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Economic value and latent demand for agricultural drought forecast: Emerging market for weather and climate information in Central-Southern Nigeria

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ABSTRACT

Provision of weather and climate services are expected to improve the capacity for rural households' preparedness and response plans to weather shocks. With increase in public investments in developing and communicating weather information on local scale in Nigeria, uncertainty in timescales that meet farmers' needs and economic value of the information is still poorly understood. It is now a policy concern on whether farmers' preferences and demands might increase its uptake. This study analyzed the economic value, latent demand, and emerging market of weather and climate information in Central-Southern Nigeria. Farm-level cross-sectional data reveals that 76% of the respondents were willing to pay for improved weather information and early warnings in taking climate smart decisions. Within farmers who showed positive responses, 86% would pay for sub-seasonal to seasonal weather information while 38% would pay for medium and short range weather information respectively. The economic value of sub-seasonal to seasonal weather information was estimated at N1600 ($3.60) per year per capita with total aggregated value of N1.3 billion ($2.9 m) yearly for the derived savannah area. Predictive total market value of N17.43billion ($39 m) would be obtained from improved weather information in Nigeria. Simulated results of 5% increase in the uptake with better dissemination channel through mobile phones in addition to robust farmers' oriented features will generate additional annual market value at N86m ($193,360) for service providers. Large farm size, good farm-income, mobile phone dissemination channels, and location-specific information were drivers of farmers' uptake decisions of weather information in the dry savannah area. The huge emerging market for improved weather information should be developed into a public–private market to efficiently facilitate uptake and use in Nigeria.

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1. Introduction

Extreme weather events are widely recognized as the major environmental threats facing global economy at multiple scales (IPCC, 2022a; UNDRR, 2020; WMO, 2020). The IPCC Sixth Assessment Report (AR6) expressed that climate change has reduced economic growth across Africa, increasing income inequality between African countries (IPCC, 2022b). Africa is an exposure and vulnerability "hot spot" for climate variability and change impacts contributing to food insecurity, stress on water resources, and population displacement (United Nations, 2022; UNFCCC, 2020; IPCC, 2014; Nwanze and Fan, 2016; World Bank, 2015). Africa faces exponential losses constituting systemic risks to its economies, water and food systems, agriculture, and livelihoods threatening to wipe off its negligible development gains, hindering efforts to achieve Sustainable Development Goals (SDGs) (AfDB, 2023; Awolala et al. 2022; IPCC, 2018). The agricultural sector and its sub-sectors are increasingly showing a high level of vulnerability to climate change impacts across geographical scales and countries (McKinsey Global Institute, 2020; Gourdji et al. 2015; Craparo et al., 2015).

Recent climate-related extreme events especially frequent dry spells and droughts are increasing evidences of climate change. West Africa has been identified as a climate-change hotspot, and potential for large increase in the number of hot days at 1.5° C which likely to lessen crop yields and production, thus resultant impacts on food security (United Nations Africa Renewal, 2020). Water stress is estimated to affect about 250 million in Africa and will displace 700 million people by 2030, therefore 80% of African countries are not likely to sustainably managed water resources by 2030 (United Nations, 2022; WMO, 2022). The future warming scenario risk projections would further have devastating effects on crop production and food security. Under the worst case climate change scenario, a decline in mean yield of 13% is expected in West and Central Africa. The most promising crops, millet and sorghum would be affected with a yield loss 5% and 8%, respectively due to their greater resilience to heat-stress conditions, while rice and wheat are expected to be the most affected crops with a yield loss of 12% and 21%, respectively by 2050 (IPCC, 2022a).

Drought is the most impactful extreme weather hazard which had affected 80% of the uninsured African smallholders, the cause of the 40% of total economic damages, thus triggered $70 billion in regional economic losses (IPCC, 2022a; UNFCCC, 2020). Drought has become a reoccurring extreme event in Nigeria, and it is expected to continue in the savannah areas due to declining rainfall and increasing temperatures. Temperature increases of about 0.2 to 0.3 °C per decade have been observed since 1980s in the various ecological zones. This has led to increasing rate of evapotranspiration and water stress as rivers and lakes are drying up (Haider, 2019; Dioha and Emodi, 2018). One major consequence of climate change is seasonal hunger arising from exposure to adverse weather conditions, especially those in highly fragile ecological terrains (Seo, 2011; Mendelsohn, 2012). In view of the increasing threats from climate extremes for food and water security and socio-economic development in Africa, there is a need of accurate and current data for adaptation planning. Science-based climate information is the foundation of building resilience as a bedrock of climate change adaptation, and an oasis for sustainable livelihoods, therefore advancements in systematic observations, research and climate services would play a key role (WMO, 2022).

Global focus has shifted towards building farmers' resilience against income losses and damages through the use of weather and climate information services. These services facilitate early adaptation decisions which enhance preparedness and response against extreme weather shocks (IPCC, 2022a; IPCC, 2022b; United Nations, 2022). The use of weather and climate information has become an important policy discussion in many decision-making literature on production risk management and resilient agriculture, for example, early dry spell forecasts have been considered important elements that enhance farmers' adaptation and management of drought shocks in the dry savannah areas (UNFCCC, 2020; IPCC, 2018; IPCC, 2012; Kiem and Verdon-Kidd, 2011). In Africa, only 40% of the present population has access to early warning systems against extreme weather and climate change impacts (United Nations, 2022) while Nigeria has about fifty-four meteorological stations to service its huge user population and land mass which is grossly inadequate because of peculiar technical and capacity challenges. As a response to this tide, Nigeria is investing on weather and climate information services as a priority to enable farmers build resilience under its Nationally Determined Contributions (NDCs).

A Memorandum of Understanding signed with the British American Tobacco Nigeria Foundation was meant to boost production of weather information especially to promote uptake among users in the agricultural sector (NiMet, 2017). Farmers who were dominantly dependent on rain-fed agriculture could have access to weather information which include the likely times of dry spell occurrences and associated advisory services that can boost decision making and enhance their adaptive capacities. Further investment have been made in the aspect of generating and communicating real time forecast and advisory services on local scale through a partnership with the Austrian Meteorological Company for precise meteorological services and severe weather warnings (NiMet, 2017; FMoE, 2017). Critical threshold of weather information and climate monitoring in the aspect of pre-season and in-season weather forecast services were expected to increase number of agricultural producers that will uptake and use weather and climate information.

Weather and climate information are expected to improve the capacity of Africa's agricultural sector to manage the risks of climate variability and change. They are importantly suited for rainfed farming systems, constituting the essential mean of livelihood for African rural households (Klopper et al, 2006; IPCC, 2022b, Hammer, 2000, Skees et al., 1999). Empirical studies among African farmers have shown that seasonal climate forecasts help farmers reduce their vulnerability to drought and climate extremes, while also optimizing their opportunities when favourable rainfall conditions are expected (Awolala, 2018; Roncoli et al., 2009). Several studies have focused on the access and use of weather and climate services for agricultural risk management decision-making in Africa (Alliagbor et al. 2020; Awolala et al. 2022; Muita et al. 2021; Ouédraogo, Ndiaye, and Zougmoré, 2018; Makaudze, 2018; Amegnaglo, Asomanin, and Mensah-bonsu, 2017; Zongo et al., 2016; Limantol et al., 2016; Oyekale, 2015; Rasmussen et al., 2014; Carr et al., 2014; Gebremariam et al, 2013; Mabe et al, 2014; Roncoli et al., 2009, 2011; Tarhule and Lamb, 2003; Roudier et al., 2011; Zinyengere et al., 2011; Roncoli, Ingram, and Kirshen, 2002). These studies indicate that use of weather information in decision making has substantially benefited farmers.

Despite this, a lack of evidence prevents a realistic analysis of whether such services are delivering on their potential. Only few studies have provided analysis of the value of weather and climate information from potential users directly by determining what users would be willing to pay for weather and climate information as potential demand in the future (Amegnaglo et al., 2017; Vaughan et al., 2019; Zongo et al., 2016; Rao et al., 2015; and Makaudze, 2005). In Burkina Faso, the estimated value of weather information derived from smallholder farmers ranged from $1.19 (Zongo et al., 2016) to $15.36 in Kenya (Ouédraogo et al.,2015) as the amount paid to access improved seasonal forecast products and services.

1.1. The impact and value of Sub-Seasonal forecasts in Africa

Africa is facing the largest capacity gaps with regard to climate services. The Sub-Saharan Africa (SSA) seriously need climate information services that are demand-driven and context specific, to support early warnings and informed adaptation responses against weather shocks and livelihoods which are heavily dependent on environment. The availability and use of Sub-Seasonal to Seasonal (S2S) information (one to four week) are still low but capable of building socio-economic resilience in Africa. Recent advancements in sub-seasonal prediction have the potential to support preparedness action providing economic benefits across the SSA, and there is a growing recognition of the multiple benefits of co-production for forecast producers, researchers and users with regards to the increasing understanding of the decision-relevance, uptake and use of weather information (Parker et al, 2022). New real-time sub-seasonal forecast information is aiding preparedness and disaster risk reduction decisions in key drought-vulnerable sectors across Africa and enabling significant progress in sub-Saharan Africa towards the UN Sustainable Development Goals. These services are demonstrating the potential for wider development of sub-seasonal user-focused services at scale across Africa (University of Leeds, 2021).

Given that science-based forecasting of local African weather is improving yet it has not sufficiently produce useful and sub-seasonal information that users could base their risk-management decisions on local scale (Youds et al., 2021). Climate-related research in Africa faces severe data constraints, inequities in funding and research leadership that reduces adaptive capacity. From 1990 to 2019, research on Africa has received only 3.8% of climate-related research funding globally (IPCC, 2022b). Another important knowledge gap still remains about how to improve the availability and uptake of operational sub-seasonal weather information products for actionable decision-making. A demand-led assessment of the economic value of weather information with the potential for developing an emerging market for public–private partnership investments becomes relevant for policy action. In recognition of these gaps that the partnership between UK and African scientists, through the Global Challenge Research Fund (GCRF) African SWIFT under the Real-Time Pilot Initiative of the World Meteorological Organisation (WMO) provided a change in the African weather forecasting capability and communication, from hourly to seasonal timescales, to protect lives and livelihoods in Africa, through effective co-production and capacity building while tailoring climate information services to individual needs (Fletcher et al., 2021; Hirons, et al, 2021). The National Meteorological Services and Regional Climate Centres in Ghana, Kenya, Nigeria, Niger, and Senegal provide invaluable expertise to co-develop useable forecast products that can be used to inform effective preparedness for events such as dry spealls, droughts and to support planning decisions in a prevailing weather (University of Leeds, 2021).

Producing reliable and actionable forecasts on sub-seasonal timescales has enormous potential to benefit the livelihoods and national economies of African countries, although the economic value of weather forecasting is not currently fully understood in economic terms across many African countries including Nigeria. From the foregoing, low uptake of weather information can significantly reduce its total utility among users. This situation provides opportunities for Africa to harness its huge resource potential to achieve the targets of the SDGs through emerging significant market opportunities, especially for the private sector and institutional investors (AfDB, 2023).

Little progress has been made in this aspect to assess the extent and value of using weather information in Nigeria, particularly among farming population despite facing serious climate uncertainties. The only evaluation which had been made on the access and use of weather information directly in the Nigerian agricultural sector was in a long time ago by (Tarhule and Lamb, 2003) but has no empirical focus of the economic value of using weather and climate information for dry spells and drought preparedness against damage and losses by farming households in Nigeria. This research gap has ignited scientific processes to evaluate value of weather and climate information by potential users in Nigeria. This study fills this research and literature gap by investigating economic value and latent demand for dry spells and drought forecasts towards developing an emerging market for weather and climate information in Central-Southern Nigeria.

2. Potential demand for weather information

2.1. Conceptual framework

This study adopts a utility maximization function in the presence of a weather risk to analyze the use of weather information as a risk management strategy to enhance drought shock preparedness decisions and resilience. Within the context of climate adaptation, the utility to a farmer, derived from adopting a weather risk management strategy implied attempt of reducing risk at the downside of the user. A risk-averse farmer maximizes utility by choosing a weather risk management strategy that reduces risk as an adaptation action if the benefits of the strategy less the cost of adapting are higher than the benefits without adaptation. If not, the cost of adapting will be higher than the benefits and likely causes higher income losses. Following Hazell and Norton (1986), the utility function is described as follows:

$$U_y = E_y - \alpha\omega_y \tag{1}$$

where U_y is the perceived utility from choosing a weather risk management strategy y, E is the non-stochastic component and ω is the disturbance term indicating variation in yields. α is a coefficient that captures risk aversion of individual farmers that would affect the degree of the variability in the yields ωy. Following Finger & Schmid (2007), we define this coefficient as:

$$\alpha = -\left(\frac{\partial U}{\partial \omega_y}\right) \Big/ \left(\frac{\partial U}{\partial y}\right) \tag{2}$$

where if$\alpha < 0$, the farmer is risk averse and hence considered more likely to adapt; $\alpha = 0$ indicates a risk neutral farmer, and$\alpha > 0$ indicates a risk taker. The utility of implementing a strategy $y(U_y)$ is given by the revenues generated by the strategy less the variable costs incurred during its implementation. In view of a list of weather risk management strategies, a risk averse-farmer will choose the strategy, *X,* that gives higher expected utility than the alternatives, *Y* as follows:

$$E(U_x) - M_x > E(U_y) - M_y \tag{3}$$

The first term expresses the expected utility of implementing strategy X and the associated costs M, while the second term expresses expected utility of implementing strategy Y and associated cost Mx. Assumptions about the relationship of disturbance terms of the adaptation equations, whether correlated or not, determines the type of qualitative choice model that was used in this study.

Contingent Valuation Method (CVM) was used to estimate demand-side market value of weather information in our study. The conceptual and theoretical framework rests on potential demand for valuation of non-market goods in a hypothetical market. Contingent Valuation Method (CVM) which elicits consumers' willingness to pay for a specific good or service is most often used to assess the value of non-priced environmental amenities. However, CVM can be used to ascertain the demand for a good when a market for the good does not exist or when a test market experiment would be costly, or otherwise difficult to develop. Market values for non-market goods such as weather and climate information which are not typically paid for by the public in an established market can be estimated using the Contingent Valuation Method (CVM) (Freebairn and Zillman, 2002). This method is an economic valuation which refers to the assignment of monetary values of changes in environmental services and functions and to stocks of environmental assets (Pearce and Turner, 1990).

The CVM is a demand-based method widely used to determine economic values for non-marketed goods and services (Mitchell and Carson 1990; Kopp *et al.,* 1997). CVM depends on the creation of hypothetical market-like scenarios in which the non-market good or service could be provided to generate experimental contexts that provide data that are used to estimate benefits (Bishop *et al.,* 1995). It involves field surveys based on hypothesized markets to elicit information on the value people assign to non-market goods, in turn, used in models that predict the maximum amounts people would be willing to pay (WTP) to receive a specific level or quality of service, contingent on the market scenario proposed. A feature of well-designed CVM studies is that respondents are rarely asked to value explicitly the good in question, rather, the experimental design alters characteristics of the good, including the price, and respondents are asked whether or not they would purchase the good at a given price. This notion of a take-it-or-leave-it response to a given price for a well-defined service is consistent with market experiences of most respondents (Mitchell and Carson, 1990).

Economic values measured by CVM are theoretically consistent with economic benefits measures that arise from market data. Weather service providers hope to market their products, thus establishing a price for the products based on individual buyers' demand. The CVM can determine the extent to which individual buyers could be expected to purchase access to the weather forecast products and the prices they would be willing to pay. Stated preference approach and revealed preference approach are the two CVM which can be used to determine the value of an environmental good. In this study, stated preference technique which allows respondents to have enough flexibility to state amount willingness to pay was used to elicit farmers' willingness to pay amount.

Several studies have assessed economic value of climate services in agriculture using the Contingent Valuation Method (CVM). Ouédraogo et al. (2018) used CVM to estimate annual Willingness to Pay (WTP) for seasonal climate forecasts, decadal climate information, daily climate information and agro-advisory services by cowpea and sesame producers in Northern Burkina Faso. Mabe et al. (2014) used the CVM to elicit the amount farmers were willing to pay for accessing unpriced weather forecast information in the Savelugu-Nanton Municipality of the Northern Region of Ghana. Zongo *et al.* (2016) used the same method to assess farmers' willingness to pay for climate information in Burkina Faso. Sultan et al. (2010) estimated the potential economic value of the seasonal forecasts as a long-term ex-ante assessment in Senegal. Meza et al. (2008) have also estimated the economic value of seasonal climate forecasts for agriculture using same method. Amegnaglo et al. (2017); Makaudze (2018); Predicatori et al. (2008) have also used the CVM to assess the willingness to pay for improved weather forecasts in Benin, Zimbabwe and Italy respectively. The CVM is underpinned on the theory of consumer behaviour and the theory of the maximization of utility. The principal assumption upon which the theory of consumer behavior is built is that a consumer is rational and attempts to allocate limited income among available goods and services in order to maximize his utility (satisfaction). In other words, an individual seeks to maximize utility of a good such as weather forecast information services subject to a given constraint. It is assumed that every farmer pursues the objective of maximizing utility, but each farmer has individual perception of utility and constraints which makes willingness to pay decisions based on the unique attributes of individual situation (Gebremariam et al., 2013). The WTP for weather information services is therefore assumed to depend upon the set of characteristics which apply to a specific farmer.

2.2. Theoretical framework

Assume a discrete choice framework in which collection and application of weather information is part of an agricultural decision-maker's utility function. Utility is a measure of benefit or satisfaction the producer derives. Information use is regarded as a choice variable (Stigler, 1961) and its collection involves cost (Feder and Slade, 1984). Using weather information can be costly in terms of expenses for subscriptions to information services or time to acquire and process it. Consider a farmer who must make numerous production decisions all year round whose outcomes depend on weather conditions. The farmer may be able to use weather information to make better decisions that is, decisions with outcomes that the farmer prefers such as increased crop yield). Let δ represent a vector of n decisions, and w represent a vector of m types of weather information. For each decision δ_i a producer may use a type of weather information w_j such that$\delta_i = \delta_i(w_1, w_2, \ldots w_m)$. This can be taking as an integer programming problem so that $w_i = 1$ if the information is used and $w_i = 0$ if not. The farmer's utility can be expressed as:

$$U = U\big(u_i\{y[\delta(w), \mathrm{x},\ \mathrm{z}(w)], \sigma_y[\delta(w), = \mathrm{x},\ \mathrm{z}(w), r], \tag{4}$$

$$c[\delta^w, \mathrm{x},\ \mathrm{z}(w)], n\}, |u_2[\delta(w), \mathrm{x},\ \mathrm{z}(w), \omega]\ ), \tag{5}$$

y = a vector of incomes from sales of different agricultural commodities;
x = a vector of operator or operation characteristics that are invariant to weather data use;
z(w) = a vector attributes associated with the extent of weather data use;
σ_y = a function capturing effects of household income variability;
r = is an indicator of attitudes toward income risk;
$c()$ = a cost function measuring monetary and nonmonetary costs of using weather data;
n = non-farm income;
u_1 = a utility sub-function which depends on income, income variability, and costs of weather.
information use;
u_2 = another utility sub-function where weather data is evaluated in terms of external and/or.
non-monetary considerations; and.
ω = vector of external or nonmonetary considerations such as environmental obligations or.
conforming to social norms, preferences of other household members, etc.

The sub-functionu_1, in the overall utility function, has the elements of a standard (expected) utility function of neoclassical economics, where utility depends on household income and income variability. The sub-function u_2 acknowledges that, while household income and income variability are important considerations, they are not the sole factors influencing farmers' use of weather information. Equation (1) further acknowledges that farm-level decisions about weather information use are not necessarily made by a single individual in isolation of considerations of other household members, fellow farmers, media sources, among others (Hu *et al.,* 2006). The reduced-form random utility model when a farmer does not use weather information type w_i is therefore stated as:

$$U_0 = u[w_{i0}, \mathrm{x},\ \mathrm{z}(w_{i0}), r, n, \omega] + \varepsilon[\mathrm{x},\ \mathrm{z}(w_{i0}), r, n, \omega.e_{i0}\ ], \tag{6}$$

where u and ε are real valued functions.

The vector e_{i0} represents unmeasured farmers' characteristics or farmers activities. Farmer's utility when using weather information is:

$$U_1 = u[w_{i1}, \mathrm{x},\ \mathrm{z}(w_{i1}), r, n, \omega] + \varepsilon[\mathrm{x},\ \mathrm{z}(w_{i1}), r, n, \omega.e_{i1}\ ], \tag{7}$$

where e_{i1} is a vector of unmeasured farmers' characteristics, farm activities, and the weather information used. If the respondent is drawn from a random sample with common socioeconomic characteristics, the vectors e_{i0} and e_{i1} will be random, and the utility function value will be stochastic (Domencich and McFadden, 1975). We therefore assume that the random components can be expressed as $\varepsilon(e_{i0})$ and$\varepsilon(e_{i1})$. The value of weather information is therefore specify as V^*:

$$V^* = u\left[w_{i1,}\mathrm{x},\ \mathrm{z}(w_{i1}),\ r, n, \omega\right] +\ \varepsilon(e_{i1})\ \text{-}\ u\ \left[w_{i0,}\mathrm{x},\ \mathrm{z}(w_{i0}),\ r, n, \omega\right] +\ \varepsilon(e_{i0}) \tag{8}$$

A utility-maximizing farmer uses weather information if value is positive:

$$V^* = \left\{u\left[w_{i1,}\mathrm{x},\ \mathrm{z}(w_{i1}),\ r, n, \omega\right]\ \text{-}\ u\ \left[w_{i0,}\mathrm{x},\ \mathrm{z}(w_{i0}),\ r, n, \omega\right]\ \right\} - \left[\varepsilon(e_{i1})\ \text{-}\ \varepsilon(e_{i0})\right]\ >\ 0 \tag{9}$$

The value of weather information V^* is not observed but the discrete choice$V$, that is, weather information used or not, is observed. If $\varepsilon(e_{i0})$ and $\varepsilon(e_{i1})$ are each normally distributed then their difference $u = \varepsilon(e_{i1}) - \varepsilon(e_{i0})$ is also normally distributed. If we assume that:

$$\{u[w_{i1}, \mathrm{x},\ \mathrm{z}(w_{i1})\ , r, n, \omega] - u[w_{i0}, \mathrm{x},\ \mathrm{z}(w_{i0}), r, n, \omega]\} \tag{10}$$

can be written as a linear function of variables, then:

$$V^* =\ \alpha' \mathrm{x}_i\ +\ \beta' z(w_{i1})\ +\ \varphi' z(w_{i0})\ +\ \rho r\ +\ \eta n\ +\ v, \tag{11}$$

where $\alpha,\ \beta, \varphi, \rho,$ and η are regression coefficients, V=1 if$V^* > 0$ and$V = 0$ if otherwise. If v is normally distributed, it becomes standard probit regression (Madalla, 1983). Much of the literature on the value of weather information focuses on estimating value of information to users. A growing number of practitioners are using Contingent Valuation Method (CVM) to directly elicit users' Willingness to Pay (WTP) for weather and climate information and services, given that people only use services they value (Anaman and Lellyett, 1996; Anaman and Lellyett, 2007; Chapman, 1992; Rollins and Shaykewich, 2003). This study applied Contingent Valuation Method to determine market value of weather information by estimating farmers' willingness to pay for improved weather information in the derived savannah of Central Southern Nigeria.

2.3. Model framework

Given that an individual seeks to maximize utility of a good (weather information) subject to a given constraint. It is assumed that every farmer pursues the objective of maximizing utility, but each farmer has personal perception of utility and constraints and makes willingness to pay decisions based on the unique attributes of his own situation (Gebremariam, 2013). Therefore, the WTP for climate information services is assumed to depend upon the set of attribute values that apply to the particular farmer. The econometric analysis for the WTP depends on the type of elicitation method, the type of question and the structures of the responses. In cases where the dependent variable has a zero value for a significant fraction of the observations, a Tobit model is required (Terra, 2004) because standard Ordinary Least Square (OLS) technique results in biased and inconsistent parameter estimates, that is, they are biased even asymptotically (Maddala, 1983). The Tobit model identified characteristics of farmers that determine WTP for the use of weather information.

Following Greene (2000), the Tobit model is generally expressed as (Tobin, 1958):

$$WTP_i = X_i\beta + u_i \quad X_i\beta + u_i > 0 \tag{12}$$

$$WTP_i = 0 \quad X_i\beta + u_i \leqslant 0 \tag{13}$$

where for the i^{th} farmer, X_i is a vector of explanatory variables, u_i is a random disturbance term, and β is a parameter vector common to all farmers. Let's assume the random error is independent and normally distributed across respondents, the expected WTP for an observation drawn at random is:

$$E(WTP) = \Phi\left(\frac{X\beta}{\sigma}\right)X\beta + \sigma\phi\left(\frac{X\beta}{\sigma}\right) \tag{14}$$

where Φ is the normal distribution function, ϕ is the normal density function, and σ is the standard deviation. Further, the expected value of WTP for observations above zero, referred to as$E(WTP^*)$, is simply $X\beta$ plus the expected value of the truncated normal error terms (Amemiya, 1973). Then, the expected WTP can be expressed as:

$$E(WTP) = \Phi\left(\frac{X\beta}{\sigma}\right)E(WTP^*) \tag{15}$$

However, it should be known that unlike linear models, the marginal effect or partial derivative for a given explanatory variable is nonlinear and thus$\neq \beta_i$. The decomposition of this marginal effect that is obtained by considering the effect of a change in the i^{th} variable of $\boldsymbol{X}$ on WTP (McDonald and Moffitt, 1980) is stated as:

$$\frac{\partial E(WTP)}{\partial X_i} = \Phi\left(\frac{X\beta}{\sigma}\right)\left(\frac{\partial E(WTP^*)}{\partial X_i}\right) + E(WTP^*)\left(\partial\Phi\frac{\left(\frac{X\beta}{\sigma}\right)}{\partial X_i}\right) \tag{16}$$

The expected value of WTP as stated in equation (7) was evaluated at the mean of theXs, $\overline{X}$ with estimates of β andσ. The fraction of the total marginal effect due to the effect above the zero bid is:

$$\frac{\partial E(WTP^*)}{\partial X_i} = 1 - X\beta\phi\frac{\left(\frac{X\beta}{\sigma}\right)}{\Phi\left(\frac{X\beta}{\sigma}\right)} - \phi\frac{\left(\frac{X\beta}{\sigma}\right)^2}{\Phi\left(\frac{X\beta}{\sigma}\right)^2} \tag{17}$$

Therefore, the total marginal effect expressed as$\frac{\partial E(WTP)}{\partial X_i}$, using equation (15).

3. Methodology

3.1. Study area, sampling techniques and data collection

The study was carried out in Edo State, inland state of Central Southern Nigeria. Edo State has a humid tropical climate based on the Köppen climatic classification scheme. Rainfall in the area depends on the interaction of the tropical maritime (mT) and tropical continental (cT) air masses which meet along the Inter-Tropical Divergence (ITD) (Emeribe, et al., 2017). The three distinct vegetation types are mangrove forest, fresh swamp, and savannah. The rural population largely depends on agriculture as major livelihood activity such that subsistent arable crop production is responsible for 80% of agricultural production in the State (https://www.edostate.gov.ng/commercialagriculture).

A multi-stage sampling technique was used to select respondents for the study. Purposive sampling technique was used to select the North agricultural zone due to its increasing aridity with negative consequences for farmers' productivity, hence need of weather information for preparedness. Etsako East Local Government Area (LGA) was purposively sampled due to the ecological nature and effect of aridity in the derived savannah area while communities that heavily depend on agricultural livelihoods were also purposively selected as validated by Office of the Agricultural Development Programme (ADP). The third stage involved the purposive selection of communities which are heavily depend on agricultural livelihoods namely Ikhideu, Likpoke, Idumebo, Ekpoma, and Ukpoke communities, as validated by the Agricultural Development Project (ADP) Office. The last stage involved the random selection of respondents on the basis of probability proportionate to population size in each community to make up one hundred and ninety-three sampled farmers in the North agricultural zone. Structured questionnaire was administered on the respondents, and face to face interviews conducted to examine socio-economic characteristics influencing their decisions on kind of weather information useful to them. Focus Group Discussions (FGDs) were also held with family heads, and female groups with an average of ten to twelve number of participants gathered to make up a group for the FGDs. The map of the study area and farming communities are indicated in Fig. 1.

3.2. Data analysis

3.2.1. Descriptive statistics

Descriptive statistics such as means, frequency distributions, percentage, standard deviation, and minimum and maximum range were used to describe socio-economic and demographic characteristics of the respondents in the study area.

3.2.2. Contingent valuation method: dichotomous-choice model

Contingent Valuation (CV) method was used to estimate economic value of weather information by estimating farmers' willingness to pay for rainfall-based forecast information in the study. A Dichotomous-Choice Contingent Valuation Method (DC-CVM) format was used to elicit willingness to pay responses because it is more cognitively manageable and similar to the real buying scenario compared to Payment Card format (Gürlük, 2006; Ramajo-Hernandez and Saz-Salazar, 2012; Ojeda and Mayer, 2008; Solomon, 2008; and Saz-Salazar et al., 2009). The bid amounts to be presented to respondents for weather information was determined through a pretest that was used to control element of biases (Venkatachalam, 2004), which might affect free mention of WTPs. The pre-test was conducted with payment card distributed to individual farmers without allowing them to speak to each other or have idea of what the other was doing. Payment cards with different bid amounts were designed for selection based on actual household expenditures which have to be

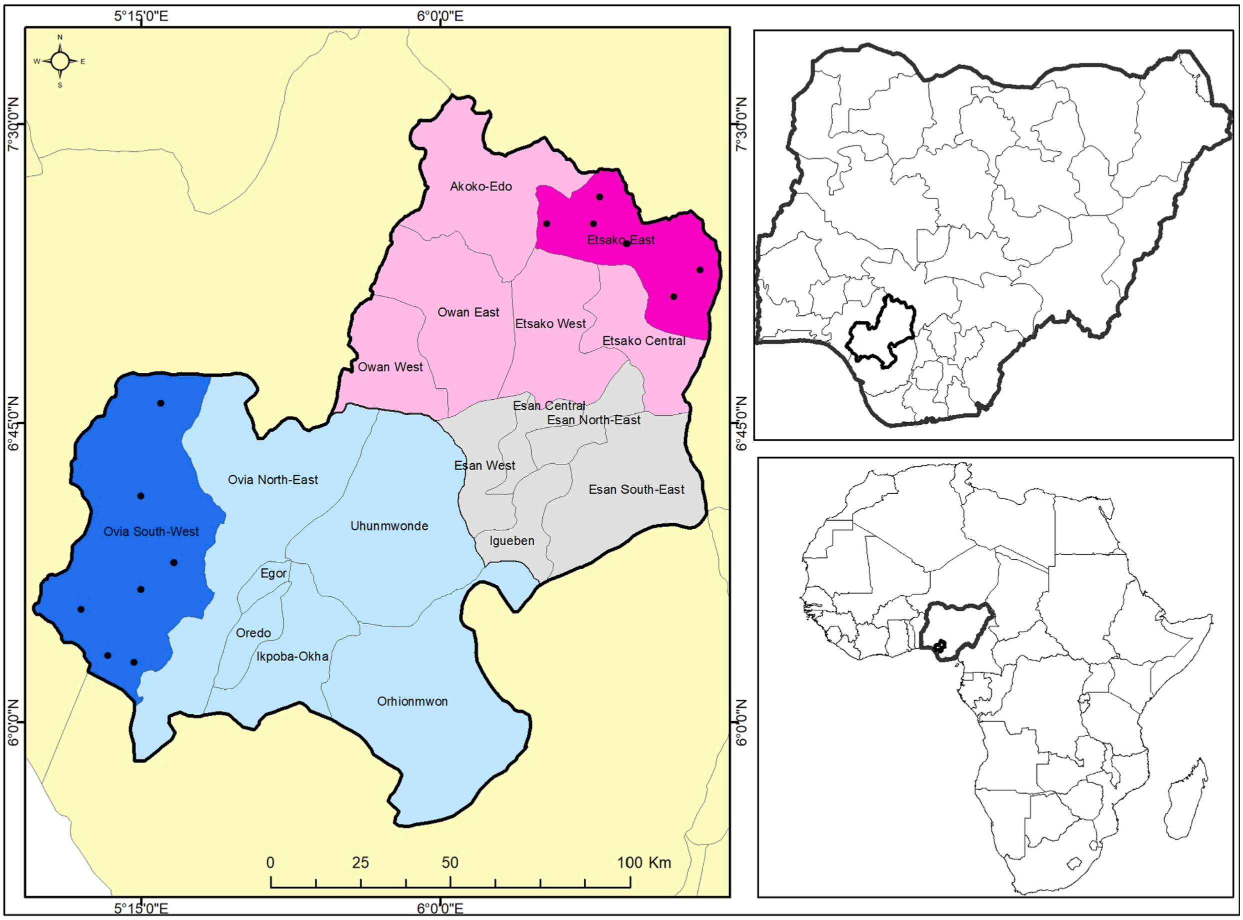

Fig. 1. Location of the Selected Communities in Edo State, Central Southern Nigeria (Source: Authors, 2019).

considered before decisions are made. This approach was helpful in fixing the bids close to reality before the main CV survey. This essence was to adjust the series of bid amounts, thereby improve the survey instrument used (Kima et al., 2007). The DC-CVM study questionnaire includes different sections in reference to theoretical literature (Amigues, 2002, Dutta et al. 2007; Johannesson et al. 1993; Ryan, 1998). The first section includes questions about respondent's socioeconomic characteristics, followed by awareness of usefulness of weather information as a strategy in weather risk management, while the final section contains the principal valuation questions with focus to evaluate the average amount of WTP.

A hypothetical market was presented to respondents to elicit their willingness to pay amount in the contingent valuation. The scenario was developed by stating that if the government or a private organization is ready to deliver weather forecasts to the respondents in which weather information will be made available through mobile phones, communicated in local languages, location-specific, and with agricultural extension services there is opportunity to request for feedbacks in form of agro-advisories on whatever weather information they wanted. The main valuation questions asked says that "*would you like to participate in the programme and pay money to financially assist government or a private agency for regular weather alerts and advisory services?*". A. Yes B. No. If "Yes", we proceeded with the question that "*in view of your household expenditures, how much are you willing to spend (a bid amount) every month to be receiving the mobile weather alerts and agro-advisory information in the next 3 years for a stable implementation*". In this format, respondents were asked to select among seven bid amounts: N50, N100, N150, N200, N300, N400, and N500 (N445 = $1 equivalent).

The theoretical model to explain respondents' WTP was based on the income compensation function if WTP is regarded as the desired benefit measure (Antony and Rao, 2010). In the equation (18), P is the prices for the marketed goods, q_1 is the benefit of the weather information, q_0 is the baseline of the weather forecast information, Q is the vector of other public goods, I is the income and C is the vector of the respondent's characteristics which affect their preferences and choices:

$$WTP_{(q1)} = F(P, q_1, q_0, Q, I, C) \tag{18}$$

The econometric analysis for the WTP in which the dependent variable has a zero value for a significant fraction of the observations, a Tobit model is required (Terra, 2004) because standard Ordinary Least Square (OLS) technique results in biased and inconsistent parameter estimates i.e., they are biased even asymptotically (Maddala, 198). The Tobit model can be defined as Tobin (1958):

$$WTP_i^* = \beta' X_i + \mu_i \tag{19}$$

$$WTP_i^* = \begin{cases} WTP_i^* \; if \; WTP_i^* > 0 \\ 0 \; if \; WTP_i^* \leqslant 0 \end{cases} \tag{20}$$

where WTP_i^* is latent or unobserved willingness to pay for weather information; WTP_i^* is farmer's willingness to pay for weather

Table 1
Distribution of Respondents by Socio-Economic Characteristics.

Farmers' Characteristics	Obs. (%)	Mean	Std. Dev.	Min.	Max.
Gender				0	1
Female	16.90				
Male	83.10				
Age of Farmers (years)	100.00	45.66	14.09	16	87
Education	100.00	8.91	6.09	1	16
No Formal education	24.00				
Adult literacy	6.10				
Primary education	18.20				
Junior Secondary education	2.60				
Senior Secondary education	17.60				
Post-Secondary education	31.60				
Farmer's experience (years)	100.00	23.98	13.44	2	76
House size (number)	100.00	10.36	5.92	1	31
Membership of Farmers' Group				0	1
Yes	65.80				
No	34.20				
Farm size (ha)		5.41	7.28	0.5	50
< 2.00	16.00				
2.00 – 10.00	75.00				
>10.00	9.00				
Formal credit (bank loan)				0	1
Accessed	24.90				
Not accessed	75.10				
Informal credit (cooperatives loan)				0	1
Accessed	63.90				
Not accessed	36.10				
Agricultural extension services				0	1
Accessed	55.30				
Not accessed	44.70				

Source: Field Survey, 2018.

information in a year; X_i is a vector of independent variables that are hypothesized to influence theWTP; β is unknown parameter vector to be estimated; ε_i is an error term which are assumed to be normally distributed with mean zero and constant variance. The expected value of WTP as stated in equation (7) was evaluated at the mean of theXs, $\overline{X}$ with estimates of β andσ. Following Souter and Bowker (1996), the sample mean WTP's were calculated by averaging the predicted WTP's for each individual in this study as follows:

$$WTP^* = \sum_{i=1,..n}^{n} \alpha + (\beta_i X_i) \tag{21}$$

The model parameters are estimated by maximizing the Tobit likelihood function of the following form:

$$L = \prod_{WTP^*>0} \frac{1}{\sigma} fln\left(\frac{WTP_i - \beta X}{\sigma}\right) \prod_{WTP^* \leqslant 0} \frac{1}{\sigma} F\left(\frac{-\beta X}{\sigma}\right) \tag{22}$$

where f and F are the density probability function and cumulative distribution function of WTP_i^* respectively. The Tobit regression was estimated using the tobit command in STATA 15.

4. Results and discussion

4.1. Socio-Economic information of the respondents

The socio-economic information of the respondents is presented in the Table 1. The result shows that there was a higher number of males (83.1%) than females (16.9%) in maize production. An average farmer is aged 45 years which implies that most of the respondents are within their economically active age. Over 70% have acquired formal education where on average a person has spent about 9 years in schooling and completed junior secondary education. Experience plays a key role in risk management decisions, hence farmers' experience distribution indicates an average of about 24 years spent in farming. On the average, household size comprises 11 members, while the largest household size was 31 persons which included both family and contract labour workers that are connected to a community leader. The large household size is an indication that adequate social interaction would have positive influence on smallholder farmers' decisions regarding use of improved weather information as a climate risk management strategy. They are better positioned to benefit from external exchange ideas on improved production technologies outside the family compared with households with small size.

The study revealed that 65.8% of the respondents hold membership of a farmers' group. Farmers' association is seen as a prominent, low cost and efficient channel of communication among members which could help facilitate use of weather information. Farm size cultivated was in the range between 0.5 and 50 ha. It was observed that 16% of the respondents were smallholders, 75% mediumholders while 9% large-holder famers (farm size above 10 ha) in the study area. This study support previous studies that majority of farmers in the savannah belt of Nigeria are medium-scale with an average farm size of 5.4 ha as indicated by the Federal Ministry of Agriculture, and the Food and Agriculture Organization (FAO). Given this result, medium scale farmers are expected to consider weather information in protecting their investments against erratic rainfall, late onset and dry spells common to the derived savannah area.

Formal credit (bank loan) was less accessed and only 24.9% of the farmers confirmed they have benefited from agricultural loans from commercial banks while 75.1% could not access any form of agricultural loans during the last farming season. In other words, informal credits through agricultural cooperatives were better accessed by 63.9% of the farmers to cushion them from the effect of poor access to commercial bank loans while 36.1% of the farmers could not access loans. Access to credit might enhance farmers' capacity in protecting their investments through climate smart activities by taking up weather information, to ensure good harvests that will enable them to pay back their loans. Weather advisory information could assist in guaranteeing loan repayments if they are used to improve decisions and minimize losses.

The distribution explained that 55.3% of the respondents have access to agricultural extension services while 44.7% do not have access. This distribution signals a weak agricultural extension service system, thus it is evident that about 45% of the respondents who have been cut off from agricultural extension services might not also have access to weather information and associated advisory services. Hansen et al. (2019) expressed that training agricultural extension services which farmers were already aware of and trusted through participatory communication processes will assist in translating climate information into advisories, and offer a potential opportunity for scaling up among users. In a study of the contribution of climate information services to agriculture and food production, and rural household incomes in selected countries of Africa, evidence showed that integration of climate information services into household decision making through extension services enhance resilient agriculture through well-informed agricultural management decisions (Alliagbor et al., 2020; Awolala, 2020; Awolala et al., 2022; Singh et al., 2018).

Similarly, the design of policies aiming to improve role of extension services in communities have great potential to improve farmer adaptation to changes in climate by encouraging farmers to adopt new technologies, improved methods of farming, using a variety of methods to reach farmers about their challenges (Maponya and Mpandeli, 2013; Muita et al., 2021).

4.2. Farmers' need of weather information timescale

On the aggregate, Fig. 2 expressed that about 86.4% of farmers were ready to pay for sub-seasonal to seasonal (S2S) forecast information, 38.6% confirmed that they will pay for weekly weather information services and 29.6% would pay for daily weather information, 86% would pay for medium range and short range time-scales respectively. Farmers are more interested in S2S which allows for sufficient time to make adequate adjustments or adaptation decisions that might likely be needed to avert future weather shocks in the savannah area. Weather service providers should focus their services more on forecasts capable of guiding farmers' agricultural planning decisions each month. The forecast timescales are importantly sufficient for farmers to take decisions on their agricultural investments and to know the overall effect of their decisions on their crops and livestock ahead of time.

The north of the savannah area is highly dry with increasing rainfall uncertainties, incidences of dry spells, and shortened growing season. Farmers in this dry area need to receive advance seasonal information for proper weather and climate risks management decisions. The Nigerian Meteorological Agency (NiMet) should give attention to this farmers' interest when designing weather products and services to meet their needs as an important factor which could influence market value of weather information in the study area.

4.3. *Willingness to pay responses*

Of all the 193 farmers interviewed on willingness to pay for S2S weather information in the North agricultural zone, 75.7% (146 respondents) of the sample reported a positive response to the willingness to pay question but 24.3% (47 farmers) reported zero WTP as presented in the Table 2 showing the willingness to pay responses. The lowest bid of N50.00 ($0.12) was accepted by 32.64% while the highest bid of N500.00 ($1.12) was accepted by 1.03% of the respondents sampled. The mean WTP was estimated after excluding the effect of protest responses as suggested by Hanemann (1989) and Heckman (1978). Given that those who reported zero WTP did not significantly differ from other respondents whose bids were accepted as legitimate and the percentage of protest zero values is negligible, hence protest zeros were censored for conciseness in the present analysis (Halstead et al., 1992; Jorgensen et al., 1999). The rationale for censoring protest zero values was based on the premise that after asking follow up questions, zero WTPs are regarded as protest responses when closed-ended dichotomous choice technique is used unlike open-ended valuation method (Loomis et al, 2022; Collins and Rosenberger, 2007).

The bid price of N50 ($0.12) for S2S weather information dominated the positive responses with 32.64% of the respondents, followed by N100 ($0.22) accepted by 22.79%, while N500 ($1.12) bid price was accepted by only 1% of the total sample by those who are willing to pay for weather information in the north agricultural zone. The frequency of the WTP bids for S2S weather information in the Fig. 3 further explains the spread of the distribution of both the positive and zero responses to the array of bid prices presented in the survey. Other bid prices such as N150, N200, N250, N300, N400, and N500 were ready to be paid each month by very few numbers of respondents. These ones are evidently those whose farm sizes and incomes were above average.

It can therefore be deduced that large numbers of farmers whose farm sizes and incomes are below average were those who largely accepted N50 ($0.12) and N100 ($0.22) bids. It is a matter of policy consideration that household incomes and farm sizes were factors that have been considered by users when deciding on the amount they were willing to pay for weather information every month. The respondents who reported zero WTPs were asked a follow-up question to mention reasons for not willing to pay for improved weather information. The main reasons given were inadequate income (44%), distrust in weather information owing to lack of weather stations in most of their areas (18%), perception that weather information is public good, hence government should pay (15%), need of

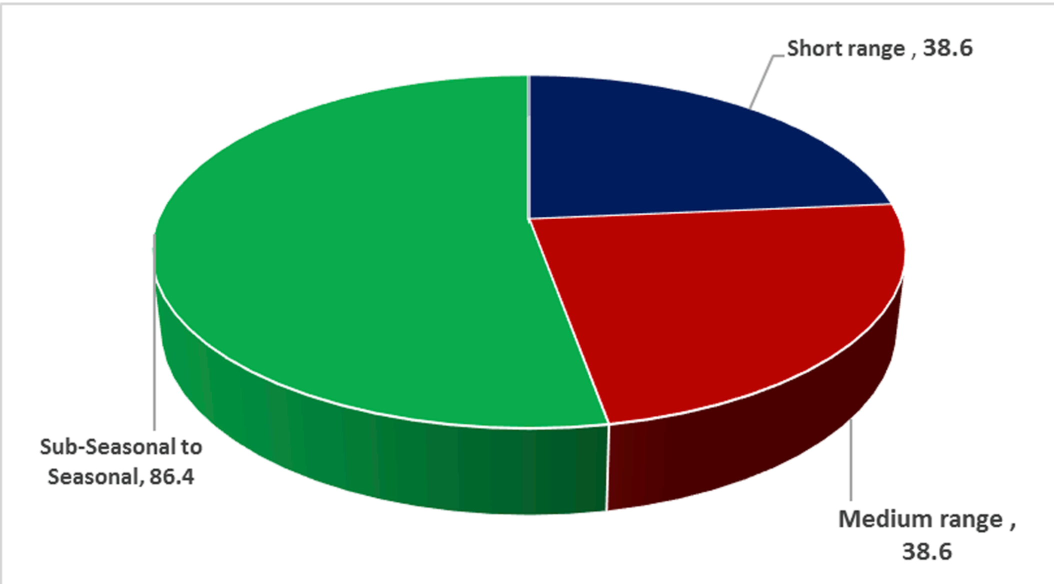

Fig. 2. Observed Responses on Willingness to Pay by Timescales.

Table 2
Distribution of WTP Amount for SubSeasonal-to-Seasonal Weather information.

Bid Amount	N50	N100	N150	N200	N250	N300	N400	N500	Sum
Sample size, N	69	55	23	17	7	10	7	5	193
WTP > 0	63	44	16	9	6	4	2	2	146
WTP = 0	6	11	7	8	1	6	5	3	47
Y(WTP > 0)%	32.64	22.79	8.29	4.66	3.11	2.07	1.03	1.03	
N(WTP = 0)%	3.10	7.53	4.79	5.47	0.68	4.10	3.42	2.05	

Source: Field Survey, 2018 (N445 = $1 equivalent).

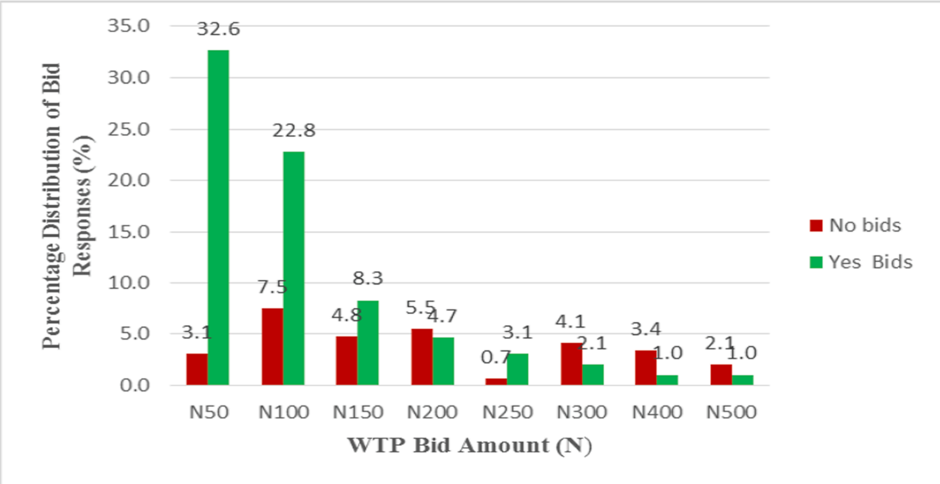

Fig. 3. WTP Bid Responses for Sub-Seasonal to Seasonal Weather Information.

Table 3
Annual WTP for Sub-Seasonal to Seasonal Forecast from Tobit Estimates.

Variables	Without protest zero		
	Coefficient (β_i)	Sample mean (X_i)	WTP (N) $\sum_{i=1,..15}^{146} \alpha + (\beta_i X_i)$
Sex	191.80	0.84	161.11
Age	5.17	45.33	234.35
Education	−54.83	3.91	−214.38
Farming experience	−8.16	24.33	−198.53
Farm size	57.83	6.99	404.23
Farmers' group membership	153.48	0.68	104.36
Access to informal loans	70.41	0.37	26.05
Agricultural extension services	72.52	0.55	39.59
Farm income (N)	0.00	559,979	0.00
Social capital	−5.54	8.85	−49.03
Access to market linkage	−321.45	0.71	−228.23
Ecology	18.69	1.59	29.71
Weather station installed	−87.50	0.26	−22.75
Radio ownership	264.33	0.67	177.10
Mobile phone ownership	−96.47	0.67	−64.64
Constant	**(a)** 1173.77		
Log likelihood	−1792.23		
LM test for tobit	68.62		
$\sum_{i=1,..15}^{146} (\beta_i X_i)$			**(b)** 398.97
$\sum_{i=1,..15}^{146} \alpha + (\beta_i X_i)$	(a) + **(b)**		
Mean WTP (N)	N1,572.74		

Source: Field Survey, 2018 (N445 = $1 equivalent). □As a reference, a N100 could only buy a small bottle of coke in rural Nigeria. Hence, a farmer will be willing to pay an average of N145 ($0.32) to access monthly weather information. This low amount might suggest that farmers are still in doubts of the gains of using weather information in their crop management decisions. However, the robust predictive margins from Tobit model estimated a WTP margin value of N1600 ($3.60) annually.

evidence that weather information will yield profit (12.6% of respondents), and 10.4% primarily do not trust such innovative initiative. Other reasons for zero WTP values which are not due to lack of value or inability to afford a positive WTP were considered as a protest vote since they do not reveal their valuation probably because of being disagreed with the payment vehicle used or they rejected some element of the valuation (García-Llorente *et al.,* 2011; Gonzalez-Caban et al., 2007). During a focus group discussion, large farm size and farm location-specific weather information were identified as major farm characteristic contributing to positive responses on the willingness to pay for weather information while higher farm-income and mobile phone communication outlet were the socioeconomic factors influencing respondents demand for weather information services.

4.4. Estimating economic value of weather information

With the clear presentation of the hypothetical market scenario, the economic value of S2S weather information was determined. The average amount estimated from respondents who were willing to pay was N145.32 ($0.32) per month with the median value of N120 ($0.27) per month was obtained. Given the more robust predictive margins from the Tobit model result, the margin value expressed the average annual amount of about N1600 ($3.60) per respondents per year. The lowest average annual WTP obtained was N600.00 ($1.34) while the highest WTP was N6000.00 ($13.5). The amount with highest frequency was N1200.00 ($2.70) while the median WTP was also N1200.00 ($2.70) per annum for sub-seasonal to seasonal weather information in the derived savannah area. The estimated value obtained from Tobit model estimates is presented in the Table 3 which indicate that the positive coefficients of the socio-economic factors increase the value of amount respondents were willing to pay for weather information while the negative coefficients reduce the value of payments.

4.5. Determinants of Farmers' willingness to pay amount

The estimates from result presented in the Table 4 show a significant inverse relationship between education and WTP for sub-seasonal to seasonal (S2S) weather information. The negative coefficients of the marginal effects are the same across both Tobit models without protest zero and with protest zero values. It shows that an additional 1 year increase in education significantly results in about N55 ($0.12) decrease in average demand from the respondents. The marginal WTP for a one hectare increase in farm size cultivated would significantly result in a N58 ($0.13) increase in the WTP. This result was found to be robust across the two Tobit models regardless of whether protest bidders are included or not. The result appears to suggest that as farmers increase their farm land, their pricing amounts for weather information will also increase. Farm income was also found to contribute infinitesimal increase in WTP when farm income increases.

Access to market linkage was found to be negatively related to the amount WTP. The negative marginal effects indicates that when access to market linkage improves, the likelihood to pay (WTP) would be reducing especially in the Tobit model without protest zero but positive to increase WTP with protest zero values. The respondents are committed to the social networking through socio-cultural affiliations that encourages free share of information and market discussions. This affiliation in turn encourages strong market linkages through which seasonal weather information are transmitted across communities. This strengthens farmers' capacity of making the right decisions on their agricultural investments. These benefits through market linkages and networks tend to reduce amount they are willing to pay for weather information which they consider as foreign to their communities in most times. Likewise, increasing radio ownership was found to significantly increase amount of WTP. Radio ownership was found to be positive in both models indicating

Table 4
Tobit regression estimates of major drivers of pricing amount.

Variables	Without protest zero		With protest zero	
	Marginal effects	Sample mean	Marginal effects	Sample mean
Sex	191.80	0.84	−189.52	0.83
Age	5.17	45.33	5.43	45.66
Education	−54.83*	3.91	−190.43	3.78
Farming experience	−8.16	24.33	8.22	24.98
Farm size	57.83***	6.99	1487.54***	5.34
Farmer_Group membership	153.48	0.68	196.513	0.65
Access to informal loans	70.41	0.37	−362.93	0.36
Agric. Extension services	72.52	0.546	−529.63	0.55
Farm Income (N)	0.00*	559,979	0.00	483,670
Social capital	−5.54	8.85	−8.97	8.66
Access to Market linkage	−321.45**	0.71	69.78	0.71
Ecology	18.69	1.59	−604.95	1.58
Weather Station Installed	−87.50	0.26	227.46	0.30
Radio_Ownership	264.33*	0.67	801.55	0.68
Mobile Phone_Ownership	−96.47	0.67	−1012.79	0.69
Constant	1173.77		311.10	
Log likelihood	−1792.23		−3161.29	
LM test for tobit	68.62		469.35	

***Statistical significance at the 1% level; **Statistical significance at the 5% level; *Statistical significance at the 10% level.

that respondents considered weather information as a public good that should be freely available for use, thus the amount of WTP was not significant in the model with zero protest values. However, in the model without zero protest values, radio ownership was significant and increases the amount of WTP. Other factors that increase amount of WTP for weather information although not significant are male gender, farmers' age, farmers' group membership, informal loans access, agricultural extension services and perceived drier ecology.

Surprisingly, mobile smartphone ownership has a negative coefficient with farmers' decisions on amount of WTP. It was found that in the both models, mobile phone ownership reduces the amount which respondents are willing to pay for weather information, although not significant. This result although contradict some studies in the sub-sahara Africa in which access to mobile phone drives uptake of weather information (Krell et al, 2020; AcreAfrica, 2020; Ouédraogo, et al., 2017; Akinola et al., 2017; Caine et al., 2015). Nevertheless, this result is specific to the rural central-Southern Nigeria where majority if the respondents complain that they prefer radio broadcast to mobile phone to access weather information because this communication channel is the most cost-effective for smallholder farmers since they do not have to spend money to recharge airtime or data before they could access some information at local scale. These are considered as additional transaction cost which had prevented increase in the amount farmers are willing to pay for accessing weather information through mobile phone. Another major mean of sharing agricultural innovations or information are commonly through membership of farmers' association or farmers' groups which majority of the respondents find so convenient and trusted in assessing information faster than any other mean.

The Guardian (2021) observes that Nigeria has about 170 million mobile phone users based on subscriptions. However, only 10 to 20% of the population uses smartphones while the rest rely on more traditional mobile phones, thereby limiting their options to voice calls and text messages. Therefore, it has become a development challenge to improve access to and the usage of mobile smartphone services for wide coverage of weather information uptake. This is an important policy variable that must be addressed to expand the uptake of weather information and willingness to pay for improved weather information in the study area.

4.6. Potential market demand from pricing of weather information

The annual aggregate market value of S2S weather information was determined by the total number of registered farmers in Edo State, Central Southern Nigeria based on the 2016 farmers' census. The aggregated annual market value of N1.30 billion ($2.9 m) was obtained in the Northern agricultural zone of Edo State in Central Southern Nigeria. With a broader policy perspective, should there be improvements in those policy variables that negatively influence farmers WTP amount decisions for weather information, especially education, farming experience, social capital, access to market linkage, weather station installation and mobile phone ownership, then the estimated market value is also expected to change given that the number of positive WTP responses will increase over time. As observed in the Table 5, in a simulated situation of improved mobile phone disseminating channel with an increase of 5% in the total number of farmers expected to have a positive valid response of WTP, the aggregated market value of weather information was valued at N1.38 billion ($3.1 m) annually from S2S forecasts annually. This represents an addition of over N86, 047,000.00 ($193,360) market value to the weather service providers each year.

The emerging market potential of S2S weather information computed from the predicted aggregate annual market value for Central-Southern Nigeria is presented in the Table 6. The Central-Southern Nigeria, which comprises six states namely Kogi, Benue, Edo, Ebonyi, Anambra, and Enugu States, has 72% of its 30million population as non-registered farmers. The aggregate market for weather information was estimated as over N17.43billion ($39 m) annually through monthly weather advisory services by the meteorological service agency. The economic value of weather information has a promising market for weather service operators and delivery institutions. This will expand the potential demand and use of weather information products and services by smallholder farmers in the dry savannah area. More capital investments in climate information infrastructure will facilitate uptake and use of climate information services and encourage co-production through public–private partnerships of operators in achieving resilient agriculture and food production among smallholder farmers in Central-Southern Nigeria.

5. Conclusions and policy implications

Farmers in the derived savannah area of Central-Southern Nigeria are vulnerable to erratic rainfall and dry spells which confirm effects of weather uncertainties in the savannah area. They are mostly interested in sub-seasonal to seasonal (S2S) weather information rather than seasonal weather outloook or long term climate predictions. The S2S forecast timescales are considered adequately

Table 5
Estimated annual value for weather information in the study area.

Weather Information	Total (Registered) Farmers	% Willing to Pay for Weather Information	Expected Farmers Willing to Pay (TWTP)	Estimated Market Value of WTP per Year (N)	Aggregated Market Value (N)*
Sub-Seasonal to Seasonal forecast	1,094,232	75.7	828,333.62	1,572.74	1,302,753,423.80
	Market value at 5 % point increase in farmers' WTP if mobile phone dissemination improves				
	1,094,232	80.7	883,045.22	1,572.74	1,388,800,545.59

*1USD ($) = N445.

Table 6
Estimated annual value for S2S weather information in Central-Southern Nigeria.

Weather Information	Total Number of Farmers	% Willing to Pay for S2S	Expected Farmers Willing to Pay (TWTP)	Predicted Market Value of WTP per Year (N)	Aggregated Market Value (N)*
Sub-Seasonal to Seasonal forecast	14,636,804	75.5	11,080,060.63	1,572.74	17,426,054,555.23

*1USD ($) = N445.

sufficient to take adjustments or adaptation decisions to avert likely future weather shocks that may affect agricultural investments ahead of time. The study found that over 75% were willing to pay for improved weather information, largely enthusiastic about dissemination channel mainly through mobile phones which will enhanced their prompt decision making without delay, and likewise through farmers' groups leveraging on their existing informal networks. Farmers with large farm sizes and higher farm-income were found to show interest in paying higher prices while mobile phone dissemination channel and farm location-specific weather information were major factors which influences how much farmers would be willing to pay for improved weather information services. The major significant reasons mentioned by the 24.3% of the population, those not willing to pay for weather information were inadequate incomes, lack of trust in accuracy of weather information, the perspective that weather information is public good, hence it is government responsibility, and the proof of evidence that improved weather information would yield profit to them in the derived savannah area.

On the average, a farmer would pay about N1,600 ($3.6) annually to receive improved weather information as monthly service. If disseminated through mobile phones, the aggregated annual market value of improved weather information was estimated to be N1.30billion ($2.9 m), as obtained in the derived savannah area of Edo State. It would be over N17.43billion ($39 m) annually from monthly forecast services in the whole area of Central-Southern Nigeria. Improved level of education and market linkages would significantly decrease farmers' average amount they are willing to pay for improved weather information while increasing farm size, rising farm incomes, and radio ownership increase the average WTP amount. Male gender, age of farmers, farmers' group membership, access to informal loans, access to agricultural extension services and perceived drier ecology were socio-economic factors that would increase average pricing of improved weather information although significantly.

The outcome of this study emphasizes the need to upscale initiatives that focus on disseminating not only weather forecasts to farmers but agro-advisory weather services so that it could facilitate uptake. The Nigerian Meteorological Agency (NiMet) that is the official weather service provider should produce weather information based on forecast time-scales that are relevant to meet farmers' climate smart decision needs specifically sub-seasonal to seasonal weather information which allows the closest sufficient time to take adaptation actions. This is an important factor which determines economic value of weather information in Central-Southern Nigeria.

The mode of disseminating weather information to farmers to enhance their uptake and early preparedness actions should be revamped given the result-based evidence that farmers' groups and existing market linkages are the dominant information dissemination pathways in the region. NiMet should consider a framework by which they co-produce and deliver weather services by linking with these local institutional arrangements and other non-governmental agencies to form a public–private partnership delivery system. NiMet should consider factors influencing farmers' positive responses towards payment for improved weather information. There should be frantic efforts by NiMet to invest in re-orientation of educated farmers, large scale farmers and farmers with high income as important part of the farming population which can be sensitized to enhance economic value of weather information. Public access to improved weather information should be enhanced by developing mobile phone delivery system and ensure provision of location-specific forecasts to farm communities to fast track uptake. This will enhance farmers' decision to pay and thereby improve the economic value of weather information services in Nigeria.

NiMet should collaborate with telecommunication service providers especially Mobile Telecommunication Nigeria (MTN) and Globacom Nigeria Limited in communicating weather information through farmers' mobile phones. This will allow farmers to have quick information and feedback mechanisms between farmers and weather service providers. It will further enhance the efficiency and performances of NiMet to broaden its service coverage in Nigeria. The predicted market value of weather information reveals an emerging market for weather services, especially for the private sector in Nigeria. The Federal government should review the NiMet Establishment Act to develop new weather services policy and legislation that will encourage Public-Private Partnership in the collection, analysis, interpretation and communication of improved weather information as a business enterprise by private institutions and agencies with the technical capacity in Nigeria. This will ensure efficient and wider uptake by the rural farming population in Nigeria.

Declaration of Competing Interest.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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