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Incorporating expert knowledge in the estimate of farmers' opportunity cost of supplying environmental services in rural Cameroon

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Abstract. This paper applies a Bayesian approach to incorporate non-data information in estimating the opportunity cost for farmers in rural Cameroon to engage in biodiversity conservation and carbon sequestration efforts. Findings from our field survey reveal that only a small percentage of farmers are willing to participate in environmental protection programmes without compensation. A multidimensional preferences analysis indicates that this behavior may be attributed to a disconnection between environmental values and socioeconomic values. Bayesian analysis of the Tobit model, examining Willingness to Accept (WTA) compensation for agroforestry participation, highlights that factors such as aging, higher educational attainment, and higher socioeconomic status are highly likely to promote pro-environmental behaviors. The estimated opportunity cost of supplying environmental services is 10,775 CFA francs with a standard deviation of 333.6 CFA francs per farmer. These results differ qualitatively from the existing literature, underscoring the relative significance of considering expert knowledge in the interpretation of environmental policies.

Keywords: Bayesian analysis, environmental services, stated preferences, opportunity cost, rural Cameroon.
JEL codes: Q57, C34, C11.

1. INTRODUCTION

Nature plays a crucial role in supporting human development; however, the increasing demand for the Earth's resources is leading to accelerated extinction rates and a decline in global biodiversity and ecosystem services. According to the International Panel on Biodiversity and Ecosystem Services (IPBES, 2019), the average abundance of native species in major land-based habitats has decreased by at least 20%, primarily since 1900. Additionally, more than 40% of amphibian species, nearly 33% of reef-forming corals, and over one-third of marine mammal species are currently facing threats. Recognizing this global challenge, governments worldwide are taking action to incorporate biodiversity and ecosystem services into their development plans, policies, and strategies (IPBES, 2019). These initiatives include targets

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such as regenerating vegetative cover in the agricultural sector, enhancing agricultural productivity, and reducing the amount of land used for agriculture through the implementation of intensive agricultural systems.

Farmers, being at the forefront of environmental conservation in agriculture, play a crucial role. The effectiveness and efficiency of government incentive mechanisms depend not only on the specific design of the schemes (Bareille et al., 2023) but also on the values farmers associate with ecosystem services and the opportunity costs associated with adopting sustainable agricultural practices (Karsenty et al., 2010; Bessie et al., 2014; Kernecker et al., 2021). By taking into account farmer preferences and expectations in the design of government incentive schemes, we can identify the factors that determine the social acceptability and economic efficiency of these schemes. Conducting research to assess farmer preferences and expectations, as well as estimating farmers' willingness to accept compensation (WTA) for providing environmental services, is essential in this context. Farmers' WTA to participate in environmental protection programmes reflects the opportunity cost of supplying environmental services. In other words, farmers express their preferences by assigning selling prices to environmental services, which can be used for their valuation (Brown and Gregory, 1999; Hanley and Czajkowski, 2019).

The economic literature on the adoption of payment for ecosystem services (PES) schemes using a Stated Preference (SP) approach is extensive (Carson, 2012; Villanueva et al., 2017; Johnston et al., 2017; Hanley and Czajkowski, 2019; Wang and Nuppenau, 2021; Raina et al., 2021; Viaggi et al., 2022). However, most SP studies rely on respondents' hypothetical choices as data to infer their preferences and, consequently, their WTA for changes in environmental services. As noted by Haghani et al. (2021), the hypothetical nature of SP choice settings introduces a hypothetical bias, leading people to systematically over or understate their WTA values in SP exercises. This bias arises because no actual payment is made or received in exchange for a change in the quantity or quality of environmental services. Current research on hypothetical bias in SP approaches focuses on understanding its causes and developing methods to mitigate it. One approach to mitigate

hypothetical bias is the use of "cheap talk" scripts, which aim to improve the realism of hypothetical scenarios and reduce the influence of social desirability biases. However, the effectiveness of cheap talk as a bias mitigation tool varies depending on the context and the specific script used, as highlighted by Bosworth and Taylor (2012) and Doyon et al. (2015).

Another approach to mitigating hypothetical bias is to use "non-hypothetical" or "real" choice experiments (Menapace and Raffaelli, 2020; Fang et al., 2021; Cerroni et al., 2023). These experiments involve asking participants to make actual choices rather than hypothetical ones, and they can be conducted in laboratory or field settings. Real-choice experiments have been found to reduce hypothetical bias in some contexts, although they can be more expensive and logistically challenging to implement compared to hypothetical choice experiments. In addition to these methodological approaches, researchers are exploring the use of behavioral interventions to reduce hypothetical bias. Vossler and Holladay (2016, 2018) suggests that framing survey questions in a way that emphasizes the importance of the decision or providing feedback on the accuracy of participants' responses may encourage more truthful and accurate responses. However, it is important to note that survey-based welfare measures for public environmental goods are often sensitive to elicitation methods, such as whether the elicitation is framed as an up-or-down vote or an open-ended willingness-to-pay question. Controlling for economic incentives, Vossler and Zawojska (2020) show that most survey response formats, including single binary choice, double-bounded binary choice, payment card, and open-ended formats, elicit statistically identical WTP distributions. This finding highlights that behavioral factors may not be the primary drivers of elicitation effects.

Overall, research on hypothetical bias in SP approaches is an active and evolving field, with ongoing efforts to understand its causes and develop effective mitigation strategies. Reducing hypothetical bias in choice experiments requires not only careful survey design but also the integration of non-survey data information and expert knowledge. Non-data information refers to prior knowledge or assumptions derived from sources other than observed or survey data, such as expert opinions, previous studies, or theoretical considerations (Knuiman and Speed, 1988; Gelman et al., 2013; Mahmoud et al., 2020; Awwad et al., 2021; Hegazy et al., 2021). Incorporating non-data information in SP studies is particularly valuable when survey data is limited, noisy, biased, or when complex problems demand additional information for accurate analysis. By accounting for non-data information, we can improve analysis accuracy, mitigate the impact of outliers or measurement errors, and enhance understanding of economic agent preferences and behaviors (Kadane and Lazar, 2004; Gelman et al., 2013; Kruschke, 2013). However, it should be noted that incorporating non-data information poses challenges compared to analyzing survey data alone. Despite its potential, there have been limited studies explicitly considering expert knowledge or non-data information to address hypothetical bias in choice experiments. This is partly explained by the difficulty to capture expert knowledge in current WTA modelling frameworks, which usually rely exclusively

on survey data to estimate the unknown parameters of agent preferences. This paper explores an approach that utilizes non-data information to constrain the range of unknown parameters of agent preferences and aims to reduce hypothetical bias in estimating WTA values.

To achieve our objective, we start by conducting a field survey in Barombi Mbo, a rural area in Cameroon, to gather data on the socio-economic and environmental conditions of farmers. The survey includes information on farmers' willingness to accept (WTA) compensation for participating in agroforestry and afforestation programmes. Additionally, we employ a Multidimensional Preferences Analysis (MPA), a technique used to develop spatial representations of proximities among psychological stimuli or other entities (Carroll and Chang, 1970; Wish and Carroll, 1982; Davison, 1983), to gain insights into the contextual socio-economic and environmental values of the farmers in Barombi Mbo. This analysis helps us understand the various factors influencing farmers' decision-making processes. We then extend a Tobit model, originally proposed by Tobin in 1958, to estimate the WTA values. The Tobit model accounts for the presence of censoring or truncation in the WTA data. Furthermore, we incorporate stochastic constraints in the model's parameters using prior distributions. These prior distributions capture our expert knowledge or expectations regarding agent preferences when engaging in environmental protection programmes. By adopting a Bayesian approach, we update our knowledge based on the data and obtain posterior estimates of the model parameters. The results of our analysis indicate that a significant majority of farmers in Barombi Mbo are willing to participate in agroforestry and afforestation programmes if their financial constraints are alleviated. Furthermore, we find that a higher socio-economic status is likely to promote pro-environmental behaviors among farmers, while increased knowledge on environmental protection strategies alone does not necessarily lead to eco-friendly behaviors. Based on our Bayesian estimation, the distribution of farmers' WTA is found to be normally distributed with a mean of 10,775CFA franc and a standard deviation of 323.59CFA franc. Moreover, we estimate the opportunity cost of providing environmental services for farmers in our study area to be approximately 3,290,448CFA fanc per year.

Our research findings demonstrate qualitative differences from the existing literature (Moukam, 2021; Gou et al., 2021; P´erez-S´anchez et al., 2021). While previous studies have acknowledged the potential of employing a Bayesian approach for modeling ecosystem services (Landuyt et al., 2013; Ban et al., 2014; Uusitalo et al., 2015; Hofer et al., 2020), a review of these studies reveals that the technique is not yet fully utilized. It has been highlighted in Hofer et al. (2020); Moukam (2021); Gou et al. (2021); P´erez-S´anchez et al. (2021) that the standard approach for modeling ecosystem service delivery relies solely on data, without incorporating expert knowledge, which can lead to controversial results regarding the drivers of economic agent behavior for environmental protection. In contrast to the aforementioned studies, our approach incorporates expert knowledge through the utilization of prior distributions for the model parameters. By doing so, we not only provide mean-

ingful insights into the determinants of economic agent preferences but also significantly improve the estimation of WTA compensation for participation in environmental conservation efforts. This allows us to account for situations where the available data may not adequately capture the tangible and intangible benefits of the environment. Our results suggest that the conditional probability of the parameters provides the best summary of the knowledge we can gain from the data.

The remaining sections of the paper are structured as follows. Section 2 provides a description of the study area, emphasizing its agroecological characteristics and the availability of agricultural extension services. In Section 3, we outline the research methodology, including details on the survey design, data collection process, and analytical methods employed. The obtained descriptive statistics, research findings, and their discussions are presented in Section 4. Finally, Section 5 serves as the conclusion of the paper, summarizing the key points and providing policy implications based on the findings.

2. BAROMBI MBO AREA IN CAMEROON

2.1. Agro-ecological characteristics

The rural area Barombi Mbo is located in the Meme Division of the Southwest region of Cameroon and is one of the villages near the periphery of Lake Barombi Mbo, just after the Forest Reserve (indicated by a black line in Figure 1). It was created in 1940 by the colonial government to protect the Lake, and the local inhabitants (natives) were granted the rights to fish in the Lake and harvest cocoa in existing farms within the Reserve (RIS, 2008). However, over the years, the resources attracted an increasing number of people, leading to the exploitation of illegal farming, hunting, timber, and non-timber forest products (NTFPs), coupled with uncontrolled fishing (Agbor, 2008; Sounders and Kimengsi, 2011; Tchouto et al., 2015).

The major food crops grown in the region include cassava (Manihot esculenta), plantain (Musa paradisiaca), Egusi melon (Cucumis sativus), maize, cocoyams, and taro (Colocasia antiquorum). Cocoa, palm oil, and rubber are the major cash crops in the zone, which is characteristic of the humid forest agro-ecological zone of the Southwest region of Cameroon. Barombi Mbo experiences a typical equatorial climate with a long rainy season from March to November and a short dry season from December to February. The village is known for its hot weather, with an average annual temperature ranging from 20°C to 30°C, as reported by the Delegation of Agriculture of Kumba. However, according to the most recent survey (RIS, 2008), the mean annual temperature is approximately 18°C or even lower at higher altitudes, with annual precipitation ranging from 1825 to 3000mm. The area has undergone significant climate change, with rains sometimes starting earlier in March and unexpected rainfall occurring during the dry seasons. In 2010, the rainy season extended until December, disrupting the planting and production of cash and food crops, as well as other economic activities, which typically end in October-November in previous years (Sounders and Kimengsi, 2011; Lebamba et al., 2012; Tchouto et al., 2015).

Furthermore, the area consists of steep slopes that are prone to erosion, and it is characterized by a mixture of soils, including limon, laterite, sandy, clay, and volcanic soils. These soils, which have a high content of andosols, are predominantly composed of dark volcanic materials. They are generally fertile and suitable for cultivating both food and cash crops. However, in deforested and degraded areas, soils are gradually losing fertility due to increased slash and burn practices, soil exposure, pollution, and overcropping (Sounders and Kimengsi, 2011; Tchouto et al., 2015). Agriculture is increasingly encroaching on the area, leading to the reduction of forested areas. As a result, the intensified use of fertilizers in agriculture has led to the pollution of the lake.

2.2. Agricultural extension services

Several types of sustainable agricultural practices have been promoted among farmers in the Meme Division by the Ministry of Agriculture and Rural Development (MINADER), including farmer field school and farmer business school. Through farmer field school, MINADER trains farmers on good agricultural practices in collaboration with cooperatives, while farmer business school focus on promoting agroforestry as a source of income. MINADER provides farmers with improved corn seedlings, maize seeds, cassava cuttings, as well as some pesticides and fertilizers. However, farmers face difficulties in adopting agroforestry practices due to the scarcity of improved agroforestry species or nurseries and limited access to productive agricultural land for planting. It is important to note that Barombi Mbo village is not one of the communities targeted by MINADER due to its proximity to the forest reserve, which is managed by the Ministry of Forestry and Wildlife (MINFOF). Due to the lack of collaboration between these two government institutions at the field level, Barombi Mbo farmers are unable to learn about or benefit from agroforestry practices supported by MINADER.

3. METHODOLOGY

This section outlines the methodology employed to estimate the opportunity cost for farmers in the Barombi Mbo area of Cameroon to adopt agroforestry and afforestation practices. We present the conceptual framework, survey design and data collection methods, modeling framework, and the integration of expert knowledge.

3.1. Conceptual framework – Contingent valuation

Sustainable agricultural systems, such as agroforestry, deliver and maintain a range of valuable positive environmental externalities, including wildlife habitat and climate mitigation. They have been proven to be less vulnerable to shocks and stresses (VERMA et al., 2016; Gama-Rodrigues et al., 2021). Since these environmental benefits are typically considered public goods, private ranches are often less motivated to supply them at their optimal levels. Additionally, a standing forest typically represents a potential source of income that can be accessed through logging or farming in the case of sudden need (Bacon et al., 2012; Gama-Rodrigues et al., 2021). Farmers may thus be unwilling to introduce changes in their production systems that involve a loss of these potential income sources. Therefore, a valuable approach to promoting biodiversity conservation and carbon sequestration is the PES, which provides financial transfers to landowners, farmers, and communities whose land-use decisions may affect the biodiversity values and climate change. PES creates incentives for the conservation of plant and animal species, as well as the soil quality (Engel et al., 2008; Ito, 2022).

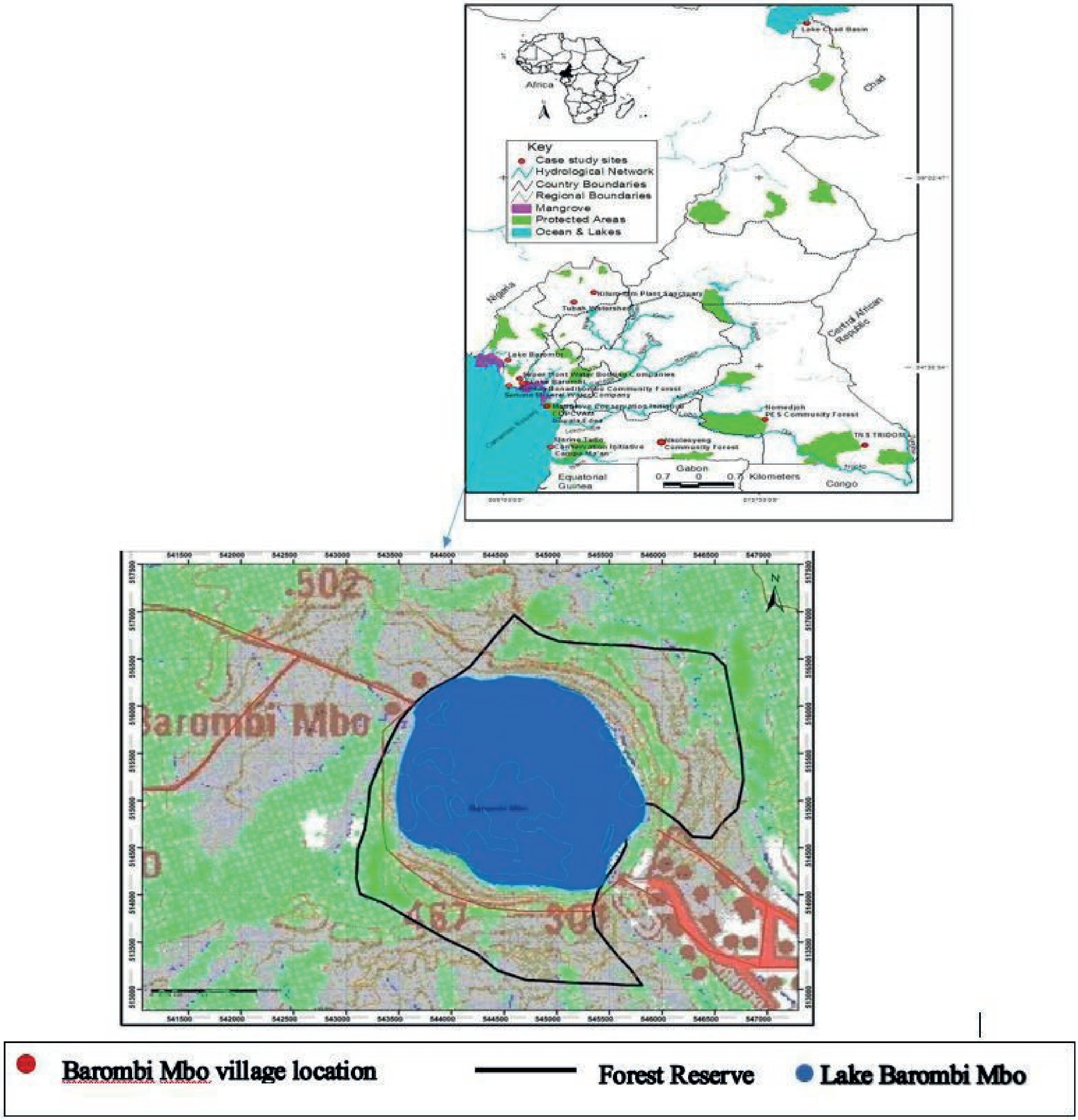

Figure 1. Location of the study area in South West region of Cameroon.

Although PES is an economic incentive mechanism for the provision of environmental services, the effectiveness and efficiency of its implementation, especially in the agricultural sector, largely depend on their social acceptability (Todorova, 2019; Viaggi et al., 2021). In addition, it is relatively difficult, and even impossible, to value environmental services through market mechanisms due to their public goods nature. Therefore, the compensation for supplying environmental services is

usually based on the opportunity cost of changing practices or restricting use rights. In other words, an economic agent may seek a monetary amount to ensure that their activities protect or deliver a range of environmental services (Divinski et al., 2018; Sheng et al., 2019). The contingent valuation methodology helps reveal the monetary amount an economic agent would like to receive to secure the value of goods or services when prices are not available (Carson, 2012; Johnston et al., 2017). If an economic agent, such as a farmer, has exclusive property or user rights over a good, such as a standing forest, and is being asked to give up or restrict that entitlement in terms of exclusivity or transfer of user rights, then the correct measurement within a contingent valuation framework is the WTA (Brown and Gregory, 1999; Carson et al., 2001; McFadden and Train, 2017).

There is evidence suggesting that farmers, through their exposure to agri-environmental schemes, have become familiar with the tradeoff between agricultural production and the provision of environmental public goods (Buckley et al., 2012; McGurk et al., 2020). According to McFadden and Train (2017), the SP methodology involves conducting surveys to elicit economic agents' preferences and their WTA for the provision of public goods, such as environmental services. The development of SP surveys aims to maximize the validity and reliability of the resulting value estimates. Validity refers to minimizing bias in estimates, while reliability pertains to reducing variability (Mitchell and Carson, 1989; Bateman et al., 2002; Bishop and Boyle, 2019). Therefore, as emphasized by Johnston et al. (2017), well-designed surveys and proper implementation procedures are crucial for achieving these goals and are necessary when extrapolating model estimates from a survey sample to an intended population.

3.2. Survey design and data collection

We design a survey instrument that clearly explains the current conditions and presents a consequential valuation question. Additionally, we select a random sample from the potentially affected population and choose a survey mode that ensures complete questionnaire responses.

Scenario description

We define a hypothetical scenario to assess agroforestry development in Barombi Mbo, capturing the impacts of current agricultural practices and potential changes. We present both the baseline or status quo conditions and the proposed changes relative to the baseline to the farmers. This approach ensures that farmers understand and accept the valuation scenario (Schultz et al., 2012; Johnston et al., 2017). Our hypothetical scenario, along with its consequential value question, is as follows: "Studies conducted in the Barombi Mbo forest reserve have observed that approximately 90% of the forest reserve, particularly the forest near the lake, has been destroyed. If the current level of activities in the reserve continues, there will be no trees left to provide fuelwood, wood, climate stabilization, wildlife habitat, and water quality and quantity for future generations, as well as for eco-tourism in the watershed. To restore the forest reserve, the government plans to implement an afforestation programme. Your participation in this programme will assist the government in estimating the cost of afforestation."

Questionnaire testing

As recommended by Johnston et al. (2017), we conducted a focus group discussion with 28 farmers from Barombi Mbo to test our questionnaire. This allowed us to assess the impacts of the information provided on farmers' responses to the valuation questions, the framing of the valuation questions, as well as the respondents' prior experience and knowledge. The testing of the questionnaire helped us clarify the questions and information with the farmers, and also enabled us to determine the monetary amounts (bids) that farmers are willing to accept for adopting agroforestry. This process is crucial not only for ensuring the validity and reliability of our estimates but also for avoiding respondent fatigue caused by the provision of unnecessary details (Mitchell and Carson, 1989; Bateman et al., 2002; Champ et al., 2017).

Value elicitation

We utilize an open-ended elicitation format to gather pilot data during the survey pretesting phase. This format enables us to collect point estimates of different monetary amounts that farmers are willing to accept for agroforestry adoption (Vossler and Zawojska, 2020). Following the presentation of the hypothetical scenario for agroforestry development, our open-ended valuation question is as follows: "What annual compensation would you expect to plant trees in or out of the Reserve?" The responses obtained from the participants provide us with a range of monetary amounts, allowing us to determine the distribution of the WTA and select a finite set of monetary amounts to be proposed to farmers in the final survey.

Instead of choosing monetary amounts between the 15th and 85th percentiles or from the tail of the distribution, as recommended by Kanninen (1995) for WTP, we retain the first two lowest monetary amounts, specifically 10,000CFA franc and 15,000CFA franc. This approach helps to reduce hypothetical bias, as economic agents often tend to overstate their WTA, as highlighted by Kahneman and Tversky' (1979). Alberini (1995) and Terra (2010) suggest that including approximately two monetary amounts for estimating WTA is theoretically optimal. Having a small number of bids is preferred over a large number as it increases estimation efficiency and the power of statistical tests. After conducting the field pilot survey, we revise the questionnaire to incorporate the monetary amounts/WTA for the provision of environmental services, as well as farmers' suggestions regarding the types and levels of activities carried out in the farm and forest reserve, as presented in Section 4.1.

The final survey employs a dichotomous-choice elicitation format. Specifically, we use a WTA question to determine the minimum amount of cash a farmer is willing to accept as compensation for changing their current land-use practices to more productive and environmentally friendly ones. This question is presented to farmers using a single binary choice format (Carson and Groves, 2007; Carson et al., 2014; Vossler and Holladay, 2018). Our single binary choice question is as follows: "Would you be willing to receive 'X amount' per year for your participation in the afforestation programme?" The 'X amount' represents either 10,000CFA franc or 15,000CFA franc. The farmer is asked to respond with either "yes" or "no."

Population and sampling procedure

The population of Barombi Mbo was estimated to be 595 inhabitants in March 2015, with 349 males and females above 15 years old (Tchouto, 2015). Limiting the age of respondents to 15 years and older allows us to account for farms owned or managed by youths when one or both of their parents are still alive or have passed away.

To obtain a sample size that represents the population of Barombi Mbo, we use the following formula (Yamane, 1967):

$$n = \frac{N}{1 + Nc^2} \tag{1}$$

In this formula, $N = 349$ represents the number of individuals older than 15 years old, and $c = 4.6\%$ is the margin of error. By plugging these values into the formula, we calculate a sample size of 200 farmers.

The selection of farmers for face-to-face interviews is done randomly within the village.

Data collection

For data collection, we assign 50% of the sample to each of the two monetary amounts to ensure an equal distribution of bids. The responses to the single binary choice question mentioned earlier are obtained through face-to-face or in-person interviews.

Our questionnaire includes auxiliary or supporting questions to aid in understanding responses to value elicitation questions and ensure construct validity (Krupnick and Adamowicz, 2006; Mitchell and Carson, 1989; Bateman et al., 2002; Champ et al., 2017; Johnston et al., 2017; Vossler and Holladay, 2018). These auxiliary questions serve multiple purposes, such as identifying demographic, household, or other relevant characteristics of the respondents. Additionally, a subset of these questions may provide covariates, which are used in valuation models to explain the variation in responses to the value elicitation questions (Johnston et al., 2017; Vossler and Holladay, 2018). To account for factors that may influence the WTA, our questionnaire collects information on the socioeconomic characteristics of farmers, farm characteristics, and environmental variables. This information helps deconstruct farmer preferences and identify factors that affect the WTA. Previous studies, such as Chatterjee et al. (2021), have shown that the adoption of conservation agriculture is related not only to ecological factors but also to adopters' characteristics, their perceptions, and the decision-making process. Specifically, our questionnaire includes questions regarding the age, gender, education level, family size, and origin of farmers. We also inquire about the location and size of farms because the ownership of large and strategically positioned agricultural land may influence farmers' participation in environmental protection programmes (Ajayi et al., 2012). Furthermore, we include questions about the current agricultural income and the use of fertilizers and pesticides to examine how the land opportunity cost or on-farm income could make compensation or payments more attractive within a PES scheme. Existing evidence suggests that farmers with higher profit levels from their existing activities generally demand higher levels of compensation to participate in a conservation scheme (Bateman, 1996; Ajayi et al., 2012).

Furthermore, our questionnaire includes questions to capture farmers' perceptions of the potential development outcomes associated with unsustainable agricultural practices, such as the heavy use of chemical fertilizers and slash and burn techniques. The poor performance of these unsustainable practices may motivate farmers to seek sustainable alternatives, such as agroforestry. As highlighted by Gama-Rodrigues et al.

(2021), agroforestry has positive effects on both income and the environment. In agroforestry systems, habitats are provided for species that can tolerate a certain level of disturbance, and the rate of natural habitat conversion is reduced compared to traditional agricultural systems (Jose, 2009). Agroforestry also contributes to biodiversity conservation as trees, crops, and/or animals enhance soil fertility, improve water quality, increase aesthetics, and sequester carbon. For instance, multi-strata cocoa agroforestry systems that incorporate timber, fruit, and native forest species create improved wildlife habitats by increasing plant diversity, enhancing landscape connectivity, and reducing edge effects between forests and agricultural land (Jose, 2009; Gama-Rodrigues et al., 2021; Bareille et al., 2023). However, it is important to acknowledge that seeking more sustainable alternatives also involves costs and potential income losses for farmers. Therefore, they may require compensation for implementing agri-environmental protection solutions (Raina et al., 2021).

Moreover, our questionnaire includes questions aimed at capturing the social, environmental, and cultural values associated with agroforestry. These values encompass the importance of non-timber forest products (NTFPs), environmental sensitivity, access to information and knowledge about agroforestry and biofertilizer technologies, as well as awareness of the PES mechanism. Recognizing and understanding these cultural and environmental values is crucial for promoting biodiversity

conservation through agroforestry in the long term. These values provide justification for farmers to conserve native forest habitat within cocoa production landscapes, maintain or restore diverse and structurally complex shade canopies within cocoa agroforestry systems, and retain other forms of on-farm tree cover to enhance landscape connectivity and habitat availability (Schroth and Harvey, 2007; Gama-Rodrigues et al., 2021; Bareille et al., 2023; Ito, 2022). However, our field survey reveals a lack of knowledge about the benefits of agroforestry in the Barombi zone. This issue will be discussed further in Section 4.1.

Non-data information or expert knowledge

In situations where the available data are limited, noisy, or biased, or when the empirical problem is complex and requires additional information to determine the WTA, non-data information can be particularly valuable. Non-data information refers to any prior knowledge or assumptions about the WTA that are not derived from observed or survey data (Knuiman and Speed, 1988; Gelman et al., 2013; Mahmoud et al., 2020; Awwad et al., 2021; Hegazy et al., 2021). Such information can be obtained from various sources, including:

- Expert opinion: Prior knowledge can be informed by the insights and expertise of professionals in the field who possess relevant experience and knowledge.
- Previous studies: Prior knowledge can be based on the findings of previous research that has investigated similar or related problems.
- Empirical data: Prior knowledge can be derived from data collected from sources other than the current study, such as pilot studies or surveys.
- Theoretical considerations: Prior knowledge can be based on theoretical frameworks and considerations regarding the relationships between the variables of interest.

Accounting for non-data information can indeed enhance the accuracy and precision of WTA estimates and mitigate the influence of outliers or measurement errors (Kadane and Lazar, 2004; Gelman et al., 2013; Kruschke, 2013). However, it is crucial to approach the use of non-data information with caution and provide adequate justification, as it introduces subjectivity into the analysis. In our study, we rely on prior knowledge derived from theoretical considerations regarding the relationship between WTA and psychological stimuli experienced by farmers. Further details on this aspect are discussed in Section 3.4.

3.3. Modeling farmer's willingness to accept

The use of a Tobit model is appropriate in our study to model farmers' WTA compensation. The Tobit model is a regression model commonly employed when the dependent variable is censored within a certain range. In our case, the WTA lies within the interval $[0, \infty[$ since there is no negative compensation observed in our experiment (as discussed in Section 3.2). Therefore, the Tobit model can effectively capture the behavior of the WTA.

In the context of the Tobit model, the choice of a farmer to participate in the agroforestry programme with compensation can be represented as a dichotomous outcome. A farmer either agrees to participate (indicating $WTA > 0$) or does not agree to participate (indicating $WTA = 0$). The Tobit model has been widely used in studies investigating technology adoption and participation in conservation programmes, as mentioned in prior research (e.g., (Buckley et al., 2012; Thompson et al., 2021)).

The conceptual model can be described in terms of a latent variable WTA^* and an observed variable WTA as follows:

$$WTA_i^* = X_i\beta + \varepsilon_i, \quad (2)$$

$$WTA_i = \begin{cases} WTA_i^* & if \quad WTA_i^* > 0 \\ 0 & if \quad WTA_i^* \leq 0 \end{cases} \quad (3)$$

where, X_i is a row vector of explanatory variables that determine the respondent i's WTA_i or participation in a sustainable agriculture or conservation programme, β is a column vector of parameters to be estimated, and ε_i is an error term with a normal distribution N (0, σ^2).

The Tobit model consists of two parts: a continuous part, represented by the linear regression equation 2, and a discrete part, represented by the censored point equation 3. The continuous part, equation 2, models the underlying relationship between the latent variable WTA_i^* and the explanatory variables X_i. It assumes a linear relationship, where the value of WTA_i^* is determined by the values of X_i multiplied by the parameter vector β, along with the error term ε_i. The censored point equation 3 introduces the censoring mechanism. It states that the observed WTA value WTA_i is determined based on the value of WTA_i^*. If WTA_i^* is greater than zero, indicating that the respondent agrees to participate, the observed WTA value equals WTA_i^*. However, if WTA_i^* is less than or equal to zero, indicating that the respondent does not agree to participate, the observed WTA value is censored at zero.

The Tobit model combines these two parts to estimate the parameters β that determine the relationship between the explanatory variables and the WTA, taking into account the censoring mechanism. The estimation procedure accounts for both the continuous and censored parts simultaneously, providing insights into the factors influencing farmers' WTA and their decision to participate in the agroforestry programme with compensation.

From (2), we derive that WTA_i^* follows a normal distribution; and the probability to reject an offer to participate in a sustainable agriculture programme is given by:

$$Prob(WTA_i^* \leq 0) = \phi\left(-\frac{X_i\beta}{\sigma}\right) = 1 - \phi\left(\frac{X_i\beta}{\sigma}\right), \quad (4)$$

where φ is the standard normal density function. It follows that the probability for WTA_i^* to take on positive values is given by:

$$Prob(WTA_i^* > 0) = 1 - Prob(WTA_i^* \leq 0) = \phi\left(\frac{X_i\beta}{\sigma}\right) \quad (5)$$

We derive the log-likelihood function of WTA from (3), (4) and (5) as follows:

$$LogL = -\frac{1}{2}\sum_{WTA_i>0}\left(Log2\pi + Log\sigma^2 + \frac{1}{\sigma^2}(WTA_i - X_i\beta)^2\right) + \sum_{WTA_i=0} Log\left(1 - \phi\left(\frac{X_i\beta}{\sigma}\right)\right) \quad (6)$$

To determine the components of the explanatory variables X_i, we draw insights from existing literature on empirical research on farmers' valuation of environmental services, adoption of agricultural technologies, and participation in conservation programmes in both developed and developing countries. These studies include research by Adesina et al. (2000); Jose (2009); Scognamillo and Sitko (2021), Chatterjee et al. (2021) and Raina et al. (2021), among others. These studies provide valuable information on the factors influencing farmers' WTA. Additionally, some of these studies offer guidance on designing a relevant questionnaire to explore the key determinants of farmers' WTA (refer to Table 1).

From (2) and (3), it can be shown that:

$$E(WTA_i/X_i) = (1 - \Phi(\alpha))(\mu - \sigma\lambda(\alpha)) \quad (7)$$

where $\alpha = -\mu/\sigma$, $\lambda(\alpha) = \phi(\alpha)/(1-\Phi(\alpha))$, ϕ and Φ are the standard normal density and distribution functions respectively, and $\mu = X_i\beta$, with

$$X_i\beta = \beta_1 + \beta_2 AGE + \beta_3 GEND + \beta_4 ORIGIN + \beta_5 EDU + \beta_6 FHSIZE + \beta_7 ONFINC + \beta_8 LOFARM + \beta_9 FASIZE + \beta_{10} ENVSTY + \beta_{11} AWPES + \beta_{12} BIOFERT + \beta_{13} OUTCPRA + \beta_{14} NTFPs \quad (8)$$

Denote by $\theta = (\beta, \sigma)$ the parameter of the empirical model (2). Using data to estimate θ, we can predict the WTA from (7). In this paper, we are interested in predicting the WTA of a representative farmer characterized by $\bar{X} = E(X_i)$. In the following section, we propose an approach to estimate θ.

3.4. Incorporating expert knowledge into farmer's willingness to accept

In most SP studies, data on farmers' hypothetical choices of the WTA are utilized to deduce their preferences for various levels of environmental services (Johnston et al., 2017; Hanley and Czajkowski, 2019; Wang

Table 1. Description of explanatory variables and their expected signs.

Variables	Description	Expected signs
AGE	Age of farmer (CONTINUOUS)	(±)
GEND	Sex of farmer (DUMMY): 1 if male and 0 if female	(±)
ORIGIN	Origin of farmers (DUMMY): 1 if native and 0 if non-native	(+)
EDU	Education level of farmers (CATEGORICAL): 0 if None (never been to school), 1 if primary and 2 if high level (secondary, high school)	(−)
FHSIZE	Size of farm households (CONTINUOUS)	(±)
ONFINC	Average yearly on-farm income (CONTINUOUS)	(+)
LOFARM	Location of the farm (DUMMY): 1 if out of the reserve and 0 if otherwise	(+)
FASIZE	Size of the farm (DUMMY): 1 if more than 5ha and 0 if not	(−)
ENVSTY	Environmental sensitivity of farmers (DUMMY): 1 if sensitive to the role of forest to protect the environment and 0 if not	(−)
AWPES	Awareness of PES scheme (DUMMY): 1 if yes and 0 otherwise	(±)
OUTCPRA	Perception of the output of current practices by farmers (DUMMY): 1 if average (average, bad) and 0 if good (good, very good)	(±)
BIOFERT	Knowledge of Bio-fertilizers (DUMMY): 1 if farmers have knowledge and 0 otherwise	(±)
NTFPs	Importance of NTFPs to the farmer: 1 if important and 0 otherwise	(−)

Source: Authors' definitions

and Nuppenau, 2021). However, the hypothetical nature of the WTA choices introduces a bias, as individuals tend to systematically overstate or understate their WTA values. This bias arises because no actual payment is made or received in exchange for an actual change in the quantity or quality of environmental services (Haghani et al., 2021).

As suggested in Section 3.2, one way to correct the bias and improve the accuracy and precision of the WTA estimates is to incorporate expert knowledge. Expert knowledge can be utilized to constrain the range of possible values for the unknown parameters, θ, related to agent preferences.

The most commonly employed statistical methods for estimating the parameter θ are referred to as frequentist (or classical) methods. Specifically, the maximum likelihood method is often utilized, making use of the log-likelihood function (6) (Xu and Lee, 2015; Xu and fei Lee, 2018; Toker et al., 2021). These methods assume that the unknown parameter θ is a fixed constant and determine the probability of its estimator through limiting relative frequencies. As a result of these assumptions, it is not possible to provide a probabilistic statement regarding the unknown parameter θ since it is considered fixed. Consequently, the frequentist approach is not suitable for incorporating expert knowledge in the estimation of the unknown parameter θ.

Bayesian estimation provides an alternative approach, treating θ as a random variable and allowing for the expression of uncertainty through probability statements and distributions known as priors (Mahmoud et al., 2020; Awwad et al., 2021; Hegazy et al., 2021). Priors are designed to incorporate any relevant information the researcher possesses before observing the data. Therefore, priors can take various forms, accommodating the inclusion of expert knowledge in the estimation of the unknown parameter θ. By leveraging our expert knowledge of farmer preferences, as captured by the prior distribution of θ, Bayesian analysis enables us to learn from data and update our knowledge accordingly. It emphasizes that the conditional probability of the unknown parameter θ serves as the optimal means of summarizing the information derived from the data (Chan et al., 2019).

The Bayesian approach provides a comprehensive probabilistic framework for empirical modeling. It enables us to address hypothetical bias in the estimates of sample characteristics such as $E(WTA_i/X_i)$ by leveraging our prior knowledge of the unknown parameters (Kadane and Lazar, 2004; Gelman et al., 2013; Kruschke, 2013).

As stated by Chan et al. (2019), Bayesian analysis involves the calculation of the posterior distribution of the parameter θ, denoted as $p(\theta/WTA)$. It can be expressed, up to an arbitrary constant, in a proportional form as:

$$p(\theta/WTA) \propto \text{Log } L \times \pi(\theta) \tag{9}$$

Here, Log L represents the log-likelihood function of the censored regression model for WTA (refer to (6)), and $\pi(\theta)$ is referred to as the prior distribution of θ, or simply the prior. As mentioned earlier, the prior distribution reflects our expert knowledge about the parameter θ before examining the data. It can assume various forms, such as uniform, normal, gamma, or other distributions, depending on the problem's nature and the available prior information. In equation (9), the prior knowledge is incorporated into the posterior distribution using Bayes' theorem. As more data is collected, the influence of the prior distribution diminishes, and the posterior distribution becomes increasingly shaped by the likelihood function. This process is known as updating the prior distribution.

As discussed in Section 3.2, there are various sources of prior knowledge. When expert opinions, previous studies, or empirical data about the parameters are lacking, theoretical considerations can be employed to generate prior knowledge. Theoretical considerations are particularly valuable for specifying uninformative priors. Chan et al. (2019) defines an uninformative, flat, or diffuse prior as any distribution that expresses vague or general information about a parameter. The use of non-informative priors in Bayesian analysis offers several advantages, including:

- **Objectivity:** Non-informative priors aim to minimize the influence of prior knowledge on posterior results by expressing ”objective” information, such as ”the parameter is positive” or ”the parameter is less than a certain limit.” They strive to be as objective as possible, allowing the data to exert the greatest influence on the final inference. This can help address concerns about subjectivity or bias in the analysis.
- **Robustness:** Non-informative priors can be valuable when prior knowledge or information is limited or unreliable. They provide a default assumption that avoids strong assumptions or bias based on incomplete or uncertain information. This is particularly beneficial in situations where there is a lack of prior knowledge or when multiple analysts with different perspectives are involved.
- **Simplicity:** Non-informative priors are often simple and unrestrictive, facilitating a more straightforward analysis. They simplify the modeling process and reduce the computational burden associated with estimating complex prior distributions.
- **Sensitivity analysis:** Non-informative priors are useful for conducting sensitivity analyses. By comparing the results obtained with non-informative priors to those obtained with informative priors, researchers can assess the impact of prior assumptions on the final inference. This helps identify the extent to which the results depend on prior specifications.
- **Communicating uncertainty:** Non-informative priors offer a means to quantify and communicate uncertainty when little or no prior knowledge is available. They enable the estimation of credible intervals or posterior distributions that reflect the uncertainty in the parameters of interest based solely on the observed data.

However, it's important to acknowledge that non-informative priors have their limitations. In certain cases, they may not fully capture all available information, resulting in less efficient inference or potentially misleading results. Table 1 outlines the expected signs for the parameters in our model based on theoretical considerations, representing the necessary prior knowledge for specifying noninformative priors. However, for robustness, we assume that all explanatory variables may have both positive and negative effects on *WTA*.

The principle of indifference, which assigns equal probabilities to all possibilities, is the simplest and oldest rule for determining a non-informative prior. In this study, we adopt a non-informative prior for β, specifically a uniform prior distribution, $\pi(\beta) \propto 1$. Additionally, it is common in the literature to use a gamma distribution as a prior for the standard deviation of a normal distribution (Chan et al., 2019). Therefore, we assume that σ follows a gamma distribution, $\pi(\sigma) \propto G(a, b)$, where a = 0.01 represents the shape parameter and b = 0.01 denotes the inverse-scale parameter. The choice of hyper-parameters a and b ensures convergence of the posterior distribution sampling. Furthermore, we assume that β and σ are independently distributed, giving $\pi(\theta) = \pi(\beta)\pi(\sigma)$.

To perform a Bayesian analysis of the Tobit model (2) and (3), we can utilize the LIFEREG procedure in the Statistical Analysis Software (SAS). This procedure incorporates an Adaptive Rejection Metropolis Sampling (ARMS) algorithm based on the programme provided by Gilks (2003) to draw a sample $\theta_k = (\beta_k, \sigma_k)k$=1...$m$ from the full-conditional distribution (9). The Bayesian estimate of the mean WTA of agent i, denoted as $E(WTA_i/X_i)$, is then calculated as:

$$(E(WTA_i/X_i)/Y) \approx \frac{1}{\mathrm{m}}\sum_{\mathrm{k}=1}^{\mathrm{m}}(1 - \Phi(\alpha_k))(\mu_k - \sigma_k\lambda_k(\alpha_k)), \tag{10}$$

as m approaches infinity,

where, $Y = \{WTA_i, X_i\}_{i=1,..,n}$ represents the data, $\alpha_k = -\mu_k/\sigma_k$, $\lambda_k(\alpha_k) = \phi(\alpha_k)/(1 - \Phi(\alpha_k))$, ϕ and Φ denote the standard normal density and distribution functions, respectively, and $\mu_k = X_i\beta_k$.

4. RESULTS AND DISCUSSION

In this section, we provide the results of implementing the methodology outlined in the previous section. Firstly, we provide a brief overview of the descriptive statistics pertaining to both traditional and eco-innovative farming practices in the study area. Subsequently, we employ a multidimensional preferences analysis to examine contextual behavior patterns that could elucidate farmer preferences. Finally, we analyze the empirical estimates of farmer willingness to accept compensation for environmental services.

4.1. Descriptive statistics of traditional and eco-innovative farming practices

Throughout generations, farmers have continuously strived to enhance agricultural land productivity through the utilization of available technologies. Table 2 provides an overview of the traditional and eco-innovative farming practices employed by farmers in the study area. It is observed that approximately 85 percent of farmers utilize chemical inputs, such as fertilizers and pesticides, to improve soil fertility and manage cocoa farms. Among the pesticides used, fungicides and insecticides are the most commonly employed, both within and outside the reserve. Regarding soil preparation techniques, 53.5% of farmers employ crop rotation, followed by a slash and burn method (34%). Despite facing challenges related to limited land availability for crop cultivation, a majority (50.5%) of farmers employ various durations of bush fallow systems to enhance land productivity. While 24.5% of farmers have their farms located within the reserve, a significant proportion of respondents (70.5%) attribute most of the observed deforestation in the reserve to the exploitation of fuelwood, timber, and NTFPs.

To mitigate the adverse impacts of deforestation, chemical fertilizers, and pesticides in the vicinity of the lake, farmers have adopted various eco-innovative practices to protect the environment. A significant number of farmers prioritize conservation by preserving old and large trees within their own farms. For example, approximately 52% of farmers have planted fruit trees, NTFPs, and other species on their land. These seedlings are typically sourced from their own nurseries or purchased from external suppliers. The planting of trees serves the dual purpose of preventing soil erosion and safeguarding the environment. However, agroforestry practices are not widely implemented, primarily due to limited awareness regarding their significance. Only a small proportion of farmers (16%) have heard about agroforestry or bio-agriculture, with information dissemination occurring through various channels, including schools, village meetings, and the farmers field school initiative of MINADER (Ministry of Agriculture and Rural Development). It is worth noting that the majority of farmers believe that chemical fertilizers are the most effective solution to combat declining soil fertility. This inclination can be attributed to the lack of awareness regarding indigenous knowledge pertaining to soil erosion prevention, soil demineralization, and the production and application of organic manure. In fact, when asked to explain their understanding of bio-fertilizers, only 30.5% of farmers demonstrated some knowledge on the subject.

Table 2. Traditional and eco-innovation farming practices.

Description	Frequency of "yes"	% of the respondents
Chemical use		
Overall	170	85
Fungicides	94	55.29
Insecticides	22	12.94
Soil preparation techniques		
Slash and burn	68	34
Rotation	107	53.50
Bush fallow practice	101	50.50
Tree conservation		
NTFPs	47	43.12
Timber	31	28.44
Fruit trees	21	19.27
Reforestation		
Fruit trees	70	67.31
NTFPs	27	27.96
Origin of seedlings		
From own nursery	48	46.15
Buy	29	27.88
Donation	22	21.15
Forest cover destroyed in the reserve		
More than 75% of forest destroyed	141	70.50
Agro-forestry knowledge	32	16
Bio-fertilizers knowledge	61	30.50

Source: Authors' calculations from survey data.

Moreover, it is noteworthy that only 48% of farmers consider the outputs from their current farming practices to be good or satisfactory (see Table 2). Almost all farmers (95.5%) acknowledge the significance of forests in providing vital ecosystem services, including climate regulation, flood control, erosion control, wildlife habitat, landscape beauty, and cultural/spiritual value. Concerning watershed protection, the majority of farmers (97.5%) recognize the positive correlation between for-

Table 3. Distribution of the willingness to accept.

Response	FCFA10,000	FCFA15,000	Total
No	14	11	25
Yes	86	89	175
Total	100	100	200
Percentage of yes	86%	89%	87.5%

Source: Authors' calculations from survey data.

est cover and water quality. However, only 27% of farmers are familiar with the PES mechanism (see Table 2). Nonetheless, considering the farmers' willingness to plant diverse tree species on their own land, it is reasonable to expect their active participation in the PES scheme if they are provided with incentives to plant and preserve trees.

4.2. Adoption of agro-forestry and multidimensional preferences analysis

According to the data presented in Table 3, a significant proportion of farmers (87.5%) are willing to accept compensation in order to participate in an afforestation programme both within and outside the reserve, as well as along the border of the lake. While the benefits of agroforestry are discussed with farmers during the survey, only a small percentage (8.5%) of farmers residing near the lake express their willingness to adopt agroforestry practices. However, among those who are willing to adopt agroforestry, a majority also demonstrate their commitment to refrain from using chemicals within an 8-meter distance from the lake, provided that they receive seedlings for agroforestry and receive training on best agroforestry practices.

In conducting a multidimensional preferences analysis (MPA), we aim to identify the primary dimensions of farmer preferences that can explain their willingness to adopt agroforestry practices. While Principal Component Analysis (PCA) focuses on reducing complexity and identifying patterns in large datasets, MPA delves into understanding individual or group preferences and priorities. It can be seen as a PCA of a data matrix, with columns representing individuals and rows representing variables or objects.

As depicted in Figure 2, the determinants of farmers' willingness to participate in an afforestation programme are classified into three groups:

- The first group comprises variables such as awareness of PES schemes (AWPES), knowledge of bio-fertilizers (BIOFERT), the importance of non-timber forest products (NTFPs), and education level (EDU). This group reflects the extent to which farmers possess knowledge about environmental management. It is reasonable to assume that farmers with higher levels of education are more likely to be aware of PES programmes, have knowledge of bio-fertilizers, and understand the importance of NTFPs.
- The second group consists of variables related to environmental sensitivity (ENVSTY), the origin of the farmer (ORIGIN) (whether native or non-native to the study area), and the location of the farm (LOFARM) (whether inside or outside the reserve). This group captures the farmers' connection (sensitivity, origin, and location) to the study area and the local community. It is evident that farmers who are native to the study area and have farms within the reserve exhibit a higher sensitivity to the role of forests in environmental protection.
- The third group includes variables such as age (AGE), gender (GEND), farm size (FASIZE), farm household size (FHSIZE), and yearly on-farm income (ONFINC). This group reflects farmers' socioeconomic status and demographic characteristics. The strong correlation between on-farm income and farm size suggests the existence of an extensive agricultural system, which often exerts significant pressure on the environment.

By analyzing these three groups of variables, multidimensional preferences analysis helps uncover the underlying dimensions driving farmers' preferences and their willingness to adopt agroforestry practices.

The perfect negative correlation between the first group of variables (related to knowledge and awareness of environmental management) and the second group of variables (related to connections with the local community) reveals an interesting pattern. It suggests that farmers who have weak connections with the local community tend to be more knowledgeable about environmental management, while those with strong connections are less informed in this regard. This finding has important implications as it may help explain why rural areas are more susceptible to environmental degradation.

In rural areas, where strong community ties and social networks are prevalent, farmers who have close connections with the local community may rely on traditional practices and knowledge passed down through generations. However, these practices may not always align with sustainable agricultural practices or modern environmental management strategies. On the other hand, farmers who have weaker connections with the local community, such as migrants or individuals with limited social integration, may have more exposure to

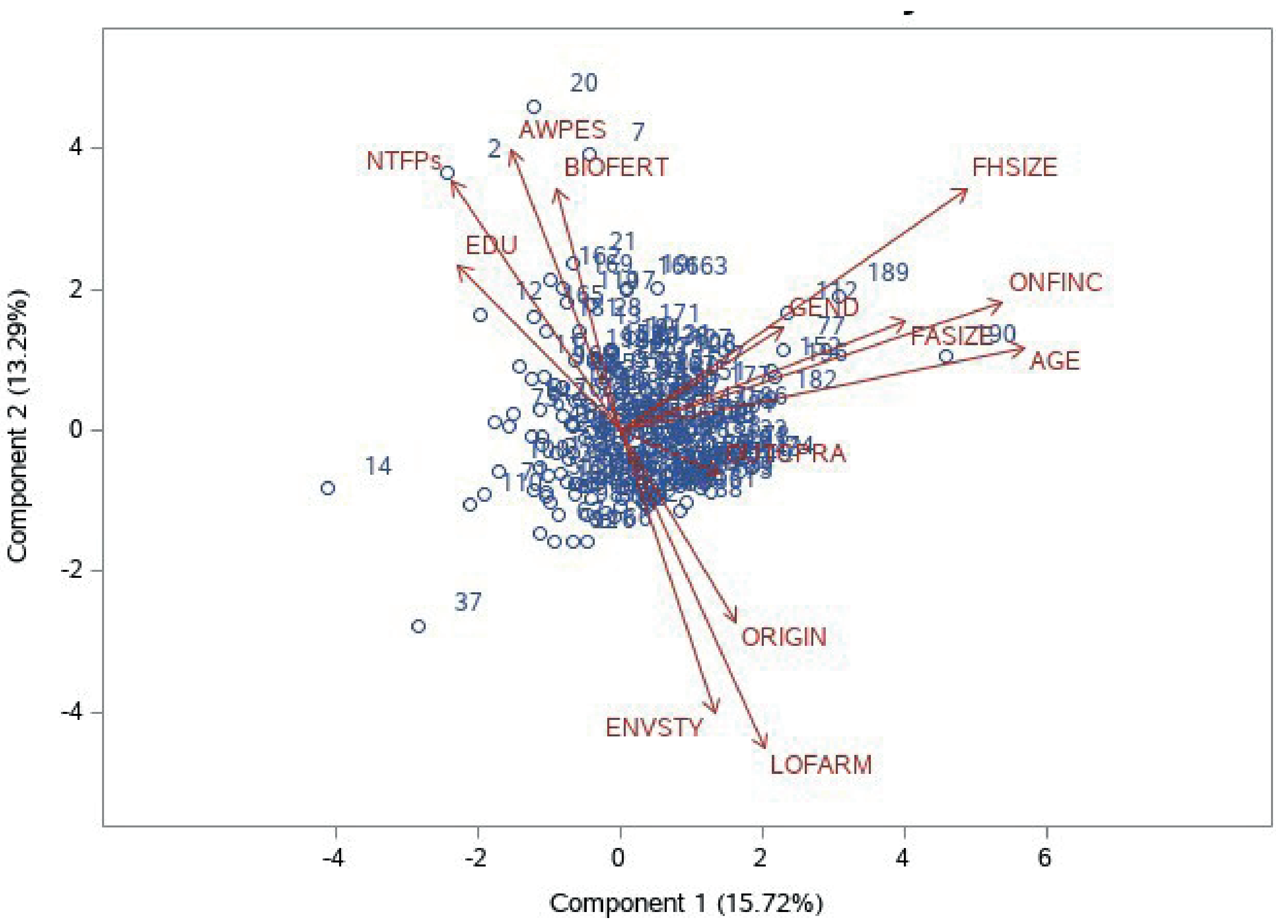

Figure 2. Multidimensional Preferences Analysis.

external information and knowledge regarding sustainable agriculture and environmental management. This finding highlights the need for capacity building and training initiatives targeting local and indigenous communities, as well as natural resources owners in rural areas like Barombi Mbo. By providing them with appropriate knowledge and skills related to sustainable agricultural practices and environmental management, we can promote behavior change and the adoption of more sustainable practices. Recognizing the ownership of natural resources, coupled with empowering individuals with the necessary knowledge, can serve as a catalyst for positive changes and contribute to the reduction of environmental degradation in the area.

The non-correlation between the third group of variables (related to socio-economic status and demographic characteristics) and both the first and second groups of variables suggests that farmers' knowledge of environmental management practices and their connections with the local community are independent of their socio-economic and demographic conditions. In other words, farmers can enhance their understanding of environmental management or improve their community connections regardless of their socio-economic status or demographic characteristics. This finding implies that efforts to build farmers' capacity in environmental management will not significantly impact their socio-economic and demographic conditions. While farmers may possess knowledge about sustainable agricultural practices, they may lack the socio-economic incentives or motivations to translate that knowledge into concrete actions that protect the environment. This may explain why farmers, despite having knowledge of sustainable practices, appear to be less sensitive to environmental degradation.

To address this gap between knowledge and action, it becomes imperative to introduce economic incentive schemes such as PES programmes. These programmes create an enabling business environment where farmers can be rewarded for their efforts in reducing environmental deterioration. By providing economic incentives, farmers are more likely to be motivated to adopt and implement sustainable agricultural practices that contribute to environmental protection. Integrating economic incentives with farmers' existing knowledge of sustainable practices, we can bridge the gap between awareness and action, ensuring that farmers are actively engaged in protecting the environment. This approach recognizes the need to align environmental goals with socio-economic conditions and provides a practical mechanism for incentivizing sustainable practices among farmers.

Overall, combining knowledge-building initiatives with economic incentive schemes can effectively encourage farmers to apply their knowledge and contribute to environmental conservation while considering their socio-economic and demographic realities.

4.3. Determinants of the WTA for the provision of environmental services

Geweke diagnostics are commonly used to assess the convergence of parameters drawn from the posterior distribution in Bayesian analysis. The fact that Geweke diagnostics (Table 4) indicate no evidence to reject the convergence suggests that the estimation process has been successful and the sample of parameters obtained from the posterior distribution (9) is representative. By using this sample of parameters, statistical inferences can be made about the effects of farmers' socio-economic, environmental, and demographic values on their WTA for environmental services.

The probabilities $Pr(\theta_i \leq 0)$ provide a basis for determining the likely direction of influence of each variable on WTA. The influence is likely negative if $Pr(\theta_i <= 0) \geq 0.5$, whereas it is positive if $Pr(\theta_i <= 0) < 0.5$. Based on the given information, it appears that variables such as the sex of farmers (GEND), origin of farmers (ORIGIN), location of farms (LOFARM), output of current practices (OUTCPRA), awareness of PES scheme (AWPES), and knowledge of bio-fertilizers (BIOFERT) have a positive influence on WTA. This means that these factors are likely to increase farmers' WTA for environmental services.

On the other hand, variables such as the age of farmers (AGE), education level of farmers (EDU), size of farm households (FHSIZE), size of the farm (FASIZE), yearly on-farm income (ONFINC), and importance of non-timber forest products (NTFPs) are likely to have a negative effect on WTA. This suggests that these variables are expected to decrease farmers' WTA for environmental services.

These findings provide valuable insights into the factors that shape farmers' preferences and willingness to accept compensation for environmental services. Understanding these determinants can inform policy and decision-making processes related to the design and implementation of effective incentive schemes, such as payment for environmental services, to promote sustainable agricultural practices and environmental conservation.

The negative effect of farmers' age (AGE) on their WTA participation in an afforestation programme can

Table 4. Bayesian Parameter Estimates.

Parameters (θ_i)	Estimates	Std. Dev.	Equal-Tail Interval		$Pr(\theta_i \leq 0)$	Geweke Diagnostics	
			Lower	Upper		z	$Pr \geq \lvert z \rvert$
Intercept	12060.4	1843.8	8529.4	15674.5	0	-1,237	0.216
AGE (age of farmer)	-79.680	36.286	-151.5	-9.6776	0.987	0.171	0.865
GEND (sex of farmer)	1276.7	732.4	-172.5	2691.3	0.043	1,422	0.155
EDU (education level of farmer)	-871.7	549.2	-1942.4	211.5	0.944	-0.101	0.920
ORIGIN (origin of farmer)	1546.9	967.3	-344.2	3469.9	0.054	0.880	0.379
FHSIZE (size of farm household)	-109.7	163.4	-436.2	206.4	0.748	-0.124	0.901
LOFARM (location of farm)	346.9	820.5	-1251.8	11973.7	0.336	-0.235	0.814
FASIZE (size of farm)	-255.3	772.2	-1749.9	1272.6	0.630	-1,505	0.133
ONFINC (yearly on-farm income)	-0.00013	0.000208	0.000281	0.000273	0.736	0.678	0.498
OUTCPRA (output of current practices)	444.7	675.8	-875.5	1770.6	0.254	-0.154	0.877
AWPES (awareness of PES scheme)	1751.6	782.2	218.3	3271.9	0.012	-0.852	0.394
BIOFERT (knowledge of bio-fertilizers)	2923.6	765.1	1416.1	4434.5	0.000	0.766	0.443
NTFPs (importance of non-timber forest products)	-538.0	746.3	-2025.3	912.9	0.763	0.236	0.814
Scale	4595.2	222.5	4182.7	5054.6	0	1,202	0.229

be explained by several factors. As individuals grow older, they tend to prioritize existential values over economic values. Existential values encompass fundamental questions regarding human existence, such as "To be or not to be?", as well as practical concerns related to protecting human life and avoiding threats to existence (Lipiec, 2000). This shift in focus towards existential values may lead older farmers to be less inclined to accept compensation in exchange for adopting eco-innovations that protect the environment and, consequently, human existence.

Additionally, the aging process often fosters a greater concern for the well-being of others, beyond one's own self-interest. As individuals age, they become more attuned to the collective and the welfare of the broader community. Older individuals may view the realization of environmental values as a means to establish the foundational basis for other values. Consequently, elderly farmers are less likely to be receptive to compensation offers aimed at incentivizing their adoption of agroforestry practices, especially when the central question revolves around human existence.

Overall, the negative relationship between age and WTA for participation in an afforestation programme can be attributed to the prioritization of existential values over economic values among older individuals. Aging prompts individuals to care not only for themselves but also for the collective well-being. Elderly farmers may view the pursuit of environmental values as crucial for establishing the existential foundation necessary to support other values. Consequently, they may be less inclined to accept compensation to adopt agroforestry practices, given the overarching importance they place on human existence.

The positive effect of farmers' origin (ORIGIN) on their WTA compensation to participate in an afforestation programme may seem counterintuitive at first. One would expect that native farmers, who have a stronger connection to the local area and a better understanding of the importance of protecting their natural heritage, would be more inclined to adopt agroforestry practices voluntarily, without requiring compensation. However, to interpret this unexpected result, we need to consider the relationship between farmers' origin and the location of their farms.

As illustrated in Figure 2 and Table 4, native farmers tend to have farms located outside the reserve. It is important to note that farmers with farms outside the reserve are more likely to demand higher compensation to participate in an afforestation programme. This can be attributed to the fact that farms located outside the reserve generally have fewer trees compared to those within the reserve. Consequently, the opportunity cost of adopting agroforestry practices on farms outside the reserve is likely to be higher than on farms within the reserve. Native farmers, therefore, may be requesting compensation to offset the higher opportunity cost associated with implementing agroforestry on their farms.

Additionally, the observed behavior of native farmers could be influenced by their lower level of education and their limited valuation of NTFPs, as indicated in Figure 2. Farmers with lower levels of education or those who do not recognize the importance of NTFPs are more likely to demand higher compensation to adopt agroforestry practices, as demonstrated in Table 4. This finding aligns with the well-established understanding that higher educational attainment promotes pro-environmental behavior (Tianyu and Meng, 2020; Zhou et al., 2021).

In summary, the positive effect of farmers' origin on their WTA for participation in an afforestation programme can be explained by several factors. Native farmers, despite their stronger connection to the local area, may request compensation due to the higher opportunity cost associated with adopting agroforestry on farms located outside the reserve. Furthermore, their lower level of education and limited recognition of the importance of NTFPs may contribute to their demand for higher compensation. These findings emphasize the complex interplay between farmers' origin, farm location, education, and value orientations in shaping their willingness to accept compensation for agroforestry adoption.

The variables representing farmers' socio-economic status, namely the size of farm households (FHSIZE), size of the farm (FASIZE), and yearly on-farm income (ONFINC), are found to have a negative effect on farmers' WTA compensation for participating in an afforestation programme, as indicated in Table 4. This implies that higher socio-economic status is associated with a greater propensity for pro-environmental behavior. Two theoretical perspectives in the literature can help explain this important finding.

The first perspective revolves around the concept of post-materialism, which suggests that individuals with higher socio-economic status are more likely to adopt values that prioritize self-expression, subjective well-being, and quality of life. As highlighted by Pampel (2014), post-materialist values are associated with concerns for issues such as environmentalism, feminism, and equality. In our context, the size of farm households, which serves as an indicator of farmers' social status, can be seen as reflecting their adherence to post-materialist values. Farmers who value self-expression and quality of life are more inclined to prioritize environmental protection and are thus more willing to participate in afforestation programmes.

The second perspective is based on the notion of affluence, suggesting that environmental quality is considered an amenity that high-income individuals can more readily afford (Franzen and Meyer, 2010). In this view, the size of the farm and yearly on-farm income, as indicators of prosperity, can positively influence farmers' inclination to protect the environment, particularly when the associated economic costs are perceived as insignificant. Higher-income farmers may be more willing to invest in environmental conservation measures because they have the financial means to do so without compromising their livelihoods. This affluence argument aligns with the observation that higher socio-economic status promotes pro-environmental attitudes and behaviors.

Both theories, post-materialism and affluence, can be applied in our context to explain why farmers with higher socio-economic status exhibit a greater willingness for participating in afforestation programmes. The size of farm households reflects post-materialist values related to self-expression, while the size of the farm and yearly on-farm income capture the affluence aspect, indicating that farmers with greater financial resources are more likely to prioritize environmental protection when the associated costs are perceived as manageable.

Overall, these findings highlight the role of socio-economic status in shaping farmers' pro-environmental behavior and suggest that individuals with higher socio-economic status are more inclined to support environmental initiatives.

The variables representing farmers' knowledge of environmental management, namely the awareness of PES scheme (AWPES) and knowledge of bio-fertilizers (BIOFERT), are found to have a positive influence on farmers' WTA compensation for participating in an afforestation programme, as shown in Table 4. This indicates that having greater knowledge about environmental management does not necessarily translate into eco-friendly behavior among farmers. There seems to be a significant gap between farmers' knowledge of environmental risk management and their actual on-the-ground actions in dealing with environmental issues.

This disparity between knowledge and behavior highlights the need to understand the factors that contribute to the "knowledge-behavior gap" in the context of sustainability. Merely providing additional information to farmers is unlikely to lead to significant improvements in environmental conditions unless certain key factors are addressed. As emphasized by Knutti (2019), securing political will and implementing simple solutions that provide immediate and local co-benefits are crucial. It is not enough for farmers to possess knowledge; they also require support, incentives, and clear pathways for action.

While environmental management strategies exist, their implementation is often hindered by various factors, including attitudes towards environmental protection, short-term and medium-term implementation costs, and doubts about the effectiveness and efficiency of proposed policy instruments. Farmers who have a positive attitude towards environmental management may perceive compensation for participating in an afforestation programme as a means to bridge the gap between their knowledge and their behavior in the context of sustainability. Offering financial incentives can serve as a motivating factor for farmers to align their behavior with their environmental knowledge.

Overall, the presence of a "knowledge-behavior gap" among farmers indicates that simply increasing their knowledge of environmental management strategies is insufficient to drive eco-friendly behavior. Addressing this gap requires a comprehensive approach that goes beyond information provision and tackles other barriers such as attitudes, costs, and doubts about the effectiveness of policy instruments. Offering compensation as a reward for participating in environmental programmes can incentivize farmers and help bridge the gap between their knowledge and their actions in a sustainability context.

4.4. The opportunity cost of environmental services

Bayesian estimation provides us with a sample of parameters $\{\theta_k = (\beta_k, \sigma_k)\}_{k=1\ldots m}$ from the full conditional distribution (9), where θ_k represents the parameters of farmer preferences. Using this sample, we can derive a distribution of the mean WTA using equation (7) for a representative farmer.[1]

The resulting distribution of the mean WTA, as depicted in Figure 3, exhibits a normal shape. To formally test the normality of the distribution, we use the Anderson-Darling statistic, which confirms that the mean WTA follows a normal distribution with a mean of 10,775CFA franc and a standard deviation of 333.6CFA franc, as shown in Table 5.

To estimate the mean WTA using a Bayesian approach, we apply formula (10). The Bayesian estimate of the mean WTA is calculated to be 10,775CFA franc, with a 95% confidence interval of 10,769-10,781CFA franc, as presented in Table 5. The narrow confidence

[1] The characteristics of the representative farmer are obtained by taking the mean of each explanatory variable.

interval indicates that the estimate of the mean WTA has low volatility or high precision, suggesting a more reliable estimate.

Overall, the Bayesian estimation allows us to obtain a distribution of the mean WTA, which is found to follow a normal distribution. The Bayesian estimate of the mean WTA, along with its confidence interval, provides a precise estimation of the mean WTA value, contributing to a better understanding of farmers' preferences in the context of willingness to accept compensation for participating in an afforestation programme.

Based on the survey design outlined in Section 3.2, we can deduce that the probability for a farmer in the Barombi Mbo community to accept compensation and participate in an afforestation programme is $P = 175/200$. To estimate the total willingness to accept (WTA) or the community opportunity cost to participate in the afforestation programme using a Bayesian approach, we can use the following formula:

$$E(Total\ WTA/Y) \approx N \times P \times \frac{1}{m} \sum_{k=1}^{m} Mean\_WTA_k, \quad (11)$$

where $Y = \{WTA_i, X_i\}_{i=1,\ldots,n}$ represents the observed data, $N = 349$ denotes the size of the eligible population in Barombi Mbo, and $\{Mean\text{–}WTA_k\}_k^m$ represents the sample of the mean WTA obtained from the Bayesian estimation. In this formula, m represents the number of samples drawn from the Bayesian estimation. As m approaches infinity, the estimate becomes more accurate.

By multiplying the probability P with the population size N and the average of the sample mean WTA values, we can estimate the total WTA or the community opportunity cost to participate in the afforestation programme. It is important to note that this estimation assumes that the sample of farmers in the survey is representative of the entire eligible population in Barombi Mbo.

The results reported in Table 5 indicate that the Bayesian estimate of the total WTA or the community opportunity cost to participate in the afforestation programme is 3,290,448CFA franc with a 95% confidence interval of 3,288,511-3,292,385CFA franc. The small confidence interval suggests that the estimate of the total WTA exhibits low volatility or high precision.

We can also derive a sample of the distribution of the community opportunity cost of providing environmental services from the sample distribution of the mean WTA using the relationship $Total\ WTA = N \times P \times Mean\ WTA$. Furthermore, a test of normality using the Anderson-Darling statistic confirms that the community opportunity cost of providing environmental services follows a normal distribution with a mean of 3,290,448CFA franc and a standard deviation of 98,818CFA franc.

Comparing these results with those obtained by Moukam (2021) using a Maximum Likelihood method to estimate the Tobit model, it can be observed that the estimated values of the mean and total WTA obtained from the Bayesian approach are almost three times higher. Specifically, the Bayesian estimate of the mean WTA is 10,775CFA franc, whereas the estimate obtained using the Maximum Likelihood method is 4,488CFA franc. Similarly, the Bayesian estimate of the total WTA is 3,290,448CFA franc, while the Maximum Likelihood estimate is 1,370,491CFA franc. This difference highlights the potential of the Bayesian approach to account for both tangible and intangible values of ecosystem services.

Overall, the results suggest that the Bayesian approach provides a more comprehensive and precise estimation of the WTA and community opportunity cost, incorporating both economic and noneconomic factors associated with environmental services.

In Bayesian analysis, sensitivity analysis is usually recommended to assess the impact of prior assumptions on the final inference using non-informative priors as the counterfactual. However, in our case, since our results are primarily based on non-informative priors, conducting a sensitivity analysis is not feasible. Consequently, our results can be interpreted as a quantification of the uncertainty in the parameters of interest based solely on the observed data.

Table 5. Opportunity Cost of Supplying Environmental Services (Fcfa).

Parameter	Estimate	Std. Dev.	95% Confidence Limits		Anderson-Darling	
			Lower	Upper	Stat.	P. Value
Mean WTA	10,775	323.59	10,769	10,781	0.587	0.131
T otal WTA	3,290,448	98,818	3,288,511	3,292,385	0.587	0.131

Note. Aderson-Darling is a Goodness-of-Fit Test for Normal Distribution.

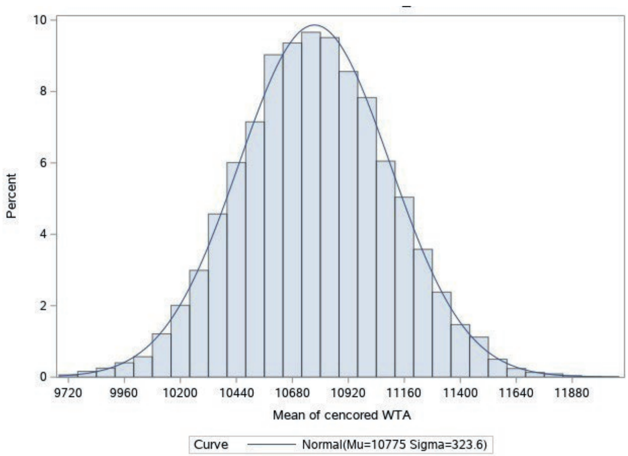

Figure 3. Distribution of *Mean WTA*.

5. CONCLUSION AND IMPLICATIONS

In this paper, we incorporate non-data information and expert knowledge into the estimation of farmers' opportunity cost for providing environmental services through agroforestry and forest regeneration in the rural area of Cameroon. To achieve this, we begin by conducting a survey to gather information on farmers' WTA and factors that may influence their preferences to participate in an environmental protection programme in Barombi Mbo, a rural region in Cameroon. Subsequently, we adjust a Tobit model of the WTA by incorporating expert knowledge through the specification of prior distributions for model parameters. Finally, a Bayesian approach is employed to estimate both the model parameters and the farmers' opportunity cost of supplying environmental services, accounting for both data and non-data information.

The paper contributes to the important economic literature on the valuation of environmental goods and services using a SP approach. Specifically, we propose a two-step survey design to determine a limited number of bids that farmers can choose from, which allows them to highlight their preferences and their WTA for changes in environmental services. Additionally, we conduct a multidimensional preference analysis to identify the primary dimensions of farmer preferences that may explain their willingness to participate in environmental conservation programmes. Furthermore, we expand the well-known Tobit model of WTA by incorporating non-data information or expert knowledge through the specification of parameter distributions. To estimate a comprehensive probabilistic model of WTA for changes in environmental services, we employ a Bayesian approach. Compared to the related literature (Moukam, 2021; Pérez-Sánchez et al., 2021), our approach to WTA modeling has the potential to significantly reduce potential hypothetical bias in data collection and analysis.[2] This reduction in hypothetical bias is achieved through an improved estimate of farmers' opportunity cost of supplying environmental services, resulting in more realistic and interpretable results. Our results align with the findings of previous authors Kadane and Lazar (2004); Gelman et al. (2013); Kruschke (2013) who have demonstrated that Bayesian methods provide more accurate estimates, better model comparison, and improved inferences compared to traditional frequentist methods. However, it is worth noting that conducting a Bayesian analysis requires a careful specification of prior distributions that incorporate our expert knowledge. As more data are collected, the influence of the prior distribution decreases, and the posterior distribution becomes increasingly influenced by the likelihood function (Chan et al., 2019).

An important result of this paper is that the majority of farmers (87.5%) are unlikely to voluntarily engage in environmental management without economic incentives. Our multidimensional preference analysis suggests that farmers' behavior may be attributed to the lack of correlation between environmental and socio-economic dimensions of their preferences. Therefore, it is crucial to implement economic incentive mechanisms, such as PES, to facilitate the alignment of environmental and socio-economic values. The Bayesian analysis reveals that aging is likely to promote pro-environmental behavior, indicating that older individuals are more sensitive to existential values compared to the youth (Lipiec, 2000). Additionally, natives are more inclined to accept compensation for adopting sustainable agricultural practices compared to migrants. This controversial finding can be partly explained by the observation that natives generally have lower educational attainment than migrants. This aligns with the widely accepted understanding that higher levels of education promote pro-environmental behavior (Tianyu and Meng, 2020; Zhou et al., 2021).

A significant finding of this paper is that higher socio-economic status, as indicated by factors such as the size of farm households, farm size, and yearly on-farm income, positively influences proenvironmental behavior. This observation can be explained by the affluence argument (Franzen and Meyer, 2010), which suggests that high-income farmers are more capable of affording environmental quality as an amenity good. Moreover, farmers with higher socio-economic status are more likely to have embraced postmaterialist values, which prioritize self-expression, subjective well-being,

[2] Hypothetical bias arises from the tendency of people to systematically overor understate their WTA in SP studies.

and quality of life, leading to increased concerns for environmental issues (Pampel, 2014). Furthermore, our analysis reveals that an increase in knowledge of environmental management strategies is less likely to promote eco-friendly behavior. This finding aligns with the research by Knutti (2019), who identified several barriers contributing to the observed knowledge-behavior gap. These barriers include attitudes towards environmental protection, implementation costs in the short and medium term, and skepticism regarding the effectiveness of proposed policy instruments.

Another important finding of this paper is that farmers' WTA follows a normal distribution with a mean of 10,775CFA franc and a standard deviation of 333.6CFA franc. Additionally, the community opportunity cost of supplying environmental services also exhibits a normal distribution, with a mean of 3,290,488CFA franc and a standard deviation of 98,818CFA franc. These distributions have significant implications for policy-making, as they enable us to make probabilistic statements about the value of environmental services. For instance, considering the significance of WTA in cost-benefit analysis (CBA), our results provide an effective means to incorporate uncertainty when assessing the welfare effects of regulatory and investment interventions that impact the environment. This allows expected outcomes in CBA, such as financial and economic net present values (NPVs), to incorporate risk and uncertainty associated with environmental management. Furthermore, our estimation of the distribution of WTA plays a crucial role in understanding the intricate financial trade-off involved in the Cameroonian government's engagement in international financial mechanisms for biodiversity conservation and climate change mitigation.

This paper presents a significant empirical framework for estimating the value of environmental services and evaluating the influence of socio-economic and demographic factors on that value. Considering that farmers in developing countries often exhibit comparable socio-economic and

demographic characteristics, along with similar concerns regarding environmental degradation, our estimation of the WTA distribution can serve as valuable prior knowledge or information regarding the value of environmental services in other rural areas of Cameroon or the developing world.

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A. APPENDIX

Figures. 4 and 5 show the draws, the autocorrelation of draws, and the empirical posterior distribution of two parameters: the Intercept and the Biofertilizer (BIOFERT) from the implementation of the Adaptative Rejection Metropolis Sampling (ARMS) algorithm based on a programme provided by Gilks (2003) using the procedure LIFEREG of the Statistical Analysis Software (SAS). We can see that the draws are randomly distributed and exhibit low correlation. This is an indication that the Bayesian estimation has converged for these two parameters. A similar result is obtained for other parameters.

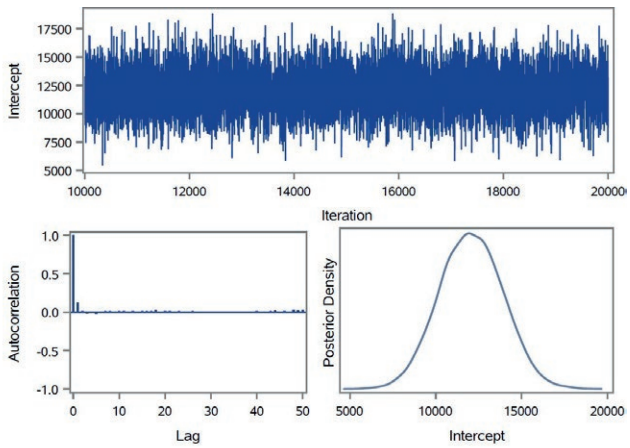

Figure 4. Bayesian diagnostics for Intercept.

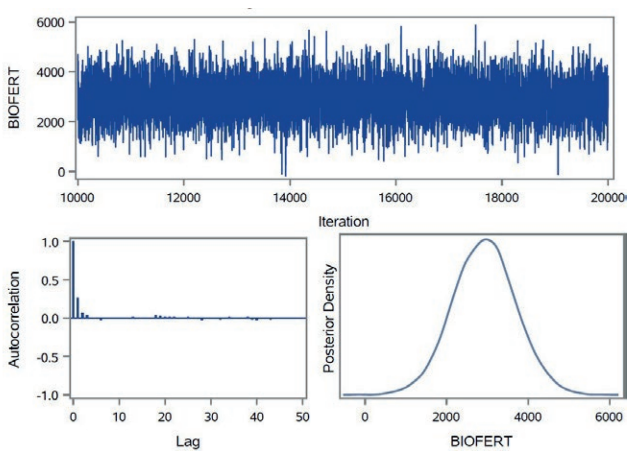

Figure 5. Bayesian diagnostics for Biofertilizer.