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Climate services bundles preferences of smallholder farmers in West Africa: a stated choice modelling

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This study investigates the preferences of rainfed farmers in West Africa for bundled agroclimate services, addressing challenges posed by climate variability and limited purchasing power. With various startups offering digital communication channels, credit, and insurance services, farmers often struggle to afford individual services, necessitating coherent service packages. The research aims to identify the most preferred attributes of agroclimate services and predict how increasing climate variability affects farmers' choices. Using a Choice Experiment and Mixed Logit model, data was collected from 1,212 farmers across four West African countries (Ghana, Senegal, Mali and Burkina Faso). The findings reveal that the most preferred service bundle (Bundle 4), which includes daily weather forecasts, seed advisories, and drought insurance, garnered a preference of 45%. In contrast, Bundle 0, which lacks these features, was selected by only 22% of farmers. Notably, the introduction of a USD 1,000 credit option increased the likelihood of selecting preferred bundles by 39%. Additionally, 62% of farmers indicated that weather-based information is a critical factor in their decision-making. Access to agricultural credit significantly influenced choices, with a 17% increase in the likelihood of selecting preferred bundles when credit was available. The study underscores the importance of designing comprehensive service packages that cater to farmers' specific and urgent needs. It highlights the necessity for partnerships among service providers to improve the delivery of these essential services. By showing the agroclimate service bundling power, the study provides valuable insights for policymakers and stakeholders to support agricultural development and sustainability in West Africa.

KEYWORDS

West Africa, farmers, agroclimate service bundles, preferences, stated choice

Introduction

The world's population is expected to reach 9.1 billion people by 2050, necessitating a 70% increase in food production (Food and Agriculture Organization, 2019). An increasing population, low agricultural productivity, and unfavorable socioeconomic conditions have increased Sub-Saharan Africa's (SSA) dependency on food imports. Just 6% of Africa's arable land is irrigated, with 3.5% in SSA, while over 90% of the continent's arable land is rainfed (Food and Agriculture Organization, 2019; Scheumann and Phiri, 2018). There is insufficient monitoring in the area, which is extremely susceptible to rain variability and climate change (De Longueville et al., 2020; Dhamija et al., 2020).

Access to real-time climate services, such as agro-advisories and weather forecasts, can significantly enhance farming success by informing decision-making, though other factors (e.g., soil quality, labor availability, and access to inputs) also play critical roles (Cooper and Coe, 2011; Biazin et al., 2012; Guido et al., 2020).

In West Africa, for example, it has been demonstrated that localized seasonal climate forecasts increase agricultural output, with an average annual economic value of $5,492 for each farmer and $66.5 million for the nation (Amegnaglo et al., 2017). Weather-based farming impacts seed selection (Adjah et al., 2022; Amole et al., 2022), fertilizer and pesticide use (Billé and Rogna, 2022; Tarchiani et al., 2021), crop insurance (Johnson, 2021; Adetoro et al., 2022; Mathithibane and Chummun, 2022), pricing (De Necker et al., 2024), and credit lending (Ayansa et al., 2021; Fox and Signé, 2022). Despite the emergence of startups offering ICT, credit, and insurance services, West African farmers face low purchasing power and conflicting individual services. Globally, bundling vital agroclimate services into coherent packages is recommended for greater impact (Ouedraogo et al., 2022; Tesfaye and Tessema, 2023).

This study aims to explore rainfed farmers' preferences for bundled agroclimate services, addressing: (i) their most preferred attributes and (ii) the impact of increased climate variability on their bundle choices in West Africa.

Materials and methods

Theoretical consideration

As users of agroclimate service bundles, farmers have to direct bundle development by determining essential attributes. For bundled items, qualities better explain decisions than the theory of consumer choice (Marshall, 1890), which implies farmers maximize utility with limited resources. Both the Lancaster theory (Lancaster, 1966) and the joint measurement theory (Debreu, 1960; Luce and Tukey, 1964) concentrate on how consumers assess service attributes. Despite its value, conjoint analysis ignores and oversimplifies socioeconomic aspects (Luce and Tukey, 1964). It is more appropriate to use Lancaster theory, which takes socioeconomic factors into account and maintains that product qualities create utility (Lancaster, 1966). McFadden (1974) Random Utility Theory, which tackles decision-making unpredictability and makes econometric modeling possible, is a supplement to this.

According to Lancaster theory, goods and services are collections of characteristics. For instance, farmers look for crops with characteristics like high yield, drought tolerance, or disease resistance, as well as equipment with high horsepower or fuel efficiency. As seen by a simplified Lancaster preference function, farmers thus select not only products but also the desired qualities they represent (Equation 1).

$$U = a_1 x_1 + a_2 x_2 + \ldots + a_n x_n \tag{1}$$

Where:

U is the utility derived by the farmer.

$X_1, X_2, \ldots, X_n$ are the levels of attributes 1 to n.

$a_1, a_2, \ldots, a_n$ are all coefficients representing the consumer's marginal utility or willingness to pay for each attribute.

The random utility theory (RUT) assumes that consumer preferences are latent and unobservable. The value of utility of individual farmer n associated with choosing agroclimate services bundle j, U_j can be expressed as a function with two components: an observable deterministic component V_i and a random component $\mathcal{E}_i$ which represents the unobservable part of the equation. The utility function can be then written as follows (Equation 2):

$$U_i = V_i + \varepsilon_i \tag{2}$$

The deterministic part of the equation is a function of various predictors that can be formulated as a regression function (Equation 3):

$$V_j = \beta X_j \tag{3}$$

Where β is the vector of parameters to be estimated and X_j is the vector of covariates. Back to Equation 2 where $\mathcal{E}_i$ captures the unobservable part of the solution. When $\mathcal{E}i$ is Independently and Identically Distributed (iid), then the probability that agro-climate service bundle is chosen from the set J of agro-climate service bundles can be captured through the standard Multinomial Logit Model (MNL). The probability of choosing an agroclimate services bundle can be expressed as the following (Equation 4):

$$\boldsymbol{P_j} = \frac{\exp\left(\boldsymbol{\beta X_j}\right)}{\sum_{\boldsymbol{j=1}}^{\boldsymbol{J}} \exp\left(\boldsymbol{\beta X_j}\right)} \tag{4}$$

Where P_i is the probability that the agroclimate service bundle is chosen from the set of J alternatives.

Experimental design

Using different attribute levels, the choice experiment (CE) method measures consumer preferences for new products (McFadden, 2001; Mariel et al., 2021a,b). Using four steps—attribute selection, scenario building, choice card design, and presentation—this study used CE to evaluate West African farmers' assessments of agroclimate services (McFadden, 1974).

Rationale for bundle selection

Based on expert interviews, empirical data, and applicability to farming systems in West Africa, five agroclimate service bundles were chosen. The study employed a four-step methodology for the Choice Experiment (CE), which included field deployment, pictogram-based choice cards, scenario preparation, and attribute selection (McFadden, 2001; Mariel et al., 2021a,b). Using information from fieldwork in Senegal, Ghana, Mali, and Burkina Faso (Baffour-Ata et al., 2022; Agbenyo et al., 2022), the following attributes were selected from literature and expert input: weather forecasts, agro-advisories, crop insurance, credit access, market information, communication channels, and price levels (Tesfaye et al., 2021; Ouedraogo et al., 2022).

Bundles 1–4 provided incremental service increases, with Bundle 4 being the most extensive (daily forecasts, seed advice, drought insurance, credit), while Bundle 0 was the control (minimum services). Real-world trade-offs were reflected in this structure (Amegnaglo et al., 2017; Lo and Dieng, 2015). Pricing ensured policy relevance by reflecting market rates and willingness-to-pay studies (Ouédraogo et al., 2018; Antwi-Agyei et al., 2021). In order to evaluate farmer choices and conform to global bundling techniques for resilience (Tesfaye et al., 2023; Byandaga et al., 2022), the design integrated theory (Lancaster, 1966; McFadden, 1974) with field data.

Step 1: attributes selection and its levels

Key bundling attributes were identified via expert interviews and literature (Ouédraogo et al., 2018; Syll and Weingärtner, 2019; Tesfaye et al., 2021; Ouedraogo et al., 2022; Getachew et al., 2022; Byandaga et al., 2022). West African farmers prefer voicemail for crop varieties, weather forecasts, market info, and crop insurance (Syll et al., 2017; Shumba, 2022; Ouedraogo et al., 2022; Tesfaye et al., 2023). Crop insurance funds operations, while forecasts guide farming activities.

Research (2021–2022) on market data and climate services informed interviews with Alliance Bioversity-CIAT (Senegal) and CGIAR-CCAFS (Mali) experts (Sept 1–15, 2022). Insights from Ghana, Senegal, Burkina Faso, and Mali highlight farmers' needs (Gbangou et al., 2019; Sultan et al., 2010; An-Vo et al., 2021). Weather forecasts aid farm management (Baffour-Ata et al., 2022; Ouédraogo et al., 2018), and weather-index insurance reduces risk (Vashisth et al., 2013; Agbenyo et al., 2022). Forecasts also impact commodity prices and loan collateral (Pelka et al., 2015; Mujeyi et al., 2021). Geo-specific tools like radios and phones are crucial (Ouédraogo et al., 2018). Suppliers in Ghana (Esoko), Mali (Orange Mali), Senegal (M-Louma & Jokalante), and Burkina Faso (Ignitia) provided price data (Table 1).

TABLE 1 Attributes and levels of agroclimate services used in the choice experiment.

Attributes	Levels
Climate Information services	1. Seasonal forecasts 2. Weekly forecasts 3. Daily forecasts
Weather-based advisories	1. Weather-based seed selection 2. Weather-based fertilizer application 3. Weather-based pesticide application
Weather based-crop insurance	1. Drought insurance (DINSUR) 2. Flood insurance (FINSUR)
Weather based-credit	1. Available 2. Not available
Weather-based- market information	1. Weather-based inputs prices 2. Weather-based outputs prices
Media (MD)	1. SMS 2. Interactive voice response system (IVRS) 3. Interactive Digital Service (IDS)
Prices	0 USD; 5 USD; 8 USD; 10 USD; 12 USD

Step 2: scenario development

Weather forecasts served as the basis for the construction of agroclimate service bundles, which concentrated on the characteristics and levels of climate information services (Roudier et al., 2014; Lo and Dieng, 2015; Amegnaglo et al., 2017; Ouedraogo et al., 2021; Sarku et al., 2021; Nhamo, 2014; De Necker et al., 2024; Manjunath et al., 2023) assists farmers in scheduling activities and anticipating the dangers of harsh weather. CIS levels consist of five bundles, one without forecasts, and seasonal, weekly, and daily forecasts.

The effects of climatic variability cannot be completely mitigated by CIS alone; additional services are necessary for well-informed decision-making. In West Africa, language and information transmission techniques have a big impact on adoption (Yegbemey and Egah, 2021; Diouf et al., 2019). Five packages were created using literature, expert opinions, and currently offered services (Table 2). Pricing was determined using current offers and studies on farmers' willingness to pay (Ouédraogo et al., 2018; Ouedraogo et al., 2022; Antwi-Agyei et al., 2021).

Step 3: choice card design

To create pictograms, 40 farmers (10 per nation) participated in workshops to find intuitive symbols (Böcker, 1996), agricultural extension agents validated the designs, and 100 farmers participated in pre-testing. Each pictogram (cloud icon for forecasts, coin stack for prices, etc.) indicated a single attribute level. To prevent bias, enumerators provided choice cards (Figure 1) in a randomized order after first explaining each pictogram using standardized scripts (Street and Burgess, 2007).

Model specifications

To account for unobserved heterogeneity, the Mixed Logit model employed random effects for farmer-specific variables (drought experience, agricultural purpose) and fixed effects for bundle features (climate information type, insurance, etc.) (Fiebig et al., 2010). The appropriateness of fixed effects was confirmed by the Hausman test ($\chi^2 = 12.7, p = 0.03$). Using 1,000 Halton draws and maximum simulated likelihood, utility coefficients were calculated (Mariel et al., 2021a, 2021b).

A choice experiment based on stated choice modeling was used to determine the most preferred agroclimate services (CIS) bundle (McFadden, 1987; Fiebig et al., 2010). Five choice cards (Bundle 0–4) were given to farmers in the targeted nations so they could express their views. Because binary models were inappropriate, preferences based on bundle properties were predicted using Lancaster's theory (Lancaster, 1966) and Random Utility Theory (McFadden, 1974).

In order to circumvent the Independence of Irrelevant Alternatives (IIA) assumption, the Mixed Logit Model (MIXL) was selected over the Multinomial Logit due to the diversity of farmers' experiences with climate variability in West Africa (Tesfaye et al., 2019). By dividing the utility function into two components—a deterministic component that gauges the perceived value of bundle attributes and a random error component that accounts for unobserved factors and is presumed to be independently and identically distributed with a Weibull distribution—MIXL takes preference heterogeneity into account.

TABLE 2 Key attributes for CIS bundling and choices cards description.

Attributes	Key levels	Bundle 0	Bundle 1	Bundle 2	Bundle 3	Bundle 4
Climate Information services	1. Seasonal forecasts 2. Weekly forecasts 3. Daily forecasts	None	Seasonal forecasts	Weekly forecasts	Daily forecasts	- Seasonal forecasts - Weekly forecasts - Daily forecasts
Weather-based advisory	1. Weather-based seed 2. Fertilizer application guidance 3. Pesticide application guidance	National extension service[a]	Weather-based seed	Weather-based fertilizer application	Weather-based Pesticide application	- Weather-based seed - Weather-based fertilizer application - Weather-based Pesticide application
Weather based-insurance	4. Drought (DINSUR) 5. Flood (FINSUR)	None	DINSUR	FINSUR	DINSUR	- DINSUR - FINSUR
Weather based-credit	1. Yes 2. No	None	Yes	No	Yes	Yes
Weather based-market Information	3. Inputs prices 4. Outputs prices	None	Weather-based Inputs prices	Weather-based Outputs prices	Weather-based Inputs prices	- Weather-based Inputs prices - Weather-based Outputs prices
Media (MD)	5. SMS 6. Interactive voice response system (IVRS) 7. Interactive Digital Service (IDS)	Radio	SMS	IVRS	IDS	IVRS
Weather-based Prices	8. No prepayment 9. Amount/Year	0 USD	5 USD	8 USD	10 USD	12 USD

Source: Author design, 2022.
[a]Different from bundled services, national extension services are government-provided crop management advises that are not weather-specific.

By taking into account both the characteristics of the bundles and the many experiences that farmers have with climatic fluctuation, this method guarantees an accurate forecast of farmers' preferences for CIS bundles (Equation 5).

Let U_{ijt} be the utility of alternative agroclimate services bundles j for farmer I *in* situation t. Given the components mentioned above, we will have X_{ijt} and ε_{ijt} respectively the deterministic and random error components (unobserved component):

$$U_{ijt} = \beta_i X_{ijt} + \varepsilon_{ijt} \tag{5}$$

Where X_{ijt} is the vector of attributes of alternative j of bundled CIS for any individual farmer iI(i = 1, 2, …n). β_i represents the vector of utility weight (generally homogenous to all farmers). The term $\varepsilon independent_{ijt}$ is independent and identically distributed (i.i.d) extreme value and it represents the Idiosyncratic error (Equation 6). Considering the heterogeneity, the utility model can be expressed as follows:

$$U_{ijt} = \left(\beta + \eta_i\right) X_{ijt} + \varepsilon_{ijt} \tag{6}$$

Where β represents the vector of mean attribute utility weights in the farmer's population and η_i corresponds to individual specific deviation from the mean (heterogeneity). ε_{ijt} remains the i.i.d extreme value (Equation 7).

The empirical model is stated as:

$$\begin{aligned} P\left(j|X_{it}\right) &= \beta_0 + \beta_1 CIS + \beta_2 MD + \beta_3 WBAdvisories \\ &+ \beta_4 CropInsur + \beta_5 Credit + \beta_6 MIS + \beta_7 FarminPurp \\ &+ \beta_8 Sex + \beta_9 nDrought + \beta_{10} nFlood + \beta_{11} nHeat + \beta_{12} nWin + \varepsilon_{it} \end{aligned} \tag{7}$$

Key variables definition

The key variables to be used in the modelling are been chosen from the agroclimate services attributes (alternatives specific variables) and some socio-economic factors (case-specific variables). Table 3 presents the included variables in the modelling.

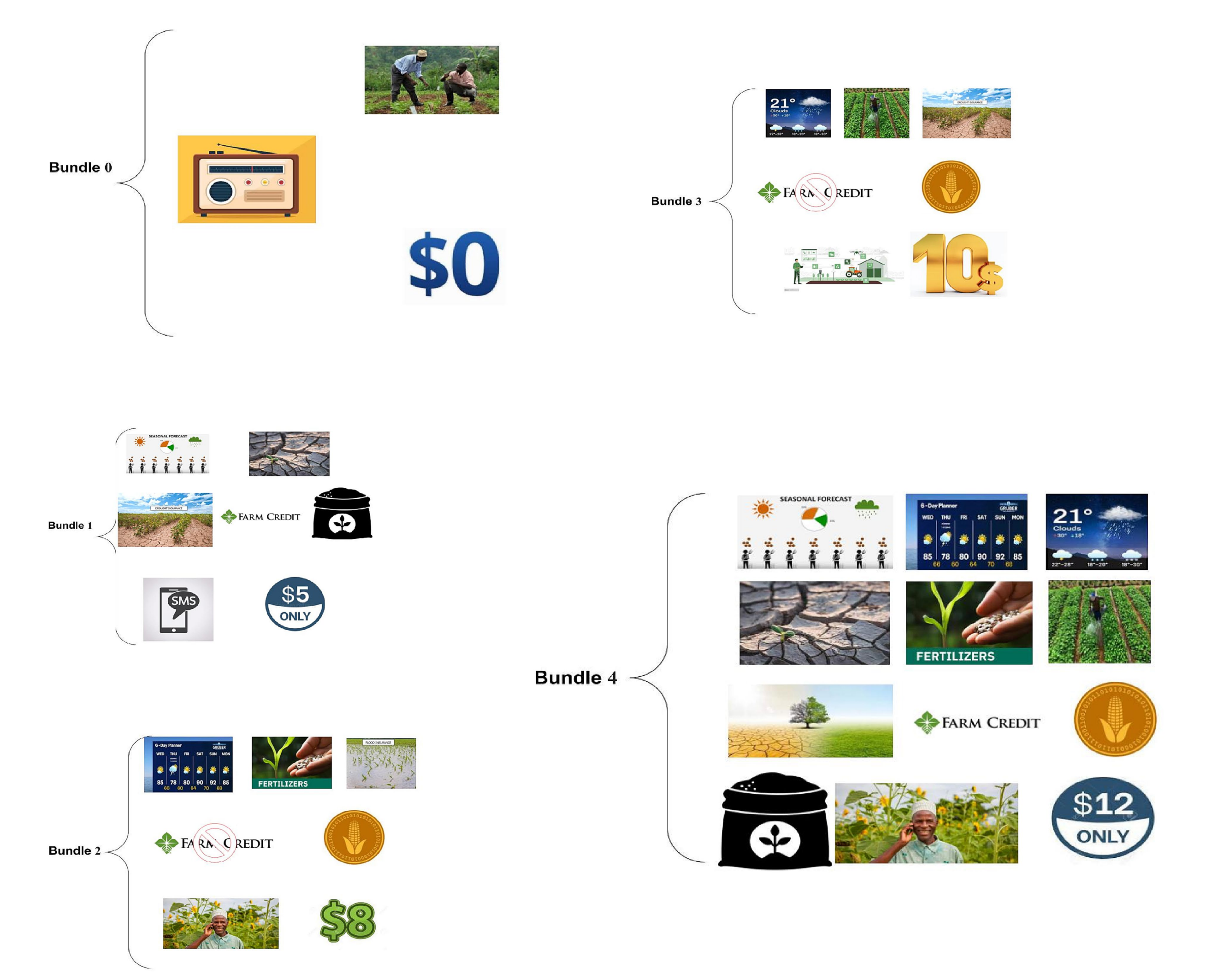

FIGURE 1
Choice cards presented to farmers.

Study areas and sampling strategy

The countries and the sites were selected based on the climate-smart villages[1] developed under Climate Change, Agriculture, and Food Security (CCAFS) and currently relied on by AICCRA project (Table 4) (see Figure 2).

The study examined how climate variability affects cash and staple crop yields in SSA nations using stratified sampling. Through Farmers Based Organizations (FBOs), two strata—cash crop and staple crop farmers—were identified. To guarantee representativeness, these strata were further divided based on age and gender (youth, women, and men). The sampling process included the following steps: (1) listing farmers by stratum; (2) calculating stratum weights; (3) establishing proportionate allocation; and (4) randomly selecting farmers within strata to reduce bias and guarantee strong sociodemographic and agroecological representation. The sample size was determined using the formula proposed by Panneerselvam (2023) stated as (Equation 8):

$$n = \frac{Z^2 * P(1 - P)}{e^2} \tag{8}$$

Where: n = Sample Size; Z = Confidence level at 95% (standard value of 1.96); P = proportion of farmers suffering from climate variability (0.73); e = Margin of error at 5% (standard value of 0.05). So, 303 farmers were randomly selected in each country making a total of 1 21 farmers in the four countries including Burkina Faso, Ghana, Mali & Senegal. With respect to the strata, 606 cash crop farmers and 606 staple crop farmers were surveyed.

The sampling procedure include a three-stage stratified process was used to select farmers: (1) Climate-Smart Villages (CSVs) were purposefully chosen based on AICCRA project sites (Campbell, 2013); (2) Farmer-Based Organizations (FBOs) in each CSV provided membership lists stratified by age (adults >35/youth ≤35); and (3) Panneerselvam's (2011) formula (n = 303/country) was used to apply

1 https://cgspace.cgiar.org/bitstream/handle/10568/79353/CSV%20Brochure%202016.pdf

TABLE 3 Variables definition, unit of measurement, and expected impact.

Variables	Definition	Unit of measurement	Apriori expectation
Dependent variable			
BDL	Bundle	0 = Bundle 0; 1 = Bundle 1; 2 = Bundle 2; 3 = Bundle 3; 4 = Bundle 4	
Independents variables (Attributes)			
CIS	Climate Information Services	1 = Seasonal forecasts; 2 = Weekly forecasts; 3 = Daily forecasts	+
MD	Media used to reach farmers	0 = SMS; 1 = Interactive voice response system (IVRS); 2 = Interactive Digital Service (IDS); 3 = All the medium	+
	Agro-advisory	1 = weather-based seed choice; 0 = weather-based Fertilizer application guidance; 2 = weather-based Pesticide application guidance	+
CropInsur	Crop insurance	1 = Drought (DINSUR); 0 = Flood (FINSUR); 2 = both Insurance	–
Credit	Access to credit	1 = Yes; 0 = No	+
MIS	Market information system	1 = Inputs prices; 0 = Outputs prices; 2 = Both prices	+
WTP	Willingness to pay bundled CIS	Amount in USD/season	–
Case-specific variables			
Country	Country	0 = Burkina Faso; 2 = Ghana; 3 = Mali; 4 = Senegal	+
FarminPurp	Farming purpose	0 = Stapple crops; 1 = Cash crop; 2 = both cash and staple crop	+
Sex	Sex of farmer	0 = Female;1 = Male	+
nDrought	Number of wet seasons during which you have suffered from DROUGHT over the last 10 years	Number of years	+
nFlood	Number of wet seasons during which you have suffered from FLOOD over the last 10 years	Number of years	+
nHeat	Number of wet seasons during which you have suffered from extreme heat over the last 10 years	Number of years	+
nWind	Number of wet seasons during which you have suffered from extreme winds over the last 10 years	Number of years	+

random sampling within strata. FBO leaders did not choose participants; they only assisted with introductions.

Results

Background of the respondents

Although most extension services utilize official languages instead of community ones, education has an impact on the uptake of climate services (Bakker and De Vries, 2021). Despite the fact that 43% of West African farmers lack literacy, education aids farmers in comprehending and implementing scientific methods (Table 5). With 75% of the population illiterate, 15% in primary school, and less than 10% enrolled in university, Burkina Faso has the lowest literacy rate. The majority of farmers are uneducated, thus agroclimate service providers should customize their services for them.

Understanding farming's purpose is key to understanding farmers' choices. Figure 3 presents farmers' distribution across farming objectives. The result shows that 73% of farmers are food & Income-driven in West Africa. Therefore, farmers are in the industry for both food and income. Only a few of them are in pure commercial farming (1%). The agroclimatic services bundle providers must consider the fact that West African farmers need solutions that can handle both staple crops and commercial crops.

Before assessing farmers' preferences for agroclimate services, it is crucial to identify the proportion of farmers affected by climate variability. Table 6 shows that 100% of farmers in West Africa experienced drought in the last 10 years, while nearly 50% faced floods and violent winds, and about 34% suffered from intense heat. The study also measured the frequency of these shocks: farmers in Mali and Senegal were most affected by drought, followed by Ghana and Burkina Faso. Strong winds were most prevalent in Mali, Senegal, and Burkina Faso, while Ghanaian farmers experienced more floods and high temperatures (Table 6).

Designing successful agroclimate services requires an understanding of farmers' methods for dealing with climate uncertainty. It ensures relevance by highlighting knowledge gaps, adaptive capacity, and local practices. Table 7 demonstrates how farmers employ a range of strategies, such as irrigation, short-duration crops, indigenous knowledge, climate information services, and relocation. Only 10% make use of science-based services, despite the fact that everyone depends on conventional knowledge. 38% of West Africans use short-duration cultivars to lessen the effects of drought.

TABLE 4 Study areas.

Country	Research areas	Targeted cash crops	Targeted staple crops
Burkina Faso	Hauts-Bassins: Non-CSV (Boni, Koumbia) Centre-Sud: Ouada	Cotton	Maize
Ghana	Upper West/Wa CSV: Doggoh and Bompari	Soybean	Sorghum/Maize
Senegal	Kaffrine CSV: Sikilo, Daga-Birame	Groundnut	Millet
Mali	Segou: CSV: Tongo, Ngakoro	Cotton/Cowpea	Maize/Sorghum

Eliciting farmer's preferences on agroclimatic services bundle in West Africa

Assessing farmers' agroclimate service package preferences guarantee cultural relevance, participation, and efficient utilization. While ongoing evaluation enables adaptability to shifting circumstances, incorporating local knowledge boosts acceptability. With the exception of Burkina Faso (31%) and Mali (21%), where bundle 0 is favored, bundle 4 is the most popular option throughout West Africa (45%), according to Figure 4. While bundle 0 should be kept as a backup, providers should give bundle 4 priority.

Mixed Logit models use fixed or random coefficients, with fixed coefficients chosen here due to lower AIC (3744.208) and BIC (4012.207) compared to random coefficients (AIC = 3810.823, BIC = 4157.645). Despite expected heterogeneity, the fixed model was more suitable (see Table 8).

Daily forecasts positively influence bundle choice in West Africa, Burkina Faso, and Ghana, while weekly forecasts are insignificant. Seasonal forecasts are significant in West Africa. SMS is significant in Ghana and Senegal, Interactive Text Messages (IDS) only in Ghana, and Voice Messages and Radio are insignificant. Malian farmers prefer weather-based seed and fertilizer advisories, while Ghanaian farmers favor general weather advisories. Drought insurance is unlikely in Mali, but flood insurance is preferred in Burkina Faso. Weather-based input prices are preferred in West Africa, and credit access influences Malian farmers.

The model includes age, sex, farming purpose, and past climate experiences (drought, flood, heat, wind):

- Bundle 1 vs. 0: Drought reduces choice in West Africa, Mali, and Senegal but increases it in Burkina Faso. Male farmers are less likely to choose Bundle 1, except in Burkina Faso.
- Bundle 2 vs. 0: Positive for drought (Burkina Faso), flood (Senegal), and wind (West Africa). Heat (West Africa) reduces choice. Commercial farmers prefer Bundle 2; mixed-purpose farmers are less likely in Ghana, Mali, and Senegal.
- Bundle 3 vs. 0: Positive for drought (West Africa), flood (West Africa), and wind (Burkina Faso). Negative for drought (Senegal), heat (West Africa), and wind (Ghana). Commercial farmers prefer Bundle 3; male and adult farmers are less likely.

TABLE 5 Socio-economic characteristics of the respondents in the four countries of West Africa.

Countries	Burkina Faso	Ghana	Mali	Senegal	West Africa
Total farmers surveyed	425	343	342	305	1,415
No. of female farmers (%)	13.2	23.6	4.4	28.2	16.8
No. of male farmers (%)	86.8	76.4	95.6	71.8	83.2
Adults (˃35 years)	85.9	70.0	92.7	86.6	83.8
Youth (≤35 years)	14.1	30.0	7.3	13.4	16.2
Illiterate (%)	74.4	38.2	36.0	12.1	42.9
Koranic school (%)	6.8	5.0	36.0	61.3	25.2
Local language literacy (%)	5.9	2.9	12.6	3.0	6.2
Primary school (%)	9.9	26.8	11.1	12.5	14.8
Secondary school (%)	2.8	21.3	3.8	8.5	8.8
University (%)	0.2	5.8	0.6	2.6	2.2

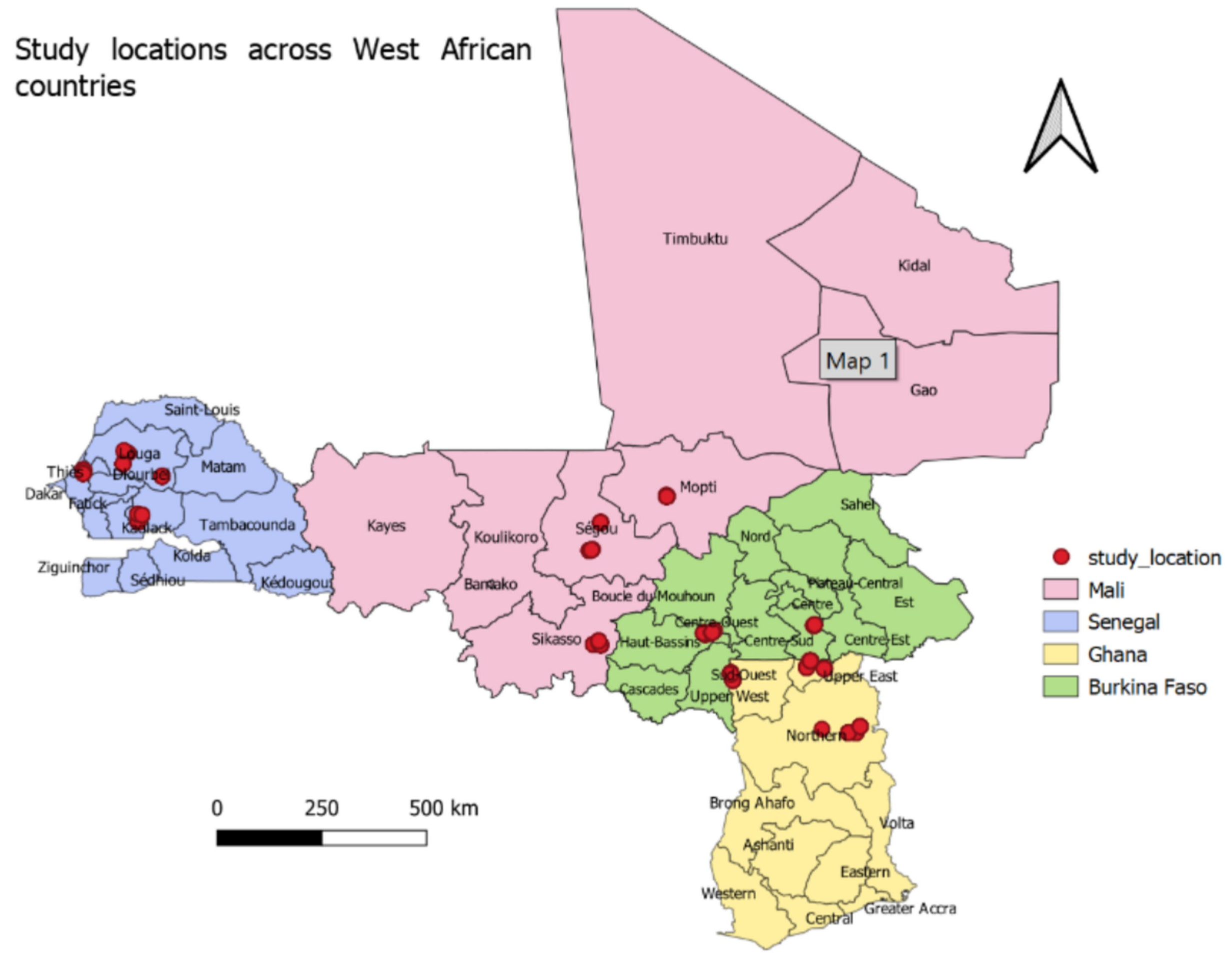

FIGURE 2
Study area.

TABLE 6 Statistics of different forms of climate variability as observed in the last 10 years in West Africa.

Form of climate variability		Burkina Faso	Ghana	Mali	Senegal	West Africa
Drought (%)		100	100	100	100	100
Floods (%)		43	59	71	25	50
Intense heat (%)		35	57	29	14	34
Violent wind (%)		48	68	49	32	50
Number of Droughts in the last 10 years	Mean	1.0	3.0	2.2	4.2	2.6
	Max	6.0	9.0	10.0	10.0	8.8
Number of FLOODS in the last 10 years	Mean	0.9	1.5	2.3	0.5	1.3
	Max	6.0	8.0	10.0	5.0	7.3
Number of HEAT in the last 10 years	Mean	0.6	1.7	1.2	0.5	1.0
	Max	6.0	8.0	10.0	8.0	8.0
Number of WINDS in the last 10 years	Mean	1.4	2.0	1.7	1.0	1.5
	Max	6.0	3.0	10.0	10.0	7.3

- Bundle 4 vs. 0: More likely if farmers experienced drought (West Africa), flood (Senegal), or heat (Ghana). Commercial farmers prefer Bundle 4; mixed-purpose farmers in Burkina Faso and Senegal are less likely.

The Margins of the Mixed Logit analysis shows that 22% of farmers prefer Bundle 0, while 18.2% choose Bundle 1. Few opt for Bundles 2 and 3, with most selecting Bundle 4 (Table 9), as it offers the most comprehensive services. Bundle 0 remains popular since it's free,

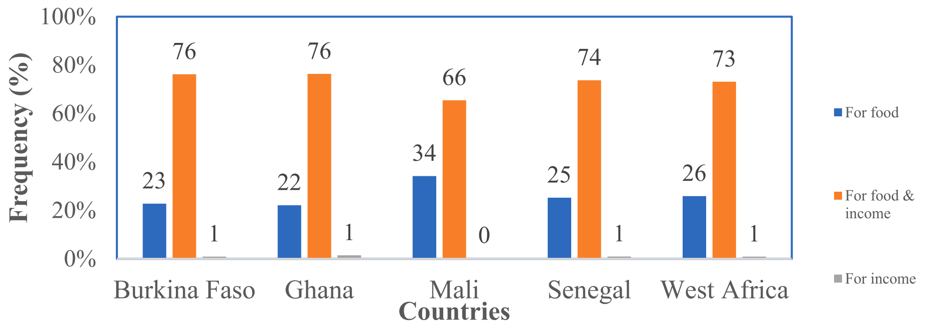

FIGURE 3
Farming objectives across West Africa.

TABLE 7 Strategies used by farmers to mitigate drought effect on their farms in West Africa.

Countries	Burkina Faso	Ghana	Mali	Senegal	West Africa
Under CIS (%)	0.24	31.49	4.09	4.26	9.61
Under indigenous knowledge (%)	100	100	100	100	100
Under irrigation (%)	0.71	7.29	7.60	4.92	4.88
Adoption short cycle varieties (%)	4.47	76.97	45.03	32.46	37.88
Moved to lowlands (%)	2.12	29.45	0.88	4.59	8.98
Seek advisories from extension agents (%)	2.12	48.98	16.96	6.89	18.09
Quitted farming because of drought (%)	0.24	2.33	0.88	12.46	3.53

with some farmers waiting for government support. The trend remains consistent even with random coefficients—Bundle 0 still gets 22%, while Bundle 4 sees a slight dip to 43.6%. Preferences for Bundles 2 and 3 remain low, confirming that farmers overwhelmingly favor Bundle 4, regardless of model variations.

Predicting the effect of climate variability increases on farmers' agroclimate services bundle choices in West Africa

A key question is how increased droughts or floods would impact farmers' choices of agroclimate service bundles. In the ECOWAS region, farmers have faced droughts an average of 2.5 times in the past decade. If this rises to 5 in the next 10 years, preference margins shift. Estimates show nearly 60 more farmers would choose Bundle 4 over Bundle 0 (Table 10), while choices for Bundles 2 and 3 remain unchanged. This suggests that as climate variability worsens, farmers increasingly prefer comprehensive agroclimate services.

The increased desire for comprehensive risk-mitigation strategies can be a mechanical explanation for the observed increase in Bundle 4 preference under doubled drought frequency. Farmers place higher value on bundled services that combine financial protection (drought insurance) and predictive ability (seasonal/daily forecasts) when climatic shocks occur more frequently. This trend has been well documented in the literature on climate adaptation (Sultan et al., 2010; Johnson, 2021). Bundle 4 is especially appealing in light of growing climatic variability because of this synergy, which enables farmers to both predict and protect against losses. The findings from Burkina Faso, where farmers affected by drought were prepared to pay more for comparable packaged services, are consistent with the 39% rise in preference likelihood (Ouédraogo et al., 2018).

Although a USD 1,000 credit option was added, Bundle 4's popularity stayed consistent, suggesting that its all-inclusiveness—which includes daily forecasts, seed recommendations, insurance, and market data—already satisfies farmers' main requirements. Given that farmers already consider Bundle 4 to be a comprehensive approach to addressing climate risks, this shows that the additional credit did not substantially increase its perceived worth. The fact that the situations are consistent shows how strongly farmers demand packaged, multifaceted services.

Farmers' decisions are influenced by their access to agricultural loans. Preferences change when a USD 1,000 credit is added to agroclimate service bundles (Table 11). Bundle 4 stays at 44%, but Bundle 0 increases from 22 to 39%, Bundle 1 from 18 to 31%, Bundle 2 from 9 to 18%, and Bundle 3 from 5 to 11%. This implies that even in the absence of agroclimate knowledge, credit enhances resilience. Bundle 4 is still the best option, though, perhaps because it comes with quick credit, even if it is not stated.

TABLE 8 Mixed logit output on the alternatives specific and the case-specific variables.

Variables	West Africa [Coefficient (SD)]	Burkina Faso [Coefficient (SD)]	Ghana [Coefficient (SD)]	Mali [Coefficient (SD)]	Senegal [Coefficient (SD)]
Alternatives specific variables					
Daily forecast	0.114 (0.079)	0.343 (0.220)	0.248* (0.154)	−0.183 (0.315)	0.155 (0.156)
Weekly forecast	−0.055 (0.079)	−0.089 (0.206)	0.004 (0.160)	0.267 (0.288)	−0.179 (0.134)
Seasonal forecast	0.110* (0.073)	0.203 (0.196)	0.159 (0.154)	0.168 (0.203)	−0.041 (0.152)
SMS alerts	−0.044 (0.075)	−0.014 (0.194)	0.221 (0.172)	−0.193 (0.209)	−0.032625
Interactive Text Response System	−0.020 (0.084)	−0.208 (0.197)	−0.096 (0.169)	0.142 (0.335)	0.007 (0.160)
Interactive voice response system	0.002 (0.078)	0.151 (0.206)	−0.097 (0.156)	−0.162 (0.307)	0.058 (0.150)
Radio broadcasts	−0.035 (0.073)	0.113 (0.132)	−0.178 (0.157)	−0.023 (0.163)	−0.084 (0.157)
Weather-based crop seed advisory	0.076 (0.143)	−0.040 (0.264)	−0.062 (0.495)	−0.113 (0.240)	1.696*** (0.611)
Weather-based fertilizer application advisory	0.044 (0.154)	−0.022 (0.269)	−0.038 (0.517)	0.075 (0.355)	−0.8574
Weather-based pesticide application advisory	−0.106 (0.078)	0.249 (0.195)	−0.493*** (0.168)	−0.278 (0.298)	−0.032 (0.161)
Drought insurance	−0.01014	−0.137 (0.199)	−0.214 (0.172)	−0.074763	0.101 (0.166)
Flood insurance	0.110 (0.080)	0.498* (0.197)	0.027 (0.166)	0.292 (0.265)	−0.174 (0.147)
Weather-based Input price information	0.109 (0.078)	0.104 (0.223)	0.222* (0.142)	0.202 (0.362)	0.102 (0.120)
Weather-based Output price information	−0.021 (0.078)	0.060 (0.182)	0.079 (0.161)	−0.064 (0.276)	−0.169 (0.151)
Credit access	−0.079 (0.081)	−0.034 (0.219)	−0.200 (0.159)	0.110* (0.271)	0.080 (0.171)
Case-specific variables					
Bundle 0 (base category)					
Bundle 1					
Drought experience (number of years)	−0.071 (0.060)	0.644** (0.294)	0.237 (0.309)	−0.299*** (0.094)	−0.344*** (0.134)
1. Age (>35 years)	−0.180209	−0.287 (0.563)	0.522 (0.881)	−0.979 (0.665)	−0.125 (0.912)
1. Sex (Male)	−0.621*** (0.238)	1.435** (0.630)	−1.117753	−0.482 (0.749)	−0.625155
Flood experience (number of years)	0.208*** (0.054)	0.292* (0.182)	0.165 (0.208)	0.227** (0.072)	1.252* (0.452)
Heat experience (number of years)	−0.042 (0.072)	−0.247 (0.434)	0.418* (0.269)	−0.006156	−0.067 (0.230)
Wind experience (number of years)	0.023 (0.066)	0.732** (0.255)	−0.130 (0.112)	−0.00572	0.149 (0.163)
Commercial farming (number of years)	0.164 (0.186)	−0.020 (0.349)	0.064 (0.742)	0.596* (0.359)	1.147* (0.590)

(Continued)

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TABLE 8 (Continued)

Variables	West Africa [Coefficient (SD)]	Burkina Faso [Coefficient (SD)]	Ghana [Coefficient (SD)]	Mali [Coefficient (SD)]	Senegal [Coefficient (SD)]
Mixed-purpose farming	0.930 (0.789)	1.506 (1.257)	−0.674 (1.606)	−21.260*** (0.000)	2.573* (1.405)
Constant	0.587 (0.406)	−2.044 (0.723)	1.143 (1.075)	0.826 (1.005)	0.856 (1.206)
Bundle 2					
Drought experience (number of years)	−0.042 (0.062)	0.735 (0.307)	−0.121 (0.319)	−0.175 (0.127)	−0.204 (0.170)
1. Age (>35 years)	−0.921*** (0.325)	−1.131 (0.534)	0.647 (0.944)	−0.986 (0.703)	−0.110 (1.325)
1. Sex (Male)	0.030 (0.315)	1.310 (0.550)	−0.084 (1.006)	17.392 (0.453)	−0.637 (0.764)
Flood experience (number of years)	−0.008 (0.064)	0.084 (0.203)	0.136 (0.189)	−0.014 (0.098)	1.254 (0.485)
Heat experience (number of years)	−0.106 (0.078)	0.194 (0.416)	−0.127 (0.326)	−0.226 (0.134)	0.265 (0.242)
Wind experience (number of years)	0.131** (0.065)	1.003 (0.254)	−0.193 (0.167)	0.103 (0.084)	−1.107 (0.632)
Commercial farming (number of years)	0.399* (0.233)	0.996 (0.442)	0.245 (0.809)	−0.509 (0.448)	0.394 (0.777)
Mixed-purpose farming	−0.164 (1.359)	2.601 (1.578)	−1.315 (0.946)	−21.422*** (0.000)	−41.640 (0.945)
Constant	−0.328 (0.472)	−2.647 (0.706)	1.136 (1.260)	−17.381 (0.853)	−0.020 (1.741)
Bundle 3					
Drought experience (number of years)	0.170*** (0.067)	0.792** (0.386)	0.087 (0.322)	−0.145 (0.171)	−0.425** (0.147)
1. AGE (>35 years)	−1.245*** (0.365)	−0.294 (1.013)	−0.632 (0.942)	16.527 (53.926)	−0.336 (0.948)
1. SEX (Male)	−0.704** (0.325)	0.336 (0.824)	0.028 (1.015)	17.473 (78.326)	−0.609 (0.694)
Flood experience (number of years)	0.273*** (0.065)	0.326 (0.292)	0.760*** (0.210)	0.046 (0.116)	0.944** (0.488)
Heat experience (number of years)	−0.016432	0.416 (0.482)	0.230 (0.290)	−0.130 (0.156)	−0.525 (0.372)
Wind experience (number of years)	0.064 (0.080)	1.228 (0.322)	−0.325 (0.159)	−0.102 (0.173)	0.140 (0.140)
Commercial farming(number of years)	0.938*** (0.318)	−0.601 (0.692)	1.497 (0.996)	1.633 (0.794)	3.995 (1.123)
Mixed-purpose farming	−11.925*** (0.905)	−10.081 (1.191)	−1.282 (1.166)	−21.569*** (0.000)	−41.403 (0.000)
Constant	−1.180** (0.543)	−4.525 (1.268)	−0.920 (1.572)	−36.656 (131.950)	−0.830 (1.677)
Bundle 4					
Drought experience (number of years)	0.245*** (0.049)	0.463 (0.338)	0.195 (0.287)	0.021 (0.070)	−0.186 (0.098)
1. Age (>35 years)	−1.418*** (0.244)	−1.789 (0.517)	−0.010 (0.827)	−0.972 (0.593)	−0.574 (0.739)
1. Sex (Male)	−0.169 (0.212)	1.985 (0.726)	0.490 (0.896)	0.100 (0.682)	−0.426 (0.481)

(Continued)

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TABLE 8 (Continued)

Variables	West Africa [Coefficient (SD)]	Burkina Faso [Coefficient (SD)]	Ghana [Coefficient (SD)]	Mali [Coefficient (SD)]	Senegal [Coefficient (SD)]
Flood experience (number of years)	−0.048 (0.054)	0.229 (0.220)	0.194 (0.188)	−0.041 (0.081)	1.183 (0.430)
Heat experience (number of years)	0.051 (0.060)	0.180 (0.432)	0.719 (0.205)	0.051 (0.071)	0.036 (0.171)
Wind experience (number of years)	0.068 (0.056)	1.573 (0.260)	−0.227 (0.113)	−0.103 (0.063)	0.069 (0.101)
Commercial farming (number of years)	0.740*** (0.166)	1.206 (0.503)	1.479 (0.730)	−0.602 (0.340)	1.263 (0.413)
Mixed-purpose farming	0.068 (0.970)	−10.483 (1.113)	0.210 (1.019)	39.849 (0.000)	−40.678 (0.726)
Constant	0.838** (0.346)	−3.454 (0.956)	0.767 (1.055)	0.612 (0.923)	2.277 (0.951)
Model parameters	AIC: 3744.208	*N* = 2,125	*N* = 1,718	*N* = 1,713	*N* = 1,528
	BIC: 4012.207	N cases = 425	N cases = 346	N cases = 345	N cases = 308
	N = 7,075	Log pseudolikelihood = −451.121	Log pseudolikelihood = −279.411	Log pseudolikelihood = −433.383	Log pseudolikelihood = −277.770
	N cases = 1,415	Wald chi2(47) = 892.50	Wald chi2(47) = 2267.67	Wald chi2(41) = 155644.50	Wald chi2(46) = 5410.29
	Log pseudolikelihood = −1821.104	Prob > chi2 = 0.0000	Prob > chi2 = 0.0003	Prob > chi2 = 0.0003	Prob > chi2 = 0.0003

SD: Standard Deviation.

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TABLE 9 Margins.

Alternatives	Mixed logit with fixed coefficients			Mixed logit with random coefficients		
	Margin	Std. err.	P > z	Margin	Std. err.	P > z
Bundle 0	0.219	0.011	0.000	0.222	0.013	0.000
Bundle 1	0.182	0.01	0.000	0.185	0.011	0.000
Bundle 2	0.095	0.008	0.000	0.099	0.008	0.000
Bundle 3	0.055	0.006	0.000	0.058	0.006	0.000
Bundle 4	0.448	0.012	0.000	0.436	0.017	0.000

TABLE 10 Impact of increasing drought frequency on the probability of choosing agroclimatic service bundles in West Africa.

Alternatives	Margin	Std. err.	z	P > z	[95 conf. interval]	
Bundle 0	0.165	0.021	7.910	0.000	0.124	0.206
Bundle 1	0.111	0.016	7.050	0.000	0.080	0.142
Bundle 2	0.062	0.010	6.080	0.000	0.042	0.082
Bundle 3	0.066	0.010	6.450	0.000	0.046	0.085
Bundle 4	0.595	0.025	23.750	0.000	0.546	0.645

Discussion

Important agroclimate service attributes for farmers in West Africa

This study examines farmers' preferences for agroclimate services in Burkina Faso, Ghana, Mali, and Senegal using the Mixed Logit model. While weekly forecasts have little effect on package selection, daily forecasts do. In all of West Africa, seasonal forecasts are quite beneficial. The intricacy of adopting agroclimate services is highlighted by the disparate effects of socioeconomic issues such as population and drought. Daily and seasonal predictions, input price, drought insurance, and weather-based seed advice are important service components that influence preferences. Decisions are influenced by farming objectives and prior experiences with wind, heat, floods, and drought. Commercial farmers prefer particular packages, indicating that marketing tactics should give priority to these traits.

These results are consistent with those of Zongo et al. (2022), who stress the significance of seasonal forecasts for farmers in West Africa. 63% of respondents from northern Burkina Faso said they would pay for daily, decadal, and seasonal climate data, according to Ouédraogo et al. (2018). Similarly, according to Fonta et al. (2015), 98% of farmers in southern Burkina Faso would insure maize, cotton, and sorghum against dry spells. According to Okoffo et al. (2016), more than 76% of cocoa growers in Ghana are prepared to pay for specialized insurance. In Senegal, Diagne et al. (2019) came to a similar conclusion regarding index-based insurance.

The advantages of weather-based agro-advisories for peanut and rice producers were emphasized by Das et al. (2022). Impact-Based Forecasts (IBF) are recommended by Nkiaka et al. (2020) in order to draw attention to the dangers of disregarding climate services. While Chakraborty et al. (2018) discovered that predictions without practical recommendations are less valuable to farmers, Stigter (2011) contends that forecasts with operational agro-advisories assist farmers better comprehend their worth.

Most preferred agroclimate service bundle for West Africa

Bundle 4 was preferred due to some attribute synergies, especially the combination of drought insurance and daily forecasts, which increased perceived utility. In line with research conducted in Ethiopia and Burkina Faso, farmers gave priority to financial risk reduction in addition to actionable, high-frequency weather data (for example, planting decisions) (Tesfaye et al., 2019; Fonta et al., 2018). The necessity for tiered pricing structures to address income gaps was highlighted by the notable trade-offs that emerged: subsistence producers frequently chose minimal-cost solutions (Bundle 0), whereas commercial farmers appreciated bundled services.

According to the survey, the majority of West African farmers (45%) favor Bundle 4, whilst Burkina Faso (31%) and Mali (21%), on the other hand, favor Bundle 0. As drought frequency doubles over the next decade, over 60% of farmers are expected to favor Bundle 4, highlighting the impact of climate variability on preferences. The probability of selecting Bundles 0, 1, 2, and 3 rises when a USD 1,000 agricultural credit is available, while Bundle 4's attraction is maintained at 44%. Farmers favor climate service bundles that include voice messages, detailed instructions on avoiding climatic shocks, and precise, geo-localized forecasts in their native tongues. Additionally, they believe that credit is crucial to putting climate-based suggestions into practice (Antwi-Agyei and Nyantakyi-Frimpong, 2021, Byandaga et al., 2023).

These results are consistent with those of Tesfaye et al. (2019), who support the integration of weather-based agro-advisories, market access, and loans in Ethiopia. While Endrias and Tesfaye (2022) highlight the necessity of agro-advisories in addition to

TABLE 11 Effect of allotting 1,000 USD as farm credit on the probability of CIS bundle to be chosen.

Alternatives	Margin	Std. err.	z	P > |z|	[95 conf. interval]	
Bundle 0 with USD	0.220	0.011	19.940	0.000	0.198	0.241
Bundle 0 with 1,000 USD	0.391	0.018	21.350	0.000	0.355	0.427
Bundle 1 with USD	0.183	0.010	18.220	0.000	0.163	0.203
Bundle 1 with 1,000 USD	0.317	0.017	18.270	0.000	0.283	0.351
Bundle 2 with USD	0.096	0.008	12.340	0.000	0.081	0.111
Bundle 2 with 1,000 USD	0.179	0.014	12.540	0.000	0.151	0.207
Bundle 3 with USD	0.056	0.006	9.240	0.000	0.044	0.068
Bundle 3 with 1,000 USD	0.113	0.012	9.200	0.000	0.089	0.137
Bundle 4 with USD	0.445	0.013	35.030	0.000	0.420	0.470
Bundle 4 with 1,000 USD	0.000	0.000	0.010	0.990	−0.000	0.000

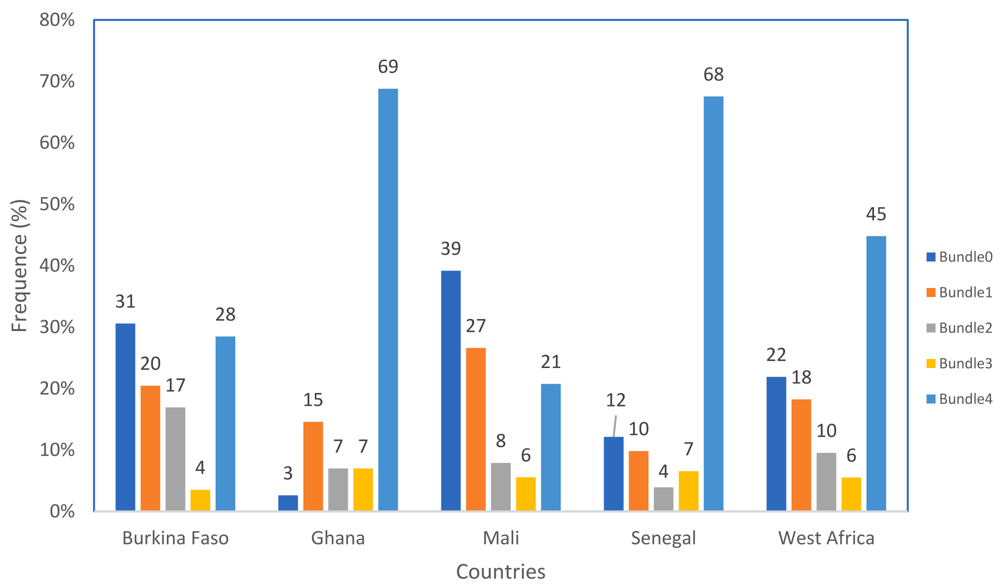

FIGURE 4
Preferred agroclimate services bundles in West Africa.

climate services, Tesfaye et al. (2020) focus on market information and extension services in Rwanda. Prager et al. (2021) offer commercial models for scaling Climate Information Services (CIS) and Climate-Smart Agriculture (CSA), whereas Tesfaye et al. (2021) offer a framework for combining CSA and CIS in Ethiopia. In a similar vein, Mvuyibwami et al. (2023) advise Ghanaian farmers to combine CIS and CSA in order to aid in decision-making.

Conclusion

The purpose of the study is to determine which agroclimate service elements are most preferred by West African farmers and to suggest packaged services in accordance with those findings. It illustrates how important it is for farmers in the area to have weather-based seed advisories, weather-based input and output pricing information, drought insurance, daily forecasts, and seasonal predictions. Preferences vary by nation, though. While daily forecasts and weather-based seed advisories are crucial in Mali, drought insurance and weather-based input pricing information are crucial in Ghana. Burkina Faso farmers place more importance on output price information than Senegalese farmers do on weather-based seed warnings and input/output pricing information.

The most popular bundles in West Africa are Bundle 4, Bundle 0, and Bundle 1, with Bundle 4 ranking highest. The paper emphasizes the value of stakeholder collaboration and recommends giving Bundle 4 manufacturing and marketing top priority. In order to ensure the sustainability of such agro-climatic services, a partnership strategy is proposed to address production, marketing, and delivery costs.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

AO: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. MO: Conceptualization, Funding acquisition, Methodology, Resources, Writing – review & editing. IE: Conceptualization, Supervision, Validation, Writing – review & editing. PL: Validation, Writing – review & editing. AM-B: Supervision, Validation, Writing – review & editing. JJ: Supervision, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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