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Socio-Economic Drivers of Benefits from Agri-Environmental Measures among Rural Farming Households in Akinyele Local Government Area of Oyo State, Nigeria

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Abstract. The study investigated the socio-economic characteristics of rural farming households, the types of Agri-Environmental Measures (AEMs) adopted, and the determinants of benefits derived from participation in Akinyele Local Government Area of Oyo State, Nigeria. A total of 240 farmers were surveyed using a multi-stage sampling procedure. The results showed that 36.7% of respondents were aged 41–50 years, 67.5% were male, and 53.4% had secondary or tertiary education. Most farmers (80.8%) had over 10 years of farming experience, while 64.2% belonged to cooperatives and **70%** had extension contact. Farmers mainly adopted organic manure (71.7%), soil conservation (67.5%), controlled chemical use (65%), agroforestry (61.7%), and climate-smart practices (57.5%).Binary logistic regression showed that farm size ($\beta = 0.311$, $p = 0.003$**)**, cooperative membership ($\beta = 0.842$, $p = 0.000$), extension contact ($\beta = 1.124$, $p = 0.000$), income ($\beta = 0.514$, $p = 0.005$), and farming experience ($\beta = 0.042$, $p = 0.020$**)** significantly increased the likelihood of benefiting from AEMs. Age had a mild negative effect ($\beta = –0.028$, $p = 0.048$**)**, while education and household size were not significant. The study concluded that socio-economic readiness, institutional support, and access to information strongly shaped the probability of deriving benefits from AEM participation. Strengthening extension services and farmer cooperatives was essential for enhancing AEM effectiveness.

Keywords: Benefit, agricultural, environmental measures, participation and farming households.

1. Introduction

Sustainable agriculture has evolved beyond the mere pursuit of increased productivity; it now emphasizes responsible management of natural resources, balanced ecosystem functioning, and climate-resilient farming systems (FAO, 2021). Agricultural–Environmental Measures (AEMs) constitute formal and informal interventions that encourage farmers to adopt environmentally friendly practices such as agroforestry, soil conservation technologies, climate-smart farming, water-efficient irrigation, biodiversity conservation, waste minimisation, and controlled use of agrichemicals (OECD, 2020). Many rural farmers engage with AEMs based on the expectation of improved soil fertility, yield stability, reduced production costs, and long-term ecological balance. Despite the proliferation of AEM programmes, farmers do not derive benefits uniformly. Some farmers gain substantial economic and ecological advantages, whereas others participate but report marginal or no benefits. Understanding the socio-economic dynamics behind these variations remains critical for effective policy design (Ajayi and Kwame, 2019). Currently, the priority is to promote environmentally friendly production methods. In the shaping and management of natural and agricultural areas, methods of pro environmental activities are of particular importance. Organic and sustainable agriculture is therefore no longer perceived as inefficient and extensive. On the contrary, there is an increasing understanding that it creates both the opportunity to produce high-quality food, as well as improve the natural environment (Kuczuk, 2005). This study therefore refocuses attention strictly on socio-economic characteristics of farmers, the types of AEMs implemented in the study area, and the logistic determinants influencing their probability of benefiting from AEMs. The structure of presentation mirrors an article format typical of applied rural development research.

This research therefore focuses on three major components:

- The socio-economic characteristics of the farmers in the study area
- The types of agricultural environmental measures practiced by the farmers in the study area.
- The determinants of benefits derived from agricultural environmental measures explained through binary logistic regression.

2. Research Methodology

2.1 Study Area

The study was conducted in Akinyele Local Government Area (LGA) of Ibadan, OyoState Nigeria It has an area of 518km2. Its geographic coordinates are 7°23' 47" N and longitude3°55'0"E with her headquarters in Moniya, and shares boundaries with Afijio Local Government to the north, Lagelu Local Government to the East, Ido local government to the West and Ibadan North local government to the south. It has a population of 105,59 males and 106,217 females (NPC, 2006). The town has a tropical climate and it is generally experiences both raining and dry season as well as harmattan, (Efenakpo *et. al.* 2016). It is one of the eleven Local Governments that make up Ibadan metropolis. Akinyele Local government Area were created in 1976 and it occupies a land area of 464.892 square kilometres with a population density of 516 persons per square kilometre. Using 3.2% growth rate from 2006 census figures, the 2010 estimated population for the Local Government is 239,745(NBS, 2009).

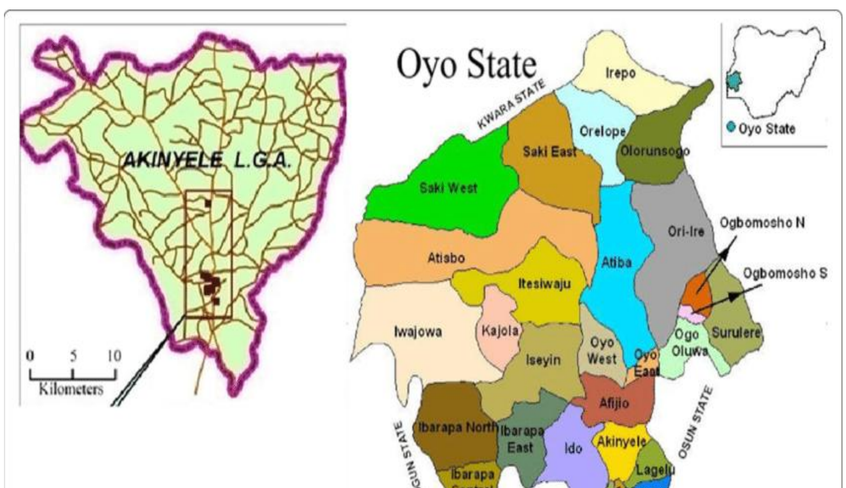

Figure 1: *Map of the Akinleye Local Government Area*

2.2 Target Population

The targeted populations of the study were Akinyele local government area of Oyo state.

2.3 Sampling Procedure and Sample Size

Multi stage sampling techniques was used to carried out the study

Stage 1: Akinyele Local Government Area consists of twelve (12) wards. These are: Ward 1 – Ikereku, Ward 2 – Arulogun, Ward 3 – Olode, Ward 4 – Akinyele, Ward 5 – Iwokoto, Ward 6 – Ojoo, Ward 9 – Ajibade, Ward 10 – Moniya, Ward 11 – Olorisa-Oko, and Ward 12 – Iroko. Purposive sampling was employed at this stage to select wards where farming constitutes the major occupation of residents. Based on this criterion, five (5) wards were chosen out of the twelve. The selected wards include Ikereku (Ward 1), Arulogun (Ward 2), Olode (Ward 3), Moniya (Ward 10), and Iroko (Ward 12).

Stage 2: Random Selection of villages in each selected ward. Three (3) villages were selected in each selected ward. Ward 1 (Ikereku): Oyada, Alakeji, Talontan, Ward 2 (Arulogun): Igbooloyin, Aroro Yerokun, Aroro Kole. Ward 3 (Olode): Olode, Onigborogbo, Amosun, Ward 10 (Moniya): Moniya, Ajibade, Olorisaoko, Ward 12 (Iroko): Oretu, Iroko, Alasoosu.

In order to carry out this research, respondents were selected in each randomly selected villages which make up a total of 240 questionnaire that were administered for this study.

Stage 3: All 12 wards were also purposively selected farmers across Akinyele LGA. In the third stage, a list of registered farmers was collected from the department of agriculture at the LGA headquarters in Moniya

Table 1: Projected and sampled population of study sites

Study sites	List of Registered Farmers	Proportionally sampled population (2.5%)
Oyada	320	8
Alakeji	305	7
Talontan	480	10
Igbooloyin	280	7
Aroro-Yerokun	413	10
Aroro-Kole	1051	37
Olode	460	12
Onigbororogbo	439	11
Amosun	474	12
Moniya	1500	37
Ajibade	188	5
Olorisaoko	154	4
Oretu	800	15
Iroko	2300	57
Alasoosu	326	8
Total	**9167**	**240**

Measurement of Variable

Model specification followed the standard logistic form:

$$In(P / (1 - P)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k + \mu$$

Where:
P = probability of benefiting from AEMs
$X_1 \ldots X_k$ = socio-economic variables (age, education, experience, income, extension access, etc.)
$\beta_0 \ldots \beta_k$ = regression coefficients
μ = error term

3. Results and Discussion

The age distribution in Table 2 showed that most respondents (36.7%) were between 41 and 50 years, which aligned with earlier findings that middle-aged farmers remained most actively involved in sustainable agriculture (Kassali and Adepoju, 2020). Farmers in this age group typically possessed adequate experience and adaptive skills needed for implementing environmental measures. The gender composition indicated that males dominated farming activities, reflecting the patriarchal land-ownership structure common in many rural settings (Adedayo and Ogunyinka, 2018). However, the 32.5% female participation suggested a growing level of inclusiveness. Also, educational attainment revealed that 53.4% of respondents had secondary or tertiary education. This was considered positive because education generally improved farmers' understanding of environmental policies, technical information, and openness to trying new practices (Nwachukwu and Odoemenem, 2019). Furthermore, household sizes showed moderate dependency levels, while farming experience indicated that 80.8% of respondents had more than 10 years of experience. This suggested that most farmers had accumulated substantial indigenous knowledge and were familiar with resource-management practices. In addition, from Table 2, farm sizes were predominantly small-scale, with most respondents cultivating less than 3 hectares. This pattern was typical of the agricultural structure in rural Nigeria (FMARD, 2022). Cooperative membership was relatively high (64.2%), indicating that most farmers belonged to social groups that enhanced access to credit, training, and information. Such social capital was commonly associated with higher participation in environmental measures (Eneji and Ocholi, 2021).it was revealed that extension contact was also high (70%), demonstrating that many respondents maintained regular interactions with extension agents who served as intermediaries for AEM training and incentives (World Bank, 2020). Lastly income distribution showed that most respondents earned ₦300,000–₦600,000 annually, reflecting a modest economic status. Overall, the socio-economic characteristics portrayed a farming population capable of understanding and adopting AEMs, although small farm sizes and moderate-income levels likely constrained the extent of adoption.

Table 2: Socio-Economic Characteristics of Respondents (n = 240)

Variable	Category	Frequency	Percentage (%)
Age	≤30 years	28	11.7
	31–40 years	54	22.5
	41–50 years	88	36.7
	>50 years	70	29.1
Gender	Male	162	67.5
	Female	78	32.5
Education	No formal education	46	19.2
	Primary	66	27.5
	Secondary	82	34.2
	Tertiary	46	19.2
Household size	1–4 persons	58	24.2
	5–8 persons	142	59.2
	>8 persons	40	16.6
Farming experience	<10 years	46	19.2
	10–20 years	112	46.7
	>20 years	82	34.1
Farm size	<1 ha	52	21.7
	1–3 ha	126	52.5
	>3 ha	62	25.8
Cooperative membership	Yes	154	64.2
	No	86	35.8
Extension contact	Yes	168	70.0
	No	72	30.0
Annual income	< ₦300,000	64	26.7
	₦300,000–₦600,000	108	45.0
	> ₦600,000	68	28.3

The result in Table 3 revealed that farmers in the study area adopted multiple types of Agricultural–Environmental Measures (AEMs), reflecting soil conservation needs, climate-related pressures, and recommendations from extension agents. Organic manure and composting (71.7%) emerged as the most widely adopted practice. This aligned with the increasing recognition that organic inputs reduced production costs and improved soil quality (Oladele & Adebisi, 2020). Also, soil conservation techniques (67.5%), including contouring and terracing, remained essential for controlling erosion, particularly in areas with sloped farmlands. In addition, agroforestry, adopted by 61.7% of respondents, reflected a growing interest in integrating trees into cropping systems. This practice was known to improve microclimates, enhance biodiversity, and provide additional income streams (Mercer, 2019). Controlled chemical use (65%) suggested progress toward safer agrochemical management, which had been strongly promoted through extension services. Furthermore water-management practices (42.5%) recorded relatively low adoption, which might have been influenced by infrastructural and financial limitations. Lastly, biodiversity conservation (35.8%) had the lowest adoption rate, likely because such practices often lacked immediate economic benefits unless supported by incentives (UNEP, 2020).

Table 3: Types of AEMs Adopted by Respondents in the Study Area

AEM Type	Frequency	Percentage (%)
Soil conservation/terracing	162	67.5
Agroforestry	148	61.7
Organic manure/composting	172	71.7
Cover cropping/mulching	134	55.8
Water management/irrigation efficiency	102	42.5
Controlled chemical use/IPM	156	65.0
Climate-smart practices	138	57.5
Biodiversity conservation	86	35.8

The Table 3 below revealed that a binary logistic regression model was used to determine factors influencing benefits derived from AEMs. Age ($\beta = -0.028$, $p = 0.048$), age had a negative effect, suggesting that younger farmers were slightly more likely to report benefits. Younger farmers may be more experimental and more likely to implement AEM recommendations fully (Adeyemi and Bello, 2021). In term of Farming Experience ($\beta = 0.042$, $p = 0.020$). This Implies that more experienced farmers were significantly more likely to benefit. Experience enables them to understand ecological responses and manage AEM practices optimally. Also, positive relationship existed in term of Farm Size ($\beta = 0.311$, $p = 0.003$), larger farm sizes increased the probability of benefiting. This is consistent with empirical reports that AEMs yield greater visible improvements on larger holdings due to economies of scale (Evenson and Gollin, 2019). Cooperative Membership ($\beta = 0.842$, $p = 0.000$) were 2.32 times more likely to benefit. Cooperatives facilitate training access, group incentives, and learning exchanges (Musa and Fajobi, 2020). Extension Contact ($\beta = 1.124$, $p = 0.000$). This implies that extension access significantly increased the odds of benefiting ($Exp\beta = 3.08$). This aligns with previous findings that extension-driven AEM training enhances correct practice application (World Bank, 2020). In addition, the Income level ($\beta = 0.514$, $p = 0.005$). The higher-income farmers were 1.67 times more likely to benefit, probably due to their better ability to invest in required materials, equipment, or labour. Education ($p = 0.061$), education was positive but not statistically significant at $p < 0.05$; however, its positive direction aligns with the expectation that better-educated farmers manage technologies more efficiently.

Table 4: Logistic Regression Estimates for Determinants of Benefits from AEM Participation

Variable	Coefficient (β)	Std. Error	Odds Ratio (Expβ)	p-value
Age	-0.028	0.014	0.97	0.048**
Education (years)	0.062	0.033	1.06	0.061
Household size	-0.015	0.027	0.98	0.563
Farming experience	0.042	0.018	1.04	0.020**
Farm size	0.311	0.102	1.36	0.003***
Cooperative membership	0.842	0.217	2.32	0.000***
Extension contact	1.124	0.254	3.08	0.000***
Income	0.514	0.181	1.67	0.005***
Constant	-3.417	0.824	—	0.000

*p < 0.01, p < 0.05

4. Conclusion

The study offers a refocused and evidence-driven analysis of how socio-economic characteristics interact with AEM participation outcomes. The socio-economic profile shows a predominance of middle-aged, moderately educated, experienced small-scale farmers with substantial cooperative involvement and extension exposure. The types of AEMs widely practised include composting, soil conservation, agroforestry, controlled chemical use, and climate-smart interventions. Logistic regression results show that farm size, income, extension contact, cooperative membership, farming experience, and age significantly determine whether farmers derive benefits from participating in AEMs. The findings reaffirm that the successful impact of environmental agricultural programmes relies heavily on socio-economic readiness, institutional support, and access to knowledge.

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