions predicted by the forecasts. But, in some cases, farmers do not change their farming strategies. About 5% of the farmers interviewed in Benin, declared that they would not change their farming strategies after receiving the seasonal climate forecasts. The farmers indicated that the non-response to seasonal climate forecasts is due to the lack of management options and the lack of trust in the information source. Ingram et al. (2002), O'Brien et al. (2000), Roncoli et al. (2009) and Tarhule and Lamb

Table 5
Response system used by maize farmers when planning for maize production in Benin in percentage in case of access to seasonal climate forecasts.

Preparedness techniques	All farmers	Kandi	Glazoué	Zè
Change of planting dates	88.2	83.1[B]	94.1	89.1
Change crop acreage	61.0	50.7[B]	79.4[C]	56.4
Change of crop varieties	56.9	72.6[A]	76.5[C]	16.8
Change of crop types	52.8	52.9[A,B]	69.6[C]	35.6
Increase the use of fertilizer	41.9	60.3[A]	55.9[C]	29.7
Change of land preparation	22.1	24.3	11.8	29.7
Change of crop spacing	18.6	27.9[A,B]	7.8[C]	16.8
Change of fertilizer application date	16.2	25.0[A]	20.6[C]	0.0
Change of fields	13.6	17.6[B]	1.0[C]	20.8
Change quantity of chemicals	12.1	25.0[A,B]	4.9	2.0
Change of chemicals application date	4.4	9.5[A,B]	1.9	0.0

A, B and C denote statistical significance at 5% between Kandi and Glazoué, Kandi and Zè and Glazoué and Zè respectively.

(2003) also found that the lack of resources (land, labour, seeds, animal traction), lack of technical assistance and institutional support (extension services, credit, market), lack of inputs, tenure insecurity and low benefit associated with the change of strategy, are the main causes of the non-response to seasonal climate forecasts.

The vast majority of farmers (95%) will respond to the introduction of seasonal climate forecasts by adopting at least one strategy (either intensified or non-intensified). About 13% of the farmers, who would change their farming decisions, responded that they would use one strategy and the other 87% would use at least two strategies. The intensification of the production is risky and that may justify the choice of all farmers interviewed to mix this option with non-intensified strategies.

The most likely used strategies would be change of planting date (88.2%), change of crop acreage (61%), change of crop variety (56.9%), change of crops planted (52.8%) and increase of fertilizer (41.9%) (Table 5). The change of planting or sowing date would be the most likely used strategy by farmers in Benin, as in a most studies related to African farmers' responses to seasonal climate forecasts (Amegnaglo and Mensah-Bonsu, 2015). The large agreement about the importance of the change of planting date is due the fact that the sowing marks the starting of the production process and the other production activities (weeding, fertilizer and chemicals application and harvesting) follow whatever the climate brings.

The change of crop acreage and of crop types, the second and fourth most probably used strategy, aims to find the best combination of crops and inputs that will maximize the climatic conditions. Farmers can reduce the quantity of land devoted or allocate zero lands to some crops with the aim to increase the quantity for other crops more suited for the coming season based on the seasonal climate predictions. These results conform to the findings of Hammer et al. (2001), O'Brien et al. (2000), Patt et al. (2005), Phillips et al. (2002), Sultan et al. (2010) and Ziervogel et al. (2005).

The change of crop variety is assumed to better fit with the predicted climatic conditions (Table 5). The change of crop variety can mean the use of improved seeds or any other maize variety that is more suitable for the predicted upcoming climatic season. The change of crop variety is commonly used by farmers in Africa (Patt et al., 2005; Ziervogel et al., 2005; Zinyengere et al., 2011). Patt et al. (2005) found that about 40% of farmers changed the crop variety in response to seasonal agrometeorological information in Zimbabwe. Zinyengere et al. (2011) suggest that the use of the appropriate crop variety can significantly increase agricultural yields. The authors estimated that the average yield difference between late maturing maize cultivars (140 days) and short maturation maize cultivars (100 days) is 1.4 t/ha under good rainfall conditions. The long term maturation maize cultivar yields more than the short term maize cultivar.

Intensification of production would be the fifth most declared strategy with about 42% of farmers speculating at increasing the quantity of fertilizer used (Table 5). Access to seasonal climate forecasts may be an incentive for farmers in the south (Zè) to use fertilizer in their maize production system. Few farmers (5.3%) in Zè were using fertilizer but access to seasonal climate forecasts could help increase the number of farmers using fertilizer to about 30%. Intensification of production will be used when farmers believe that forecasts are perfect or close to perfect because of the possible high financial losses associated with intensification (Roudier et al., 2012).

4.5. Benefits of seasonal climate forecasts

The majority of the farmers indicated their interest in using seasonal climate forecasts with just 18.64% stating they were not willing to pay for and use these forecasts. Two thirds of the farmers that were not willing to receive the seasonal climate forecasts thought that they lacked management options, while one quarter of the farmers (mainly in Zè and Kandi) expressed their uncertainty of getting the information on time, continuously, and of difficulties in understanding the information.

It is has been reported that inadequacy of resources (land, labour, seeds, animal traction), technical assistance and institutional support (extension services, credit, market) and inputs are some reasons of the farmers' refusal to acquire and use seasonal climate forecasts (Ingram et al., 2002; O'Brien et al., 2000; Roncoli et al., 2009; Tarhule and Lamb, 2003). Some farmers (12.5%), exclusively in Zè, claimed the credibility of the seasonal climate information as the cause of their refusal to pay for the seasonal climate forecasts. O'Brien et al. (2000) suggest that the lack of trust of farmers in the seasonal climate information can justify the low use of the seasonal climate forecasts.

The analysis indicates that the computed minimum average annual economic value is about USD 5492 for the 293 maize producers who were willing to pay for the seasonal climate forecasts. The individual mean WTP is about USD 19 (Table 6) or USD 4.8 per hectare and represents the minimum increase in farmers' benefit due to use of seasonal climate forecasts. The aggregation of the benefits of use of seasonal climate forecasts at the national level gives a benefit of 66.5 million dollars.

The initial mean WTP was increased by about 40% to reach the final maximum amount farmers are willing to pay (Table 6). The mean WTP values in Benin were lower than the mean WTP values derived by Anaman and Lellyett (1996) in Australia, but higher than the mean WTP values established by Makaudze (2005) for Zimbabwe. What is interesting to observe is the differential WTP pattern across municipalities. Farmers' average WTP was consistently higher in the drier areas (Kandi) than in the other two areas (Glazoué and Zè). Farmers' average WTP in Kandi was about 34.7%

Table 6
WTP for seasonal climate forecasts across municipalities.

		All farmers	Kandi	Glazoué	Zè
WTP > 0 (USD)	Initial bid	13.22 (21.81)	18.12 (25.81)	11.98 (19.18)	6.50 (14.34)
	Final bid	18.74 (26.92)	24.08 (31.80)	19.70 (23.86)	8.78 (17.14)

Note: 1USD = 500 Franc CFA; Values in bracket are standard deviations.

Table 7
Heckman two-step selection results for WTP for seasonal climate forecasts.

Variable	Probit			OLS		
	Coeff.	T-value	P-values	Coeff.	T-value	P-values
SEX	−0.1173	−0.48	0.632	−0.0073	−0.05	0.962
EXPE	−0.0066	−0.79	0.431	0.0068	1.00	0.317
EDUC	−0.0113	−0.43	0.667	0.0037	0.23	0.821
LAND	−0.0507	−2.41	0.016**	0.0370	1.80	0.072*
MPHONE	0.2187	0.97	0.331	0.4689	2.68	0.007***
FERTI	0.0008	0.70	0.484	0.0024	3.21	0.001***
MARKET	0.2260	0.84	0.400	0.2573	1.07	0.284
EXTEN	0.9773	3.10	0.002***	0.462	1.90	0.058*
CREDIT	0.2617	1.29	0.197	0.4677	3.21	0.001***
FBO	0.0510	0.16	0.873	0.5409	2.87	0.004***
OFFARM	−0.3148	−1.48	0.139	–	–	–
REGION1	0.8802	2.38	0.017**	0.1771	0.55	0.585
REGION2	0.5870	2.58	0.010**	0.8820	3.37	0.001***
TRADIMET	−02782	−0.96	0.336	0.1355	0.63	0.528
CONSTANT	0.6238	1.56	0.118	6.1515	11.63	0.000***
Lambda				0.6596	0.83	0.407

Number of obs = 354; Censored obs = 61; Wald chi2 = 82.14; Prob > chi2 = 0.0000; *, ** and *** denote 10%, 5% and 1% significant level.

and 224.5% higher than the average farmers' WTP in Glazoué and Zè respectively (Table 6). Farmers' WTP in Glazoué was about 140% higher than farmers' WTP in Zè (Table 6). Similar results were obtained by Makaudze (2005) in Zimbabwe where farmers in the relatively wet districts revealed consistently lower WTP than those in drier districts. The mean WTP value represents about 3% of maize farmers' mean net income. This result is consistent with the finding of Roudier et al. (2012). The authors found that the use of seasonal climate forecasts in Niger was associated with an increase in millet growers' net income of 6.9% using an ex-ante approach.

A two-step Heckman analysis was used to determine the factors that influence the decision to pay for seasonal climate forecasts and the maximum WTP amount. Econometric results are presented in Table 7. The coefficient of the inverse Mill's ratio (IMR) is not statistically significant (Table 7). This means that there is no selection bias resulting from the use of non-zero WTP values. Therefore, the second stage OLS is useful in explaining the factors that determine the size of the WTP amount.

The results of the probit model analysis indicates that access to extension services, farm size and regional dummies are significant (Table 7). Access to extension services increases the likelihood of using seasonal climate forecasts significantly. Extension workers can provide further explanation about the probabilistic nature of the seasonal climate prediction and give advice about the best practices or options (crop and land selection, timing of various activities) suited with the seasonal climate predictions (Ingram et al., 2002; Roncoli et al., 2009; Shankar et al., 2011).

Farm size decreases the likelihood of adoption of seasonal climate forecasts significantly. A similar result was found by Kenkel and Norris (1995). The negative relationship between farm size and the use of climate services suggests that the diversification effect of larger farms reduces climate risks and thereby reduces the likelihood of adoption of another climate risk management tool like climate information (Kenkel and Norris, 1995). Smallholder farmers are more exposed because of their lack of resources so that access to seasonal climate information can be seen as a cornerstone in the improvement of their agricultural performance (Roncoli et al., 2009; Vogel, 2000; Ziervogel and Calder, 2003).

Considering geographical location, the regression results indicate that farmers living in Kandi and Glazoué were more likely to use seasonal climate forecasts than farmers in Zè. Zè is an area that is much closer to the economic capital city of Benin, Cotonou. Hence farmers in Zè are certainly less likely to benefits from seasonal climate forecasts because of low access to external inputs.

The results of the OLS regression model summarized in Table 7 show that FBO membership, access to extension services, access to credit, ownership of a mobile phone, farm size, intensity of use of fertilizer and living in Glazoué increased the benefits farmers can derive from seasonal climate forecasts significantly.

Be member of a FBO is likely to increase benefits derived from the use of seasonal climate forecasts by about 14.7%. This might be due to the fact that if the FBO adopts the seasonal climate forecasts, members will be trained and educated on the best farming practices suited according to the predictions and on the benefits of these predictions. Access to extension services also increases the WTP amount significantly. Switching from non-having access to extension services to having access to extension services is assumed to increase net return from the use of seasonal climate forecasts by up to 12.6%.

Farm size had a significant and positive influence on WTP. As the farm size increases by one hectare, the WTP amount increases by 3.7%. Farmers with larger farm sizes are more likely to be commercially oriented farmers and therefore the access to seasonal climate forecasts is likely to help them avoid cost and production losses. The intensity of fertilizer use also affects the benefits farmers get from the use of seasonal climate forecasts positively and significantly. The use of seasonal climate forecasts is assumed to optimize the net return of fertilizer by reducing the likelihood of crop failure due to adverse weather conditions.

Access to credit increases the WTP amount significantly because access to credit offers to farmers the means to change their farming systems to take advantage of the seasonal climate forecasts the meteorologists come up with. Access to credit increases by 12.7% the maximum WTP amount. Vogel (2000) found similar results in South Africa and postulated that access to credit helps farmers to take benefits of seasonal climate forecasts. Ownership of a mobile phone also increases the WTP amount. This is certainly due to the possibility of the farmer obtaining the seasonal climate information's associated advisory information on time. Farmers living in Glazoué are likely to see their net return from seasonal climate forecasts increase by up to 24%. Glazoué is located in a transitional zone with erratic climatic conditions which affect the WTP amount.

5. Conclusion

The vast majority of farmers indicated their interest in paying for seasonal climate forecasts with just 18.64% stating that they are not willing to pay for these forecasts. Respondents were asked to rate the type of seasonal climate information they need on a 1–5 scale (with 1 being not at all needed and 5 being extremely needed). Farmers would like to receive seasonal climate forecasts about rainfall (onset, distribution and amount) and the intensity of dry season. Farmers would also like to receive the seasonal climate forecasts minimum one month and maximum two months before the onset of rains. The mean desirable accuracy level of seasonal climate forecasts is about 77%.

A large majority of farmers would prefer to receive the seasonal climate forecasts through radio, local elders, local farmers meetings, and extension agents, in decreasing order with regional differences. The most likely used strategies after receiving the seasonal climate forecasts are change of planting date, change of crop acreage, change of crop variety, change of crops planted and increase of fertilizer used in decreasing order. The analysis indicates that the average minimum annual aggregate gross benefits were about US dollar 5492 for the 354 maize farmers sampled. The aggregation of the benefits of use of seasonal climate forecasts at the national level gives a benefit of USD 66.5 million. This work highlights very clearly the expectations of and the benefit to farmers in terms of the accuracy of forecast at the seasonal scale. It is worth investing resources in studying and producing high quality seasonal climate information and services. The seasonal climate forecasts should be integrated into national extension services packages to enable farmers to have timely access to the information.

The econometric analysis suggests that the gross benefits are likely to increase with better access to FBO membership, to extension services, to credit, to modern communication tools (mobile phone), intensity of use of fertilizer and with larger farm size. The organisation of farmers in FBO will also help farmers to overcome market constraints and thereby for them to benefit fully from their access to the seasonal climate forecasts. With agriculture being the backbone of the economy of Benin and maize the major commodity produced, the government of Benin may have to design programmes to increase farmers' access to key inputs. Doing so would allow farmers to take better advantages from the use of seasonal climate forecasts.

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