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ORIGINAL ARTICLE

Farmers' preference and willingness to pay for weather forecast services in Benin (West Africa)

Fèmi E. Hounnou[1] · Albertine M. Houessou[2] · Houinsou Dedehouanou[1]

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Abstract

The development of adaptive strategies to improve farmers' resilience to climate change and to strengthen rural population livelihoods is at the forefront of most debates on achieving sustainable development goals at the national, regional, and international levels. This study aims at analyzing Beninese farmers' preferences for weather forecasting services with the application of discrete choice experiments. Conducted in eight districts in four agro-ecological zones of Benin, data were collected from 716 randomly selected farmers. Based on financial and non-financial attributes, a mixed logit model was executed to elicit farmers' utilities among weather forecast service attributes and to perform the implicit value associated with each attribute. The findings showed that almost five-sixths of the choices refer to the proposed improved weather forecast. Farmers indicate more interest in long-run weather forecasts, high accuracy of the information, media other than radio for dissemination, and use of local language for information transmission. The results also highlight that farmers allocate the highest implicit value for various communication channel attributes, followed by the type of weather forecast information, quality of weather forecast services, and local language for communication. Projects supporting agricultural productivity improvement should consider the role of weather forecasts in improving farmers' livelihoods when defining climate change adaptation strategies. This consideration should include the essential characteristics that farmers desire for their large-scale participation in such an initiative. Agricultural development agencies need to define the best strategies to make accessible to farmers weather forecasting, an essential element of agricultural decision-making.

Keywords Weather forecast services · Climate change · Discrete choice experiment · Adaptation strategies · Crop productivity

Introduction

In the developing countries, smallholder farmers are the most affected by the effects of climate change (Dobardzi et al. 2019; FAO 2019; Naab et al. 2019). Indeed, family farming practiced by these farmers is characterized by rainfed production systems which are very sensitive to climate change and variability (Ouédraogo et al. 2018). In particular, temperature and water availability represent the two crucial components that influence crop growth and development (FAO 2019) and seriously need to be considered by implementing climate change adaptation strategies. The improvement of adaptive capacity in favor of resourceless farmers should be done through resilient livelihood building. The agricultural sector in those countries faces several challenges including a lack of irrigation, fertilizers, pesticides, improved seed, etc. The agricultural productivity then results from farming management (based on farmers' decisions taken) and environmental conditions (climate, soil, water, pests, etc.), on the one hand, and climate change adds complex challenges to the agricultural sector on the other hand. Development practitioners and scholars therefore recognize that improving smallholder farmers' adaptation strategies to address the adverse effects of climate change would improve livelihoods and food security (Wilkinson et al. 2015). There are many approaches, but smallholder farmers' access to weather services for farming decision-making could appear

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✉ Fèmi E. Hounnou
hounnou.femi@gmail.com

1 University of Abomey-Calavi, Faculty of Agricultural Sciences, Abomey-Calavi, Benin

2 National University of Agriculture, School of Agribusiness and Agricultural Policy, Kétou, Benin

vital for reducing climate adverse effects (Das et al. 2010). The climate forecast services are new and stand as one of the principal factors affecting the farmers' activities and their productivity. Thus, smallholder farmers can tactically organize their farm activities or tasks using weather forecast services and adopt approaches to cope with climate change. Weather information is often used for operational decisions about when to start field works? When to plant according to soil moisture? When to fertilize? When to harvest? When to irrigate? etc. (Dobardzi et al. 2019). As such, climate should be considered a resource and not merely as a hazard. Then, the climate forecast could be integrated into agricultural advisories to assist farmers with planning their activities.

In Benin, more than 70% of the active population works in the agricultural sector as smallholder farmers and this sector is essential for household welfare and the country's stability (MAEP 2018). Smallholder farmers are mainly family farming and count for 51% of the total farmers. In addition, they hold an average of 4 ha and rely on the use of family labor as well as the traditional equipment (Sossou et al. 2021). As the country's agriculture is a rainfed type, its production is often volatile. The main reasons could be weather, insects and pests, diseases, and fluctuations of input and output prices. In this country, climate variability and change are causing crucial distress (Awoye et al. 2017; Hounnou et al. 2019). Within the agricultural system and the local conditions, farmers are turning to using the improved climate-resilient seeds, crop nutrients, and water management practices; changes in tillage practices; change in sowing time based on climate information; etc. (Dunnett et al. 2018). These practices have some limitations to efficiently address the issues of climatic risks in agriculture due to the lack of access to updated information (Gangopadhyay et al. 2019). Generally, farmers leverage on proverbs, folklore, and experiences in rural areas to anticipate local weather and timing of agricultural operations. As in most sub-Saharan African countries, farmers in Benin use local knowledge to get access to climate information provided by the traditional practices which predict rainfall variability and other climate information (Antwi-Agyei et al. 2012). However, inconsistencies in predictions from the endogenous knowledge make it difficult to rely on the traditional practices. As a result, farmers can no longer take advantage of the potentials of the socioeconomic transformation of agriculture. Considering the challenges of climate change, the use of weather forecast services (WFS) for smallholder farmers and vulnerable communities has proven to be a wise alternative or the principal element to adapt to impacts and reduce climate change risks (Naab et al. 2019). These services are one of the most effective adaptation tools to overcome climate change. The availability of timely information on weather forecasts, climate information-based input use and crop management practices, and market information play a crucial role in climatic risk management (Magawata 2014). Weather plays an essential role in the rainfed system in agricultural production. It has a significant effect on different stages of crop production (growth, development, and yields); on the incidence of disease and pests; on water needs; and on fertilization requirements (Das et al. 2010). Weather abnormality could lead to physical damage to crops and soil erosion. Even out the farms, the quality of agricultural products stocked and transported relies on climatic conditions. Hence, weather impacts all aspects of crop production and varies among crops, crops varieties, different growth stages, locations, times, and years. In crop production, it is important to consider for weather over short periods and year-to-year fluctuations in the local area. However, despite the efforts of the Beninese Government and development agencies, producers are still facing challenges to develop adequate and sustainable adaptation strategies (Satoguina 2019). The non-use of appropriate climate or weather forecasts information to plan agricultural activities or operations disturbs the classic adaptation strategies to cope with climatic parameters changes. The production of climate information for agricultural purpose is not effective even though the great effort in agricultural sector. For example, about 9 to 25% of food crop yields losses are linked to inaccurate WFS (Awoye et al. 2017; Hounnou et al. 2019). To this end, the literature reveals a vital gap between the demand for and supply of services provided on WFS (Hoa et al. 2018). In other words, WFS cannot meet the current needs of producers for weather and climate information (World-Bank 2015). Indeed, farmers have difficulty accessing information timely for integrating it into decision-making and crop year planning processes (Naab et al. 2019). These inadequacies could explain the damage and loss of economic gains experienced by farmers in Benin. It is well known that access to reliable information is vital to anticipate risks and build capacity for adaptation to the effects of climate change (Hellmuth et al. 2011). Accessibility of farmers to viable weather services could adequately support climate risks management and climate resource exploitations in order to benefit from favorable weather and reduce the adverse effects of weather conditions (Dobardzi et al. 2019). To achieve this, WFS must be adapted to the needs of users. In some circumstances, the weather information is available but not advantageous due to its inadequacy to the farming scale or no use of local language (FAO 2019). Previous studies have analyzed factors affecting smallholder farmers' willingness to pay for weather forecast services and their results are heterogeneous and inconsistent (Amegnaglo et al. 2017; Ouédraogo et al. 2018; Ibrahim et al. 2019). These findings imply that the factors determining smallholder farmers' WTP are location and time sensitivity (Ibrahim et al. 2019). It is a significant challenge, especially when, despite the importance of the research on WFS, there is little information on Benin about the economic aspects of WFS (Amegnaglo et al. 2017). Considering these gaps, this research aims at analyzing the channels through which to provide information and the weather forecast needed to improve the resilience of Beninese smallholder farmers to the effects of climate change. Specifically, it aims at (i) analyzing smallholder farmers' perception and their preference for different attributes of weather forecast services and (ii) assessing the factors that influence smallholder farmers' willingness to pay for weather forecast services. This research will strengthen the capacity of national or private WFS providers to meet farmers' needs for weather information.

Because of the climate change effects, many farmers suffer from crop yield losses (Awoye et al. 2017) and the weather is a determinant factor for the success or not of crop production. Then, adaptation strategies appear as the most applied to improve household livelihoods in rural areas. One of the adaptive strategies is the WFS use. This strategy can help farmers to adapt to climate change and reinforce their ability to withstand future unexpected climate change and to deal with food insecurity issues (WMO 2016). In Africa, many efforts remain to promote WFS such as availability, accessibility, and usefulness for smallholder farmers (Vaughan et al. 2019). The literature revealed that WFS leads to adopting higher improved seed crops (WMO 2015) and it is also assumed that WFS could alleviate poverty among smallholder farmers (Amegnaglo et al. 2017). The use and adoption of WFS for agriculture purposes remain low (Clements et al. 2013) due to the lack of awareness of the benefit of WFS. The non-use of climate and weather information to change crop management is a loss in value (FAO 2019). Another WFS issue concerns farmers' unawareness due to its unsuitability to the farming scale and the lack of information in the local language. The main reasons could be the centralization of weather services and unrealistic information to represent the specific farming environment. Therefore, there is a need for scientific studies to justify the economic value of using WFS (WMO 2015). The literature supported the economic analysis of WFS because it could help introduce the WFS into climate documents and to plead technical and financial support of development agencies (WMO 2016). Particularly, WFS could improve food security and rural livelihoods could be enhanced by better managing agricultural risks due to climate change (Clements et al. 2013). In West Africa, many studies quantified the economic value of WFS among farmers (Zongo et al. 2016; Ouédraogo et al. 2018) and particularly in Benin (Amegnaglo et al. 2017). The present research is not a continuum of the past studies; it will particularly choose all the agro-ecological zones affected by climate change and involve farmers of several crops. The past studies used contingent valuation, which had shown several limits in assessing the willingness to pay. Thus, this research proposes to use a discrete choice experiment (DCE) approach and to analyze the smallholder farmers' willingness to pay the improved WFS.

Methodological approach

Theoretical framework: experimental design

Based on Lancaster's theory of value, the discrete choice experiment considers the good or service according to its attributes and corresponding levels of these attributes (Lancaster 1966). The DCE is set to value in monetary terms the existing (Champ et al. 2003) and non-existing (Louviere et al. 2010) good or service that may have no or restricted market or new to be introduced into the market. Since the weather forecast is a complex service with several attributes (Nguyen and Robinson 2015; Tesfaye et al. 2020), the DCE approach is adequate to assess farmers' WTP and their preferences in weather forecast service. Literature had provided enough information (Nguyen and Robinson 2015; Tesfaye et al. 2019, 2020) about WFS and was a base of attributes and their level choice. The process of attributes selections was based on three steps. The first one was related to the literature review in weather and climate information services for agriculture where twelve attributes were identified. The second step was constituted of five focus groups discussion with farmers to analyze attributes retained from literature. During this step, the twelve attributes were classified according to their importance, need, and local context. The last step concern the validation and reformulation of attributes and their respective level consulting expects in agricultural sector such as extension agents, personal of NGO, and researcher where five attributes were eliminated from the list. Thus, this research considered six attributes: type of information received, quality of the information received, the language of communication, communication channel, market information, and price (XOF).

The first attribute of WFS, type of information, has four levels such as daily WF, Decade WF, seasonal WF, and agromet advisories. Having information related to WFS more than 72 h in advance should increase farmers' income due to the possibility to adjust their decisions about crops and varieties to grow and days of sowing (Gunda et al. 2017; FAO 2019). Additional to information on WF, their application into the farm management was found to improve and preserve farmers' livelihood (Chattopadhyay and Chandras 2018).

The second attribute, the quality of WF information, is regarded as the most essential characteristic of WFS useful for farming decision-making. It constitutes the base of decisions farmers should make for better management of climate risks. The inconsistency of WF could lead to crop yield losses and welfare deterioration, and discourage farmers in their adoption process (WMO 2016). This research uses two levels for this attribute, accurate and not accurate.

The third attribute concerns the language used to deliver information, which is also essential as most of farmers in developing countries are illiterate. In Benin, 57.64% of people over 15 years old cannot express themselves in the official language (World-Bank 2015[1]). Specifically, in the rural area, there is more than ten local language for different socioeconomic groups. This research considers the native language an attribute because it offers an opportunity for farmers to ask questions to understand better (Hellmuth et al. 2011; Tesfaye et al. 2019). Official (French) or local language is considered to look for farmers' preferences.

The channel of communication was tested showing the alternative to traditional (radio) the improved way to disseminate WF (meeting with extension agents; phone via short text message; phone via interactive (voice or text) response system). The preference of farmers about communication channels is not homogenous in literature. Some farmers prefer a meeting with extension agents (Birachi et al. 2020), others choose phone short text messages due to the easy way to deal with them (Tesfaye et al. 2019), and another group prefers the possibility to interact in order to dissipate misunderstandings during the communication and have the feedback about some specific issue (Tesfaye et al. 2020).

Information related to the market could help the farmer to be aware of the market movement regarding commodity prices. It is helpful for decision-making on the storage of the product for a while or not, or for helping farmers to negotiate at the same level as the traders (Tesfaye et al. 2019). Association of WF and market information appeared to increase the accuracy of decisions made by farmers (Haile et al. 2015). This research had considered two levels of this attribute access or not to market information. Finally, a monetary criterion was added with four levels to assess the farmers' WTP for weather forecast services through the considered attributes (500, 700, 900, and 1000 XOF). The price level was monthly expressed and determination of the level was based on an exploratory survey. Table 1 resumes different attributes and their levels used in this paper.

Data collection

The study was conducted within four agroecological zones (AEZ) in Benin which are considered as the most vulnerable to climate change effects (Hounkponou 2015). A multi-stage approach was applied to select randomly respondents in these AEZ based on four stages (AEZ, districts, sub-districts, and farmers/households) according to the climate conditions. As mentioned at the beginning, four AEZ were selected according to their susceptible to climate change effects. At the second stage, two districts were then randomly selected in each AEZ where two sub-districts are chosen before one rural village was randomly retained for households' selection at the last stage. However, any criteria were considered during the process of households surveyed. All households living in villages selected have the same possibility to be included in the sample. Through the stage, random sampling technique was adopted. The distribution of the survey sub-districts is illustrated in Fig. 1.

Generally, Benin is divided into three parts according to climatic parameter distributions. The first, southern Benin, is dominated by a subequatorial climate with two wet seasons and two dry seasons. The annual precipitation ranks between 950 and 1500 mm. The second part, the center region of the country, is defined by the transition regime where the difference between two wets tend to disappear with annual precipitation varies between 1000 and 1200 mm. The last part concerns northern Benin is characterized by two seasons (wet and dry) and particularly a harmattan regime (wind neither hot nor cold) with annual rainfall ranks between 700 and 1200 mm.

As the majority of rural people practices agriculture and considering the extent of the study area, this study has adopted sample size technique estimation (Eq. (1)) based on a finite population (Durand 2002):

Table 1 WFS attributes and their levels

N°	Attributes	Levels
1	Type of information received	(i) Daily weather forecast; (ii) decade weather forecast; (iii) seasonal weather forecast; (iv) agro-met advisories
2	Quality of information received	(i) Not accurate; (ii) accurate
3	Language of communication	(i) Native/local language; (ii) official language
4	Communication channel	(i) Radio; (ii) meeting with extension agents; (iii) phone via short text message; (iv) phone via interact response system
5	Market information	(i) No information on the market; (ii) availability of market information
6	Price (monthly payment) (XOF)[a]	0; 500; 700; 900; 1000

[a]West African CFA franc (XOF) is currency applied in this study (1 USD is equivalent to 550 XOF as of August 5, 2021)

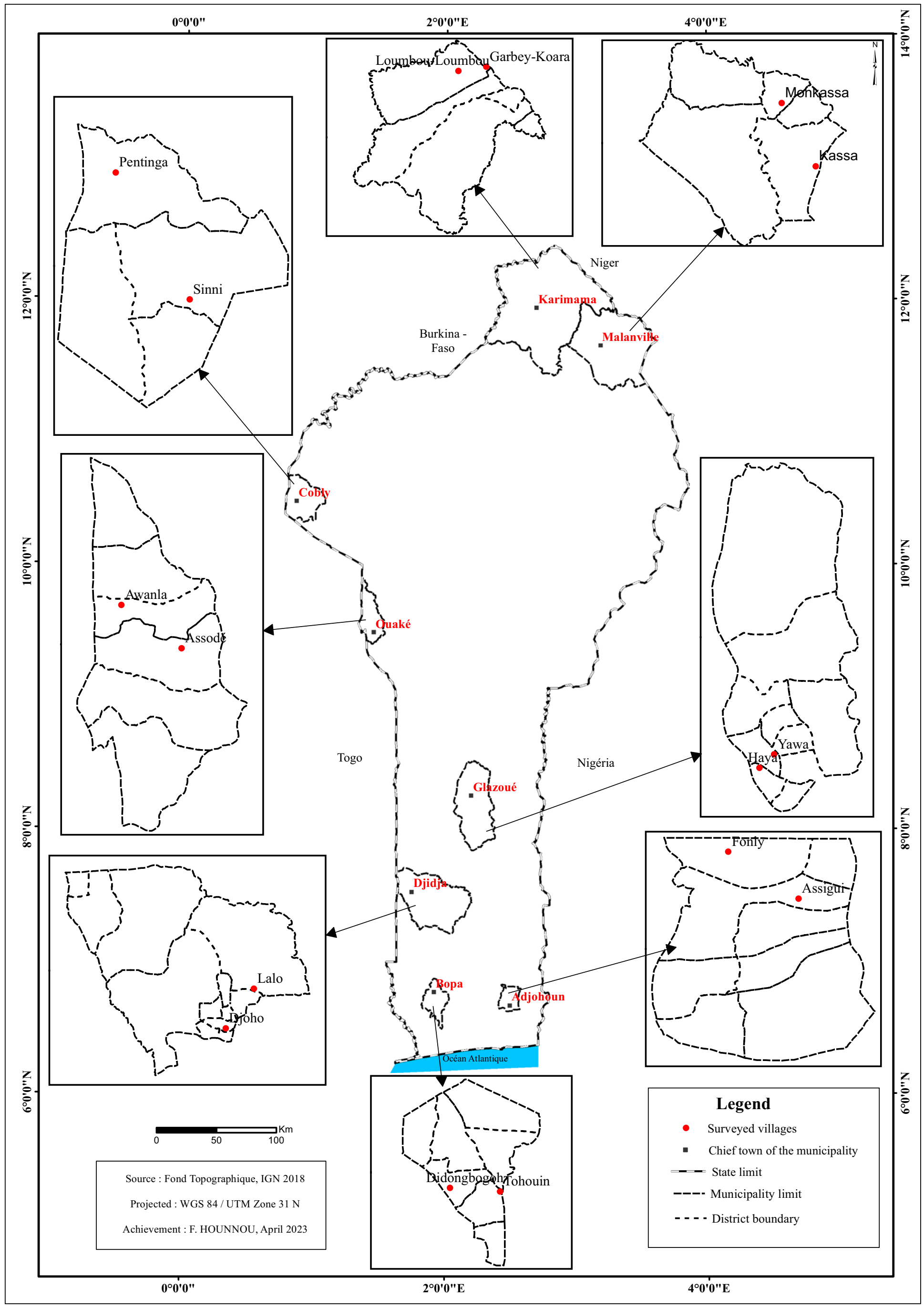


Fig. 1 Map of study area (Benin/West Africa)

$$n = \left[p \times (1-p) + \frac{e^2}{Z_\alpha^2}\right] / \left[\frac{e^2}{Z_\alpha^2} + \frac{p \times (1-p)}{N}\right] \quad (1)$$

Except for the Cotonou District and other big cities, the proportion of Beninese working in crop production could be approximately 75% (MAEP 2017) that is $p = 0.75$, and the confidence level considered is 95% ($Z_\alpha = 1.96$). The study assumed a margin error of 3% ($e = 0.03$) and population size is N (4573, the total of households in study area); then, the sample size following the computing expression (Durand 2002) is 682 households. But because of respondent reluctance to filling the questionnaire which could result in a questionnaire dropping with missed data, 720 households were surveyed. Four observations were dropped out of the data base and 716 observations were finally considered for analysis. In each village, 45 smallholder farmers have been randomly selected from exhaustive list. Data were collected by eight experienced enumerators who received comprehensive training to perform the choice experiment (CE) surveys. The survey questionnaire

Table 2 Respondents' socio-demographic characteristics (Sample characteristics) n=716

Quantitative variables	Mean	Standard deviation	Minimum	Maximum
Heard household age	46.39	10.20	35.00	82.00
Head of household farming activities/ experiences (years)	19.04	11.13	2.00	65.00
Household size	8.00	4.00	2.00	35.00
Monthly household income	75035	75189	5000	600000
Total own land (ha)	5.6	6.74	0.15	65.00
Total cultivated land for staple crop	3.41	3.17	0.00	52.00
Total cultivated land for cash crop	1.55	2.34	0.00	22.00

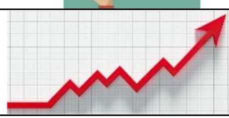
Categorical variables	Modality	Frequency (%)
Sex of household head	Male	83.05
	Female	16.95
Head household education level	None	61.34
	Primary	23.67
	Secondary 1	8.68
	Secondary 2	3.78
	University	1.68
	Trained in local language only	0.84
Head household main occupation	Agriculture	91.60
	Livestock	1.26
	Processing/trade	2.66
	Handicraft and small services	1.82
	Catering/bar	0.14
	Public servant	0.56
	Driver	0.84
	Others activities	1.12
Satisfied from agricultural activities	Yes	65.27
Trained about agricultural activities	Yes	6.16
Pesticide use	Yes	71.29
Herbicide use	Yes	74.23
Agricultural association member	Yes	35.01
Access to credit	Yes	41.04
Access to extension services	Yes	43.70
Access to market	Yes	66.11
Access to irrigation system	Yes	3.22
Owner of mobile phone	Yes	74.51

was structured in three parts: (i) general information about the farmer and farmer' household; (ii) the farmer's perception about climate change; and (iii) discrete choice experiment. Filling out each questionnaire took an average of 20 min and respondents were free to continue the process or not. No incentives were promised to respondents.

Farmers involved within this study produce as well as staple crops (maize, rice, cassava, sorghum, yam, tomato, chili pepper, etc.) and cash crops (cotton, cashew nut, pineapple, palm tree, shea tree, etc.) with an average cropped land of 3.14 ha and 1.55 ha per household surveyed, respectively (Table 2). However, the average land holding size is 5.6 ha with 6.74 as standard deviation meaning that the land is unequally distributed among farmers considered for this study. The effects of climate change in crop production are pronounced because of the limited access to irrigation system through the country. Only 3.22% of farmers have declared access to irrigation, but for mainly vegetable production.

The attributes levels have been combined resulting in alternative scenarios. A fractional factorial design was applied to determine the attribute's combinations and different options using R software version 4.0.3. To simplify the choice for respondents, 32 options have been generated and sixteen cards of three options (one opt-out option) were presented to each respondent. Enumerators have presented and explained

Table 3 Example of choice card presented to respondents

Attributes	Option A	Option B	Option C
Type of weather forecasts 	Daily weather forecast	Decade weather forecast	
Quality of weather forecast 	Not accurate	Not accurate	
Language of communication 	Official language	Native language	
Communication channel 	Phone via interact response system	Radio	
Market information 	No	Yes	
Monthly price to pay			

an example of the card to respondents to ensure they had understood the choice process before presenting the research experiments. Also, to make a choice consistent, pictograms were used to represent the attributes and their levels shown an example in Table 3. This table displays two improved weather scenarios (option A and option B) with status quo (option C), among which the option choice has been made.

Empirical model

Smallholder farmers' expectations or perception toward weather services

To analyze smallholder farmers' perception about weather service, a list of weather components related to weather service provision was developed with farmers during the exploratory survey. This method involves getting smallholder farmers to rate the weather components in terms of their level of importance to agriculture to help improve crop productivity (Mabe et al. 2014). The following formula (Eq.(2)) has been used to determine the average score value for rankings the level of importance of the weather service:

$$MS_{WFSc} = \frac{Total\ Score\ for\ j^{th}\ WFSc}{Number\ of\ respondent} \tag{2}$$

where MS_{WFSc} corresponds to the mean score value of weather component j.

It implies that the higher the mean score value is, the more essential and preference farmers attached to the phenomena of weather forecast variable concerned.

In order to generate the perception score, an approach developed in the literature has been adapted (Reed et al. 1991). Its implementation applies quasi-ordinary arbitrary weights in which farmers rank each attribute in terms of importance and actual quality. Then, the level of significance of each identified component for smallholder farmers was coded 1 (not at all important for agriculture), 2 (important), and 3 (very important for the agricultural sector). Also, the quality of weather service of each component was recorded as 1 (currently poor), 2 (good), and 3 (very good). Smallholder farmers were asked to rank their perception of the weather forecast component according to their importance and quality. The perception scores of demand, supply, and attainment were calculated using (Reed et al. 1991) approach. The first index (D) measures the importance that farmers perceive attach to a particular weather forecast characteristic. It takes a value between 0 and 1 where a value of 1 reveals that farmers perceive a characteristic as very important. Secondly, the supply index (S) indicates how farmers perceive how the weather forecast component is offered or the current conditions of the various attributes. Comprised between 0 and 1 where value 1 means that farmers consider the weather forecast attributes as very good quality. Lastly, the attainment index (W) measures the difference (matching) between farmers' perceptions of the importance and the current status of the weather forecast components. The maximum value of W is 1 implying an exact match. In this case, all farmers rank the particular attribute as very important and rank the quality offered as very good. The procedure can be consulted from previous studies (Sall et al. 2000; Bishaw and Alemu 2017) for more details on how to run the perception indices.

Smallholder farmers' willingness to pay weather service forecasts

The willingness to pay of smallholder farmers for weather forecast service has been analyzed using the discrete choice experiment (DCE). This method is an attribute-based quantitative method that can be applied to assess a monetary value for an existing good or service that may have no market, limited market, or incomplete market (Champ et al. 2003). The DCE has been applied because of its usefulness to analyze the individual's choice in relation to the attributes of the service based on the random utility theory (Tesfaye et al. 2018).

The essential stage of the DCE approach has been the setting of a suitable selection of attributes. Before designing the choice sets for this project, a broad review of WFS literature has been conducted. The relevant attributes include WFS price, public and private media, farmers' training, the language of communication, the source of WFS, etc. (Tesfaye et al. 2019). The next step has been to match the attribute levels to raise alternative scenarios and require the respondents to choose the option they prefer to form a choice set. For this project, factorial design by using the experimental design technique in R software has been applied to generate the profile of each combination.

For this study, the approach of previous study (Wang et al. 2018) has been adopted. The main objective in DCE modeling is to analyze, according to McFadden (1974), Lancaster's attribute-based utility theory. The conventional utility function includes deterministic and random components based on the random utility theory. While the random component indicates those factors of separate choice interacted but unobserved, the deterministic component involves factors observed by the researcher. Thus, the utility U associated with individual n who chooses alternative i is given by Eq.(3):

$$U_{in} = V\left(X_{in}\right) + \varepsilon\left(X_{in}\right) \tag{3}$$

where X is the vector of attributes, $V(\cdot)$ represents the deterministic component, and ε $(\cdot)$ means the error component. The probability of individual n choosing alternative i from a set of alternative J could be valued using the conditional logit (CL) model. The estimated probability is given by Eq.(4):

$$Pr_{in} = \frac{exp\left[V(X_{in})\right]}{\sum_{j=1}^{j} exp\left[V(X_{in})\right]} \tag{4}$$

where exp(·) indicates exponent utility. If V (·) is assumed as a linear function with *iid* random error term and a type I extreme value distribution, the indirect utility function is:

$$V_{jn} = \beta_0 \times ASC + \sum(\beta_{jk} \times X_{jk}) + \sum \varphi_{jk}(S_n \times ASC) \tag{5}$$

where ASC is an alternative-specific constant that captures the utility specifically to the status quo. ASC was designed as a dummy (1 if respondents choose either weather forecast service or 0 otherwise). X_{jk} is the k characteristic value of the choice j; β_{jk} is the parameter allied to the k characteristic; S_n is the socioeconomic characteristics vector of individual n; and φ_{jk} is the vector of the coefficients related to the individual socioeconomic characteristics. In this study, ASC will be regarded as a parameter for a unique alternative expressing the role of unobserved sources of utility. It has been argued that ASC is crucial for the purpose of interpreting the preferences of the individuals (Morrison et al. 2002). Due to its sign, ASC has been interpreted as a status quo bias or endowment effect or as a utility premium for moving away from the status quo (Mogas et al. 2006).

The CL model was the most used for analyzing DCE data. Yet, this model has several well-known limitations: (i) it cannot account for preference heterogeneity among respondents and (ii) it can lead to unrealistic predictions (IIA property) (McFadden 1974). The IIA assumption of the CL model fails to hold with the possible existing preference heterogeneity, thus resulting in biased estimations (Sandor and Wedel 2005). However, according to these authors, the mixed logit (MXL) model does not require the IIA assumption. The MXL models were optimal as they allow for the examination of unobserved preference heterogeneity. These models facilitated the evaluation of heterogeneity among respondents and relaxed the assumption of independence from irrelevant alternatives. The MXL regression allowed for increased flexibility by specifying some coefficients to be randomly distributed across individuals (Thomson et al. 2017). Since the MXL model accounts for the unobserved heterogeneity, the utility function is:

$$U_{in} = V\left(X_n\left(\gamma + \delta_i\right)\right) + \varepsilon(X_n) \tag{6}$$

where δ is a parameter which varies by random component due to preference heterogeneity across individuals. The probability of individual n choosing alternative i from a set of alternatives J can be estimated as the MXL model:

$$Pr_{in} = \frac{exp\left[V\left(X_n\left(\gamma + \delta_i\right)\right)\right]}{\sum_{j=1}^{j} exp\left[V\left(X_n\left(\gamma + \delta_i\right)\right)\right]} \tag{7}$$

Considering the preference deviations, the indirect utility function is:

$$\begin{aligned} V_{jn} &= \beta_0 \times ASCopout + \sum(\beta_{jk} \times X_{jk}) \\ &+ \sum(\iota_{nk} \times X_{jk}) + \sum \varphi_{jk}(S_n \times ASC) \end{aligned} \tag{8}$$

where ι represents a vector of deviation parameters. The estimated coefficients of mean preference values β are taken to be either log-normally or normally distributed. The individual tastes ι_{nk} are assumed to be constant over all choices but varying from one respondent to another. When the cost of choosing an option is involved as an attribute, the part-worth price can be estimated by the marginal rate of substitutions. The process of estimation required price coefficient fixation allowing to obtain an estimated model in WTP space where coefficients are directly interpretable as WTP values (Bass et al. 2021). During the WTP estimation, negative WTP is avoided, preferable property, because it is not generally assumed to be plausible (Hensher et al. 2015). It is common in these models to force the price coefficient to be negative, which assumes increasing prices are associated with marginal disutility and is reasonable given the law of demand. However, forcing WTP to be positive for attributes assumes that it provides marginal utility, which may not always be reasonable (Bass et al. 2021). The part-worth price of an attribute j is:

$$WTP_j = -1 \times (\beta_i / \beta_{price}) \tag{9}$$

The positive WTP indicates the additional payments that farmers would accept to trade-off to acquire a more preferable attribute weather forecast service (Admasu et al. 2021). In the same line, the higher WTP is, the better utility farmers are likely to procure from it.

Lastly, compensating surplus (CS) can be estimated to reveal the diverse weather forecast service plans related with variation in attributes.

$$CS = -1/\beta_{price} \times (ln \sum_i \exp\left(V_{i0}\right) - ln \sum_i \exp(V_{i1})) \tag{10}$$

From WTP, the compensating surplus was calculated considering six scenarios in comparison with the status quo. The scenarios correspond to the improvement of each attribute for the first five scenarios added their combination at sixth scenario (best improvement of WFS).

Results and discussion

Smallholder farmers' expectations or perception toward weather services

The weather variables for agricultural sector used vary significantly among farmers regarding their importance in Benin. Each farmer's utility from weather forecast (WF) components is not homogenous. Indeed, the most WF components valuable in the study area are the probability of rain, forecasting period, amount of rain, and soil moisture respective for first (mean score 4.48), second (mean score 4.45), third (mean score 4.28), and fourth (mean score 3.98) places (Table 4). These first four components of WF are helpful for agricultural production and are related to water availability. The results imply that the main challenge for agricultural production within a rainfed system is water availability and getting information on its pattern and falling quantity could contribute to agricultural productivity improvement with informed farming decisions. Particularly, the possibility of having rain was perceived by producers as necessary who opt to be often instructed on this weather indicator. This particular component and the knowledge of the forecast period allow producers to plan their activities and grow at the suitable period and start preparing a new agricultural campaign. This result confirms the previous finding in Rwanda where rain distribution and its extreme in terms of intensity have been found to be the most crucial weather information that meets the needs of the producers (Tesfaye et al. 2020). Also, precipitation and soil moisture information determine soil conditions and affect agricultural productivity. Indeed, the plowing operation is highly dependent on the quantity of precipitation and soil moisture (Mabe et al. 2014) and low precipitation is hard/difficult plowing operation is. Other components of WF are of little importance for agriculture, revealing their less effect in Benin agricultural sector compared to components related to the rain.

Farmers' perceptions about weather forecasting services in the agricultural sector are analyzed through the perception indices. Thus, the demand index represents what agricultural producers want in terms of weather forecasting attributes. In contrast, the supply index indicates the state of proposition related to each attribute to fill the existing gaps. The results

Table 4 Mean score ranking of weather forecasting components

Weather forecast components	Mean score of weather components	Rankings
Forecasting period	4.45	2
Probability of rain	4.48	1
Amount of rain	4.28	3
Cloudy aspect of the sky	3.38	10
Low level of temperature	3.49	9
High level of temperature	3.69	8
Speed of wind	3.85	6
Direction of wind	3.82	7
Relative humidity	3.86	5
Soil moisture	3.90	4

Table 5 Demand, supply, and attainment indices for weather forecasting services attributes

Weather forecasting attributes	Demand index	Supply index	Attainment index
Content of information	0.89	0.11	0.047
Accuracy information	0.89	0.09	0.034
Market information	0.83	0.39	0.256
Channel of information	0.87	0.35	0.256
Language of diffusion	0.91	0.47	0.407
Time of diffusion	0.88	0.51	0.412

Weighted applied to perform indices: d[3, 2, 1] s[2, 1,-1]

show that all items of the weather forecasting package were considered most important by farmers (Table 5). Indeed, the demand indices revealed high value, closed to 1, for all attributes. The first three attributes were the language of dissemination, elements of weather forecasting, and accuracy of information to provide. Currently, little information related to weather forecasting is through the official language (French) which is not accessible for most farmers. To be implemented at the farms level and gain from their use, weather forecasting information was preferred to be disseminated in local language specific to each socioeconomic group. It appears that weather information production is only one of the steps to serve the agricultural sector. The second attribute with a high degree of demand is the composition of weather forecasting. Farmers in the study area are dependent on rainfall for all farming activities. Thus, any weather forecasting without rain probability and quantity is claimed useless for producers. Also, the third attribute quoted with a higher demand index is the forecasting accuracy. Associate with the uncertainties, they lead to misinterpretation and poor decisions for producer activities. As producers have no access to the irrigation system, the water required for crop growth is supplied by natural rainfall patterns indicating that the agricultural productivity is highly sensitive to local weather contexts (Dobardzi et al. 2019). The accuracy of weather forecasting is of important for successful farming activities or operations management. Dealing with precision issues to become more reliable, weather forecasting services have to inform about location-specific and not providing for large areas or regional level. The single information needed by farmers is when sufficient rain is projected to allow starting sowing or when the current drought will be followed by the first rain (van der Burgt et al. 2018).

Concerning the supply indices represented in Table 5, the main point to note is that only the time of the weather diffusion was being better supplied (its value higher than 0.5). It means that farmers declare in majority good quality of the current state of the time of weather diffusion. All other attributes were then being less made available for agricultural purposes, according to farmers. Particularly, the element of weather information (0.11) and their accuracy (0.09) were less offered in the study area. These findings are not surprising since these two attributes were the most important and demanded by farmers to better manage the farming activities. Currently, it exists no initiative to provide farmers with tailored weather forecasting information. The future adaptive strategies to cope with climate change effects oriented to weather services should emphasize the accuracy character of weather forecasting and the type of information farmers need such as the probability and the quantity of rain.

Turning to attainment indices depicted in Table 5, the results confirm the previous findings of this study indicating that farmers' expectations are being less met for all attributes related to weather forecasting particularly the type of information (0.047) and the accuracy of the weather forecasting (0.034). Indeed, this index indicates agricultural producers' perceptions of how well their needs about weather forecasting are offered or supplied (Sall et al. 2000). These findings confirm weather forecasting needs exist and remain unsatisfactory in Benin. Evidently, a priority needs to address this in government and partner of the development plan in favor of the agricultural sector.

Farmers' willingness to pay for weather forecasting services

Estimation results of mixed logit models

Before the estimation of the mixed logit model, the choice data have been examined. The proportion of the three alternative choices shows the favorable behavior of farmers surveyed toward the offered weather forecasting services. Both improved alternatives were chosen by 82.08% (37.77% and 47.42% choices respective for the first and the second alternatives) of the cases. The status quo scenario was less chosen and it represents approximately 17.82% of overall choices. The rate of farmers' preference of status quo option is expected and is consistent with other studies (Tesfaye et al. 2019, 2020; Admasu et al. 2021). This implies that some farmers prefer to stay in their current conditions although they acknowledged the importance of weather forecasts for agricultural production

Table 6 Results of mixed logit model of weather forecasting service preference

Variable	Basic		Interaction	
	Coefficient	Standard error	Coefficient	Standard error
Means				
Daily weather forecast	Reference			
Decade weather forecast	0.06	0.043	0.06	0.042
Seasonal weather forecast	0.035***	0.014	0.034***	0.014
Agrometeorological	0.147***	0.037	0.147***	0.037
Quality of weather forecast	0.073***	0.023	0.074***	0.023
Local language	0.078***	0.028	0.073***	0.027
Radio	Reference			
Meeting with extension agents	0.723***	0.041	0.724***	0.041
Phone via short text message	0.402***	0.037	0.402***	0.036
Phone via interact response system	0.132***	0.044	0.136***	0.043
Market information	0.04	0.025	−0.037	0.024
Price	−0.0002***	0.0001	−0.0002***	0.0001
ASCoptout	−0.621**	0.071	−1.137****	0.178
ASC*age			−0.004	0.004
ASC*sex			−0.151**	0.077
ASC*year of agricultural experiences			−0.027***	0.004
ASC*household's size			0.018***	0.007
Formal education (none)	Reference			
ASC*primary school			0.542***	0.071
ASC*secondary school 1			0.575***	0.117
ASC*secondary school 2			0.264*	0.151
ASC*university			1.339***	0.341
Standard deviation				
Daily weather forecast	Reference			
Decade weather forecast	0.6***	0.049	0.559***	0.05
Seasonal weather forecast	0.056	0.082	0.046	0.08
Agrometeorological	0.207***	0.069	0.197***	0.07
Quality of weather forecast	0.336***	0.035	0.123	0.076
Local language	0.443***	0.033	0.416***	0.033
Radio	Reference			
Meeting with extension agents	0.12	0.09	0.165**	0.08
Phone via short text message	0.088	0.103	0.053	0.093
Phone via interact response system	0.602***	0.052	0.573***	0.053
Market information	0.326***	0.037	0.29***	0.04
Number of events	716			
Number of observations	34,368			
AIC	23,119.12	22,828.67		
BIC	23,288.02	23,065.13		
LR χ^2 (5)	313.00	245.73		
Prob > χ^2	0.000	0.0000		
Log likelihood	−11,539.559	−11,386.335		

***, **, and * significant at 1%, 5%, and 10% respectively; [ns]non-significant

in climate disruption. To understand the reasons of their preference, an additional question has been asked. It appears that it is a monetary-oriented choice and was mainly based on financial difficulties for agricultural activities. Thus, the status quo's choice could be seen as the inability of some producers to afford the costs associated with weather forecast services. Despite the cost to obtain information about weather forecasting, WFS were still attractive to most farmers.

In the mixed models used for this study, the coefficients of ASCoptout (Alternative Specific Constant of status quo) and cost for services are considered fixed, and other model variables are randomly and normally distributed. The cost coefficient involved getting weather forecast services is held fixed for two reasons (Yin et al. 2017). Foremost, WTP's distribution is consistent in this case with the distribution of each attribute coefficient in place of both distributions making easy the estimation of WTP distribution. Additionally, ruling on the distribution of the cost coefficient follows the demand theory where it should be negative, yet, the assumption of normal distribution does not guarantee the negative value of the cost coefficient. The results of mixed logit models are shown in Table 6. Attribute-based specification and interaction model, which include farmer socioeconomic characteristics, have been performed using the Wald procedure. Both models produced consistent results for all attribute levels except for market information. The AIC and BIC values confirm that the interaction model produces better results based on the model selection criterion. This means that this model better represents the collected data. Thus, the remaining interpretation of mixed logit results will be focused only on the interaction model. The results show that all coefficients of the random parameter model have the expected and theoretically consistent signs. The cost to pay before accessing WFS adversely influences the preference for WFS, a similar result is found in the previous studies (Tesfaye et al. 2020). It implies that offering WFS as a standalone service could not be attractive, and farmers are opposed to being charged more for access to weather forecasting information. This is consistent with the behavior of economic rationality or the theory of demand (Tandon 2015; Admasu et al. 2021). The amount of payment to have the benefit of WFS increases as farmers' preferences decrease. As expected, the positive sign and the significance of seasonal weather forecast and agrometeorological information coefficients indicate the good behavior of farmers toward the improved weather services over a long period and specific to different agroecological zones. This finding is in the same line with previous studies reporting a positive preference for long period forecasts in crop productivity improvement (Amegnaglo et al. 2017; Ouédraogo et al. 2018). Indeed, weather forecasts over a short period do not give producers any leeway to adapt as needed. A producer with information on the beginning and end of the rainy season has a greater opportunity taking informed decisions, and ultimately better performances. The good decisions at farm level is correlated to higher yields and, in turn, higher farm income through varietal, timing, or crop adjustment choices (Gunda et al. 2017). The opposite result was found in Rwanda when studying climate services for agriculture (Tesfaye et al. 2020). The practical application of weather forecasts to agricultural use, such as information on seeds and fertilizer applications, is a producer preference and could improve their livelihoods (Chattopadhyay and Chandras 2018). Contrary to those attribute levels, decade weather forecast coefficient is insignificant. It appears that the short-term forecast is inadequate to readjust agricultural activities. As for the previous attribute, the positive sign of the quality of weather information illustrates the favorable attitude of farmers that improved weather forecast quality is preferred as it determines the successfulness of any adaptation strategy implemented according to the weather forecast. It has been mentioned in previous studies that the trust of farmers in the weather forecast is dependent on its accuracy which yields an increase in farm income (Truelove et al. 2015; Gunda et al. 2017). Also, the accuracy of the forecasts affects the potential impacts of WFS (Vaughan et al. 2019). Based on the positive sign of language, there is a positive utility for farmers to get weather forecast information into the local language. Providing weather forecast information in the local language is very important but presents huge challenges for translation into different dialects (van der Burgt et al. 2018). In Benin, there are more than 56 spoken dialects, some of which are more important and are spoken or understood by most Beninese: Fon, Yoruba, Bariba, Dendi, Adja (INSAE 2016). Thus, local experts may be solicited for the use of local meteorological jargon and appropriate indicators to facilitate the understanding and proper use of weather forecasting services. The attribute related to communication channels shows positive and significant coefficients for all levels, indicating that farmers are better with communication channels other than radio. Sharing weather forecast information through extension agents and phone (SMS and interact response system) was significantly valued by Beninese farmers. This result is aligned with other previous work (Feleke 2015) which pointed to the fact that informing oneself with the radio is neither flexible nor does it offer opportunities to store information nor to manifest needs for understandings. Particularly, the farmers' preferences for phone-based communication could be linked to their familiarity with receiving a message via the phone and the practicability of mobile phones, even in rural areas (Tesfaye et al. 2019). Unlike the other attributes, access to market information (price, availability, scarcity, etc.) shows a positive and insignificant coefficient. This result means that farmers' weather forecasting choices are independent of market indications for agricultural products. Dissimilarly, farmers' impartiality concerning market news to make a choice is inconsistent with other findings from Ethiopia (Tesfaye et al. 2020), Tanzania (Magesa et al. 2014), Benin (Arinloye et al. 2016), etc. It could be said that Beninese producers value weather information more than market information. Thus, they prioritize production to address food insecurity and nutrition before considering marketing or at least this information is already available in their communities. In fact, several structures, including the government and technical partners (Program of Communal Approach for the Agricultural Market in Benin; Belgian Development Agency; Agricultural Policy Analysis Program, etc.), intervene to facilitate producers' access to information on the agricultural products market.

Table 7 WTP values for weather forecast services attributes

Attributes/levels	Mean	Confidence interval (95%)
Decade weather forecast	280.59 [ns]	[– 138.4; 699.57]
Seasonal weather forecast	159.30**	[222.98; 541.58]
Agro-met advisories	686.76***	[131.31; 1242.20]
Meeting with extension agents	3373.89***	[1165.05; 5582.73]
Phone via short text message	1872.35***	[622.42; 3122.27]
Phone via interact response system	631.57****	[65.01; 1198.12]
Local language	340.12***	[669.29; 10.95]
Quality (accuracy)	342.37***	[40.65; 644.1]
Availability of market information	– 173.62 [ns]	[– 422.96; 75.72]

***, **, and * significant at 1%, 5%, and 10% respectively; [ns]non-significant

In addition, the mixed logit model results show that the estimated standard deviations are significant for all attributes, except for seasonal weather forecast, quality of weather, and SMS use for communication channels (Table 6). This finding indicates that the estimated coefficient varies and heterogeneity of preferences is confirmed. Also, the significance of such coefficients shows the relevance in the use of the random utility model for this study. It means that farmers diverge preferences according to all attributes, excluding the quality. It highlights how critical the weather forecast accuracy is where all farmers surveyed have given a high weighting (Vaughan et al. 2019). Therefore, the accuracy of the information to be received is at the top of the rankings.

The socioeconomic variables have been interacted with the alternative-specific constant while performing the mixed logit model (Table 6). The results show that gender, the number of years in farming, the level of formal education of the householder, and the size of the respondent's household have a significant influence on WFS choices. Looking at gender coefficient indicates a great probability that female farmers will opt for improved WFS. The negative sign of the experience coefficient means that as the number of years in production increases, the more unlikely that the producer is to choose the proposed improvements. Assuming the high correlation between age and years of experience, this finding is consistent with a previous study (Tesfaye et al. 2019) and means that younger farmers express their preference for weather forecasts. Likewise, the results show that households with large family sizes and educated heads were favorable to receive WFS.

Marginal willingness to pay and compensating surplus

The random parameter logit model was used to estimate the marginal WTP between each attribute (i.e., attribute level) and the monthly payment to receive WFS. The results show that monetary contributions are needed for WFS implementation in Benin (Table 7). As displayed in Table 7, the WTP for communication channels suitable for WFS sharing is highly valued by farmers. Indeed, average farmers are willing to increase XOF 3373.89, XOF 1872.35, and XOF 631.57, respectively, for a face-to-face discussion with extension agents, receiving SMS and phone interact response system compared to radio use (1 USD = 550 XOF). Regarding weather information needed, on average, farmers are willing to trade off a lump sum of XOF 686.76 and XOF 159.3 monthly to obtain agro-met advisories and seasonal weather forecasts, respectively. The marginal WTP to get WFS in the local language is XOF 340.12 relative to the official language (French). Lastly, the exchange cost for high quality (accuracy) of WF for agricultural uses over

Table 8 Compensating surplus for improved weather forecast attributes

Attributes	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Type of information received	√					√
Quality of information received		√				√
Language of communication			√			√
Media used to deliver information				√		√
Market information					√	√
Compensating surplus	423.03[a]	342.37	340.12	1959.27[a]	0[b]	3328.52

[a]This value represents the mean of the different level of the attribute

[b]Utility function parameter of the attribute is significate

[c]CS is expressed in local currency (XOF where 1 USD = 550 XOF)

low quality is XOF 342.37 per month. This result seems little consistent concerning the WTP value for each attribute. Unexpectedly, the additional payment for weather forecast quality is too low compared to other attributes. However, this attribute is related to the accuracy of weather information and has received more credit from farmers, making it the most important attribute. It is, therefore, inconsistent with previous results, which show that the WTP of the quality attribute is the highest (Tesfaye et al. 2020). WTP for the attribute decade weather forecast is insignificant suggesting no difference in utility provided compared to the daily weather forecast. The same statement is valid for attribute access to market information.

The compensating surplus estimated using the mixed logit model and WTP indicates that the best scenario is obtained simultaneously when all attributes are improved. Indeed, the cumulative gains of scenario 6 is XOF 3328.52 equivalent to 6.05 USD (Table 8). Considering each attribute, the compensating surpluses for other scenarios are numerically equal to the willingness to pay when it is two levels attributes and average when the attributes' levels are more than two. For instance, improvement of weather information received while keeping unchanged the quality, the language, communication channel (scenario 1) rises WTP to XOF 423.03. In scenarios 2, 3, and 4, the average CS increases to XOF 342.37, XOF 340.12, and XOF 1959.27, respectively, ceteris paribus.

Conclusion

This study analyzed farmers' preferences and willingness to pay for weather forecasting services running a discrete choice experiments. It highlights the importance of farmers' behaviors toward WFS across the choice sets. The results showed Beninese farmers would likely rate all non-monetary attributes to improve managerial decisions in agricultural except for access to market information show that activities. On average, farmers prefer seasonal weather forecasts and agro-met information compared to daily and decade weather forecasts. Also, farmers show a positive and significant preference for the extension agent face-to-face meetings and devise phone use for communication channels compared to the traditional channel (radio). On the other hand, farmers are inclined to use the local language for information dissemination as well as high forecast information quality. The valuation of each attribute of improved weather services was illustrated through the implicit values farmers accorded or allocated to the WFS characteristics. The preference for proposed weather forecasting services was influenced by farmers' traits such as their experiences, gender, and education level.

Three main lessons are learned from this study. Accuracy of weather forecasting services is the best preference of farmers in their decision-making process. Similarly, the preferred channel for disseminating WFS is diverse, but the main ones are the telephone (SMS and interactive response system) and extension agents where they appear to be favorites. Finally, the preference of extension agents can be very labor intensive for a project-type implementation. A combination of unique attribute levels could provide high utility to farmers, and a cost–benefit analysis could support the ranking of practical options.

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Declarations

Competing interest The authors declare no competing interests.

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