Research Article

Does Agroforestry Technology Adoption Affect Income Inequality among Arable Crop Farmers in Southwest, Nigeria? A Gender Perspective

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Abstract | Variations in agroforestry technology adoption and level of income inequality across genders have not been given adequate attention in the literature. Hence, this study examined the effect of agroforestry technology adoption on income inequality among the gender of arable crop farmers in Southwest, Nigeria. A multistage selection process was employed to pick 450 arable crop farmers. The collected data were analyzed with the use of descriptive statistics, probit regression model and Gini coefficient analysis. Findings from this study revealed that the adoption of agroforestry technology increased income inequality among male and female crop farmers. Also, the difference in the income inequality level between adopters and non-adopters of agroforestry technology among female farmers was more than what was obtained among male farmers. Income inequality among female crop farmers was more than that of male crop farmers, while more male farmers adopted agroforestry technology than female ones. Credit constraints, experience and education had the highest contributions to inequality among male farmers, while education and credit constraints had the highest contributions among their female counterparts. Therefore, policy measures targeted at promoting the acceptance of agroforestry technology, especially among female crop farmers, should be applied.

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Introduction

Degradation of soil creates a serious challenge to Nigerian agriculture (Owombo and Idumah, 2017). The scale of land degradation and deforestation is greater than the conservation actions in developing countries (Bekele and Mekonnen, 2010). There is variation in the land conservation-related technologies embraced by the inhabitants of rural communities on the basis of purpose and individual preferences. Using inorganic fertilizers is a rapid and easy way of restocking nitrogen and other important elements in the soil. However, resource constraints have precluded a large number of inhabitants of rural communities from affording inorganic fertilizers (Kabwe *et al*., 2009). Hence, agroforestry technologies suggest another remedy to smallholder farmers' resource constraints, who would grow crops without inorganic fertilizers with minimal destruction of soil nutrients and structure (Owombo and Idumah, 2017). According to Waldron *et al*. (2017), agroforestry is becoming more prominent being a land-use policy to assist in solving the worldwide climate change problem while also providing other environmental, economic, and social gains. Agroforestry is the deliberate combination of woody vegetation (shrubs and trees) with livestock and/or crops, concurrently or consecutively, on a unit of land (Atangana *et al*., 2014).

Agroforestry technology is capable of improving the health of the soil as it checks soil erosion, increases soil richness and reduces other soil parameters that adversely affect soil (such as salinity and acidity). Ultimately, agroforestry makes land suitable for sustainable food production (Sharma *et al*., 2017). In reality, literature on the use of agroforestry in farming systems supports the idea that agroforestry may improve rural people's welfare and protect natural assets from negative human activities (Kirui, 2016). It has been empirically revealed that the acceptance of agroforestry brought about an increase in the revenue of the farmers (Saqib and Khan, 2022). The importance of the technology is in its soil richness, which maintains benefits and the capability to mix woody perennials with crops and/or animals being organized by one management unit that provides economic gains. This enhances rising income of farmers via the effective use of inputs (Lambert and Ozioma, 2011).

Shita *et al*. (2020) stated that technological acceptance meaningfully lessens poverty and advances the living standard of humanity mainly through an increase in productivity. Once agricultural productivity is enhanced, the welfare of farmers is improved via a rise in food availability and a reduction in the prices of agricultural commodities (Mekonnen, 2017). Agroforestry can help increase farmers' social, economic, and environmental gains by diversifying and sustaining agricultural production. Specifically, agroforestry technology is vital to smallholder farmers as it enhances the supply of food, revenue, and healthiness among farmers (Food and Agriculture Organization (FAO, 2013). According to Reyes *et al*. (2005), households that embraced improved agroforestry technology realized twice the annual income of households that applied traditional practices.

Empirical evidence in the literature shows that studies on agroforestry technology tilt toward the determinants of agroforestry technology adoption (Kabwe *et al*., 2009; Owombo and Idumah, 2017), the association between agroforestry and income from non-farm diversification activities (Kassie, 2017), the socioeconomic and ecological gains of the agroforestry technology (Kiyani *et al*., 2017), and the acceptance of improved agroforestry technologies (Lambert and Ozioma, 2011). There is a dearth of information on the effect of agroforestry technology adoption on income inequality among arable crop farmers in Nigeria. Very few studies, such as Kilima *et al*. (2013) and Shita *et al*. (2020), investigated the influence of agricultural technology adoption on income disparity in Tanzania and Ethiopia, respectively. However, it should also be noted that agroforestry technology adoption and level of income inequality may vary significantly across gender and country. According to Santos *et al*. (2017), technology adoption effects may differ from country to country.

Also, the influence of technology adoption on income disparity, as shown in the literature, is not clear. For example, Kilima *et al*. (2013) and Becerril and Abdulai (2010) found that the adoption of technology reduced income inequality. According to Lin (1999) and Ding *et al*. (2011), the effect of technology acceptance on income inequality was insignificant because lower-income farming households adopted technology at nearly the same rate as higher-income farming households, whereas Shita *et al*. (2020) discovered that acceptance of agricultural technologies increased income disparity. To the best of our knowledge, variation in agroforestry technology adoption and level of income inequality across gender has not been given adequate attention in the literature. Hence, there is a need to carry out a study that examines whether the adoption of agroforestry technology affects income inequality across genders in Southwest Nigeria or not. The study specifically examined factors influencing adoption of agroforestry technology among arable crop farmers across gender, checked the effect of agroforestry technology adoption on income inequality across gender, and examined the determining factors of the income inequality level (Gini coefficient) across gender. Evidence from this study will assist policymakers and other stakeholders in formulating policies that engender sustainable development in Nigeria.

Materials and Methods

The study was done in Southwest, Nigeria between October and December 2021. A multistage selection process was employed to pick 450 arable crop farmers. In the first step, two (2) states were picked using a random sampling technique. The second step had to do with a random choice of five (5) Local Government Areas (LGAs) from each of the chosen States. There are 18 and 16 Local Government Areas in Ondo State and Ekiti State, respectively. Using random sampling, five (5) communities were picked from each of the chosen LGAs. The fourth step involved the choice of five (5) male and four (4) female respondents from each of the chosen communities, bringing the total number to four hundred (450) respondents. Though only 400 copies (male= 298 and female= 102) of the survey instrument were deemed useful for the analysis because of the inadequate data supplied in the remaining 50 copies of the questionnaire. Data on socioeconomic variables, agroforestry techniques, farm income, credit constraints, land ownership, and others were gathered. Descriptive statistics, probit regression model and Gini coefficient analysis were used to analyse the collected data.

Table 1 shows the descriptions and summary statistics of the variables used in this study. Some of the variables have significant differences between male and female arable crop farmers. For example, the average number of years spent in school by male arable crop farmers ismore than that of female arable crop farmers. Also, male farmers had a larger farm than female farmers. This may not be unconnected with the fact that men have more access to agricultural land in the study area. According to Mukasa and Salami (2015), agricultural land held by

Table 1: *Descriptions and summary statistics of the variables used in the study.*

Variable	Description	Male (N=298)	Female (N= 102)	Difference
		Mean value	Mean value	
Adoption	1 if the respondent adopted agroforestry technology and 0 otherwise	0.591	0.608	-0.017
Years of formal education	Number of years spent in school	10.487	9.118	1.369**
Age	Age of the respondent	47.861	47.012	0.849
Marital status	1 if the respondent is married and 0 otherwise	0.922	0.916	-0.005
Household size	Number of persons living in the family and sharing meals	7.490	7.087	0.403
Farm size	Size of farm in hectares	2.622	2.222	0.400*
Farming experience	Number of years spent in farming	12.180	11.480	0.699
Number of hours spent on farm daily	Number of hours spent on farm on daily basis	6.090	5.716	0.374
Number of extension visits	Number of time the respondent was visited by extension agents in a month	0.936	0.598	0.338**
Access to information on agroforestry	1 if the respondent had access to information on agroforestry and 0 otherwise	0.547	0.647	-0.100
Cooperative membership	1 if the respondent belongs to a cooperative society and 0 otherwise	0.570	0.431	0.139***
Credit constraints	1 if the respondent is non-credit constrained and 0 otherwise	0.513	0.471	0.043
Log of income	Income from farming activities	12.915	12.870	0.045
Land ownership				
Inherited	1 if land for the farm is purchased and 0 otherwise	0.834	0.347	0.487***
Borrowed	1 if land for the farm is borrowed and 0 otherwise	0.554	0.643	-0.089
Rented	1 if land for the farm is rented and 0 otherwise	0.453	0.398	0.055

****, ** and * represent 1%, 5% and 10% level of significance, respectively.*

women is outrageously little, as they are seriously discriminated against with respects to land ownership in Nigeria. Also, male arable crop farmers were more visited than their female colleagues. This could be linked to the greater involvement of men in agricultural activities than women in the study area. More male farmers were members of cooperative societies and inherited their farm land. This may be due to the tradition of giving male children the right to inherit their fathers' farmland without any serious consideration being given to female children in the study area.

Model specifications

A probit regression model was employed to examine factors influencing the adoption of agroforestry technology among the respondents. Binary regression is a type of regression widely used in the case of a dichotomous response variable (0 or 1). For this reason, ordinary least squares (OLS) could not be considered for this study since the dependent variable does not conform to the linear relationship using a continuous variable. According to Gujarati and Porter (2009), logit and probit regressions are commonly used to predict regressions with a dichotomous dependent variable. Despite the fact that there is no compelling reason to select one model over the other, the study prefers the probit model because the logistic distribution has slightly flatter tails, which implies that the conditional probability approaches the axes (0 or 1) faster in the probit model than in the logit model (Gujarati and Porter, 2009). It was also reported that the probit model predicts small sample sizes better than the logit model (Gujarati and Porter, 2009; Olutumise *et al*., 2021). Following Mwangi *et al*. (2009); Oparinde *et al*. (2020), farmers were categorized into adopters and non-adopters of agroforestry technology, which makes the dependent variable (agroforestry technology adoption) to be dummy. Hence, the reason for the use of probit regression model. Let k_i^* represents the probability connected to agroforestry technology adoption by farmer *t*. The regression equation is expressed as:

$$k_i^* = \alpha' m_i + \varepsilon_i \ \dots (1)$$

Where; α represents the coefficients to be calculated, m_i stands for the observed regressors for farmer *i*, while ε_i represents the normally spread residual terms with $E(\varepsilon_i) = 0$. Having known that true probability k_i^* is not observable and there are two observed discrete options adopter (probability is positive) and non-adopter (negative probability), let k_i stand for the observed outcome which is expressed as:

$$k_i = \begin{cases} 1 \text{ if } k_i^* \geq 0 & \textit{Adopter of agroforestry technology} \\ 0 \text{ if } k_i^* < 0 & \textit{Non-adopter of agroforestry technology} \end{cases}$$

Equation 2 presents the probit model as:

$$Prob(k_i = 1) = Prob(k_i^* \geq 0) = \int_{-\infty}^{-\alpha' m_i} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \ \dots (2)$$

The marginal effect is estimated using Equation 3.

$$\frac{\partial E(k_i \mid m_i)}{\partial k_{ij}} = \frac{\partial F(m_i' \alpha)}{\partial k_{ij}} = f(m_i'\alpha)\alpha_j \ \dots (3)$$

Where *f* (.) represents probability density function (p.d.f.) of a standard normal spreading, α_j stands for the jth element of α and m_{ij} is the jth element of m_i.

The same model was used for the two groups (male and female) separately. Therefore, the explanatory variables used in the two model specifications include m_1 =Age of the respondents (years), m_2 = Formal education (Number of years spent in schooling), m_3 = Marital status (1= married, 0 otherwise), m_4 = Household size (numbers), m_5 = Farm size (ha), m_6 = Farming experience (years), m_7 = Time spent on farm daily (hours), m_8 = Extension visits (numbers), m_9 = Access to information on agroforestry (1 = Yes, 0 otherwise), m_{10} = Cooperative membership (1 = Yes, 0 otherwise), m_{11} = Credit constraints (1= Non-credit constrained and 0 otherwise), m_{12} =log of income (Naira) and m_{13} = Land ownership (1= inherited, 2 = Borrowed, 3 = Rented).

The Gini coefficient is estimated using a variety of techniques. This study used the method by Oparinde and Ojo (2014). The Gini-coefficient is used to calculate statistical dispersion most conspicuously used to present the level of revenue distribution among different households (Olutumise *et al*., 2019). Gini coefficient is expressed as:

$$G = \frac{A}{A+B} \ \dots (4)$$

Where *G* represents the Gini coefficient, *A* is the area that is between the equality line and the Lorenz curve, while *A+B* is the total area under the equality line. The value of Gini coefficient is between zero and one. A low value of Gini coefficient implies higher equal income distribution, while a high value implies higher unequal distribution. Zero (0) means equality that is perfect while one (1) implies inequality that is perfect. Lorenz curve shows the percentage of income gotten by any given percentage of the population. There is inequality in the population when the curve bows outwards towards the southeast.

The study went further to find out how adoption decisions and selected socioeconomic variables determine the level of inequality using the field approach (Fields, 2003). The study is built on the human capital model, where investments are made in human capital to generate more future benefits (Saira and Anther, 2016). The concept is that productivity is a function of human capital investment. Therefore, an individual maximizes satisfaction when the marginal returns are equal to the marginal cost. The income of individuals has been used as an outcome variable, with several factors estimated as their determinants (Saira and Anther, 2016). In this study, we modeled the adoption of agroforestry and other variables as determinants of the level of inequality, which makes it different from the previous studies. Two steps of analysis were involved following Fields (2003) to determine the income inequality by focusing on the adoption decisions.

Step 1: This involves the use of OLS regression to find out the determinants of income of the respondents. The model is explicitly expressed as:

$$lnHHI_i = \omega_0 + \omega_1 ADD_1 + \omega_2 AAI_2 + \omega_3 AGE_3 + \omega_4 SCH_4 + \omega_5 HHS_5 + \omega_6 FMS_6 + \omega_7 EXP_7 + \omega_8 ACT_8 + \omega_9 COM_9 + \varepsilon_i \quad ...(5)$$

Where; $lnHHI_i$ is the log of annual household income of individual i^{th} in naira, ADD_1 = Adoption decision (1= adopter and 0, otherwise), AAI_2 = Access to information on agroforestry (1 = Yes, 0 otherwise), AGE_3 = Age of the respondents (years), SCH_4 = Formal education (years), HHS_5 = Household size (numbers), FMS_6 = Farm size (Ha), EXP_7 = Farming experience (years), ACT_8 = Credit constraints (1= Non-credit constrained and 0 otherwise), COM_9 = Cooperative membership (1 = Yes, 0 otherwise), and ε_i = error term.

Step 2: The coefficients from the OLS regression in Equation 5 were used to compute the percentage contribution of the adoption decision and other variables to the level of inequality (Gini coefficient) which is also known as the factor inequality weights (FIW). The model is stated as:

$$FIW_j = \frac{cov(\omega_j Z_j, lnHHI)}{\sigma^2(lnHHI)} = \omega_j * \sigma(Z_j) * \frac{cor(Z_j\, lnHHI)}{\sigma(lnHHI)} \quad ...(6)$$

Where; ω_j denotes the estimated coefficient from Equation 5 of the j^{th} individual, Z_j denotes the mean value of the explanatory variables, $\sigma(Z_j)$ and $\sigma(lnHHI)$ are the standard deviation of Z_j and of $lnHHI$, respectively, cor $(Z_j, lnHHI)$ is the correlation between factor j and $lnHHI$. Therefore, FIW_j indicates the share of j^{th} characteristic in inequality (Gini index) because it is assumed that Z_j is unequally distributed among the households. The positive FIW_j implies that j is an inequality-increasing factor whereas the negative FIW_j means that factor j decreases the inequality. Again, the FIW_j are summed to unity ($\sum FIW_j + FIW_\varepsilon = 1$). Where FIW_ε is the inequality arising from the unknown (error term), while FIW_j is the independent variables of the above OLS regression that determines the proportion of inequality explained, that is, R-square ($FIW_j = R^2$).

Therefore, the FIW_j will be large if ω_j is large or Z_j is highly correlated with the household income (HHI).

Results and Discussion

Factors influencing agroforestry technology adoption among arable crop farmers

The probit regression results of factors influencing the adoption of agroforestry technology among arable crop farmers are presented in Table 2. Columns 2 and 3 present the regression estimates for male arable crop farmers, while columns 4 and 5 present the regression estimates for female arable crop farmers. The likelihood ratio statistics for male and female respondents that are indicated by χ^2 statistics (73.34) and (31.50), respectively, are highly statistically significant, suggesting that the models have strong explanatory power. Also, the Pseudo-R^2 values of 0.182 and 0.231 for male and female respondents imply that the independent variables explained 18.2% and 23.1% of the changes in the dependent variable in male and female model specifications, respectively.

The results of the analysis show that the age of the respondents, years of formal education, number of extension visits, credit constraints, income, and land ownership through inheritance significantly influenced the adoption of agroforestry technology among the male respondents. In the case of female respondents, marital status, household size, number of

Table 2: *Probit regression results of factors influencing adoption of agroforestry technology among arable crop farmers in the study area.*

Independent variable	Male		Female	
	Coefficients (Z-value)	Marginal effects (Z-value)	Coefficients (Z-value)	Marginal effects (Z-value)
Constant	1.339 (1.07)		-5.855 (0.56)	
Age of the respondents	-0.009***(4.50	-0.004*** (4.50)	0.014 (0.62)	0.005 (0.62
Years of formal education	0.027**(2.01)	0.010** (2.00)	0.036 (0.56)	0.013 (1.00)
Marital status	-0.687 (0.45)	-0.263 (0.44)	0.488*** (2.78)	0.184*** (2.76)
Household size	0.132 (1.23)	0.051 (1.20)	0.129** (1.89)	0.049** (1.88)
Farm size	-0.009 (1.02)	-0.004 (1.01)	0.142 (0.53)	0.054 (0.43)
Farming experience	-0.006 (1.62)	-0.002 (1.60)	-0.006 (1.54)	-0.002 (1.53)
Number of hours spent on farm daily	0.089 (0.34)	0.034 (0.33)	0.051* (1.78)	0.019* (1.76)
Number of extension visits	0.093* (1.92)	0.036* (1.90)	0.120 (0.67)	0.045 (0.66)
Access to information on agroforestry	0.314 (1.40)	0.520 (1.38)	0.738** (1.99)	0.278** (1.98)
Cooperative membership	0.247 (0.65)	0.095 (0.64)	0.399* (1.88)	0.150* (1.86)
Credit constraints	0.012*** (7.69)	0.005*** (7.53)	0.059 (0.46)	0.220 (0.45)
Log of income	0.059*** (9.74)	0.022*** (9.65)	0.029 (0.33)	0.108 (0.32)
Land ownership				
Inherited	0.610*** (3.20)	0.197*** (3.18)	0.526*** (2.79)	0.178*** (2.76)
Borrowed	-0.591 (1.23)	-0.232 (1.21)	-0.789 (1.44)	-0.306 (1.42)
Rented	-0.249 (0.95)	-0.097 (0.86)	0.305 (1.31)	0.109 (1.30)
Loglikelihood	-164.97		-52.56	
LR Chi2 (15)	73.34***		31.50***	
Pseudo R^2	0.182		0.231	

****, ** and * represent 1%, 5% and 10% level of significance, respectively.*

hours spent on the farm daily, access to information on agroforestry, cooperative membership, and land ownership through inheritance were the significant factors influencing agroforestry technology adoption. In the male model specification, years of formal education, number of extensions visits and income were directly related to the adoption of agroforestry technology, indicating that a rise in any of these variables would lead to a rise in the likelihood of choosing agroforestry technology by 1.0%, 3.6% and 2.2%, respectively. These results are in congruence with Shita *et al*. (2020), where education and access to extension services were reported to have increasing influence on the probability of adopting agroforestry technology. Oparinde (2021) also reported the importance of education in the adoption of climate change adaptation strategies. According to Kassie *et al*. (2011), education boosts awareness about the likely benefits of agricultural technology, which can improve its adoption. Also, Mahouna *et al*. (2018) clarified that well-educated farmers could easily look for information and decide based on their preferences using the collected information. Access to extension services can enhance technology acceptance by increasing farmers' consciousness of the importance and implementation of innovations (Husen *et al*., 2017; Adetula *et al*., 2020). However, the age of the respondents had a negative but significant relationship with agroforestry technology adoption, which implies that a rise in the respondents age would lead to a 0.5% rise in the likelihood of being a non-adopter of the technology. This could be linked to the fact that fairly old farmers might be hesitant and conservative towards the acceptance of agricultural technologies (Hailu *et al*., 2014). Being non-credit constrained and having land ownership through inheritance increases the probability of adopting agroforestry technology by 0.5% and 19.7%, respectively. The increasing influence of land ownership through inheritance on the adoption of agroforestry technology could be linked to the sense of ownership, which encourages the adoption of technologies that boost farm productivity and subsequently increase the welfare of the farmers. This supports the findings of Owombo and Idumah

(2017), where it was reported that owning agricultural land would increase the likelihood of adopting agroforestry technology. According to Abate *et al.* (2016), farming households' access to credit increases the technology adoption rate since credit lowers the challenge of capital shortages to invest in improved technologies.

In the female model specification, marital status, household size, number of hours spent on the farm daily, access to information on agroforestry, cooperative membership, and land ownership through inheritance had a direct and momentous influence on agroforestry technology adoption, signifying that being a married arable crop farmer, a rise in household size, an increase in number of days spent on the farm daily, having access to information on agroforestry, cooperative society membership and having land ownership through inheritance would lead to a rise in the likelihood of choosing agroforestry technology by 18.4%, 4.9%, 1.9%, 27.8%, 15.0%, and 12.8%, respectively. Having large family members raises technology acceptance since it requires more labour for farming activities than non-adopters (Adofu *et al.*, 2013). According to Wossen *et al.* (2017), cooperatives had a positive effect on technology adoption through the provision of market information. The reason for the direct relationship between land ownership through inheritance and the adoption of agroforestry technology is the willingness of landowners to invest in land improvement measures such as agroforestry technology since they have secured land rights through inheritance. Also, adoption of agroforestry technology is always encouraged among farming households with larger family sizes because of the labourious nature of agroforestry technology adoption, which requires more hands. This is in line with Lambert and Ozioma (2011), where it was stated that family size had a direct and significant influence on the adoption of agroforestry technology.

Effect of agroforestry technology adoption on income inequality across gender

Table 3 and Figures 1, 2 present the outcome of the income inequality analysis using the Gini coefficient and Lorenz curve for income distribution across gender and agroforestry technology adoption among arable crop farmers. Here, the estimated income distributions of adopters and non-adopters of agroforestry technology for male and female farmers were compared. The effect of agroforestry technology adoption on income inequality is the difference in the respective distributions. A Gini coefficient comparison in the male column, as shown in Table 3, reveals that adopters of agroforestry technology had a Gini coefficient of 0.528, which is higher than the Gini coefficient value of 0.508 for the non-adopters of agroforestry technology. A comparison of Gini coefficients in the female column in Table 3 indicates that the Gini coefficient value of 0.560 was estimated for agroforestry technology adopters. In contrast, a Gini coefficient value of 0.448 was estimated for non-adopters of agroforestry technology. This could be attributed to the uneven distribution of farm income realized as a result of agroforestry technology adoption, indicating that lower-income arable crop farmers gained less than the higher-income arable crop farmers (Huang *et al.*, 2015). This suggests that being a user of agroforestry technology increases income inequality among crop farmers. This confirms the results of Shita *et al.* (2020), where it was stated that adopting agricultural technologies increased income inequality.

The graphical representation of the degree of income inequality among arable crop farmers across gender is presented in Figures 1 and 2. The higher the distance between the curve and the diagonal, the more the level of inequality, and vice versa. The income inequality difference between adopters and non-adopters of agroforestry technology among female arable crop farmers is more than what was obtained among male arable crop farmers. The slimmer income inequality difference between adopters and non-adopters of agroforestry technology among male farmers could be linked to the fact that lower-income arable crop farming households had almost the same rate of technology adoption as higher-income arable crop

Table 3: *Values of Gini coefficient by agroforestry technology adoption status and gender of arable crop farmers.*

Adoption status	Gini coefficient		Male		Female	
	Male	Female	Frequency	Percentage	Frequency	Percentage
Adopters	0.528	0.560	176	59.06	62	60.78
Non-adopters	0.508	0.448	122	40.94	40	39.22
Total			298	100.00	102	100.00

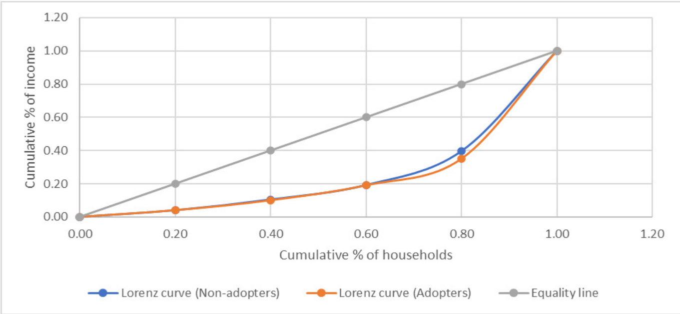

Figure 1: *Lorenz curve for male adopters and non-adopters of agroforestry technology.*

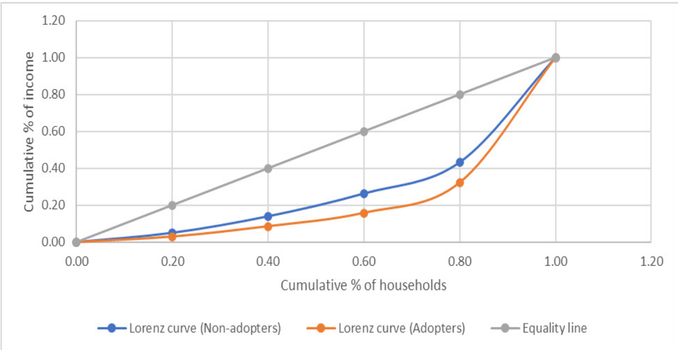

Figure 2: *Lorenz curve for female agroforestry technology adopters and non-adopters.*

farming households (Ding *et al*., 2011). The wider difference in income inequality between the two groups of female farmers could be attributed to the significant difference in the rate of agroforestry technology adoption between higher-income and lower-income arable crop farmers.

The Gini coefficients of the adopters of agroforestry technology between males and females were compared, and the Gini coefficient for female farmers was higher than for male farmers. This result corroborates the findings of Costa (2019), who reported that income inequality among female-headed households was more than that of male-headed households. In the case of non-adopters of agroforestry technology, the reverse was the case, with male and female farmers having Gini coefficient values of 0.508 and 0.448, respectively. This result is like the finding of Awotide *et al*. (2012), where it was reported that income disparity was higher among male farmers than their female colleagues.

Table 3 also shows that more male arable crop farmers (59.06%) adopted agroforestry technology than their female colleagues. This could be linked to low or no access to productive resources (for example, secure rights to land) by female-headed families in the study area. This finding is consistent with Shita *et al*. (2020) and Kassie (2017), where it was reported that the adoption rate of male-headed families was higher than that of female-headed families. In the same vein, more male arable crop farmers (40.94%) were non-adopters of agroforestry technology than their female counterparts. This implies that arable crop farming is a male-dominated business in the study area.

Determinants of the level of inequality (Gini coefficient) among male and female farmers

The results in Table 4 serve two purposes: (i) it shows the determinants of income, and (ii) It explores the determining factors of the level of disparity by computing the percentage contribution of the selected

Table 4: *Results of factor inequality weight (FIW) as determinants of inequality.*

Variable	Male			Female		
	Coeff.	**SE**	**FIW**	**Coeff.**	**SE**	**FIW**
Adoption decision	0.137***	0.062	0.015	0.025**	0.010	0.002
Access to agroforestry information	0.058**	0.021	0.013	0.075***	0.012	0.013
Age	0.007	0.008	-0.046	0.004**	0.002	-0.010
Education	0.019***	0.007	-0.108	0.021**	0.010	-0.145
Household size	-0.026	0.027	-0.084	0.018***	0.004	0.043
Farm size	-0.032	0.040	0.032	-0.025	0.034	0.019
Experience	0.015**	0.007	-0.119	0.012***	0.004	-0.070
Credit constraints	0.308**	0.138	0.141	0.275**	0.122	0.126
Cooperative	0.269**	0.132	0.103	0.186	0.116	0.028
Constant	12.564	0.458		12.712	0.406	
R^2	0.789			0.851		
F-value	16.63***			15.36***		
VIF	1.212			1.203		

****, ** and * represent 1%, 5% and 10% level of significance, respectively.*

socioeconomic factors to the Gini coefficient, which is the FIW. For results desirability, we perform some diagnostic tests for the variables. The F-statistics (16.63 and 15.36) for males and females were statistically significant at a 1% level. This shows that the model has goodness of fit and all the regressors in the model jointly influence the income of the farmers. Likewise, the values of R-square of 0.789 and 0.851 indicated that the explanatory variables explained nearly 79% and 85% of male and female incomes, respectively. The overall variance inflation factor (VIF) for male (1.212) and female (1.203) regression models indicates that there are no multicollinearity problems among the variables since the values are less than 4.00.

The OLS results showed that 6 and 7 out of 9 variables were statistically significant in explaining the income of the male and female farmers, respectively. It was also noted that 3 and 2 out of 9 variables were negatively associated with the incomes of male and female farmers, respectively. They are adoption decision, household size, and farm size for male respondents, while adoption decision and farm size are for the female farmers. It should be noted that the focus is on the level of inequality. According to Fields (2003) and Saira and Anther (2016), the regression-based inequality decomposition helps to know how much inequality is explained by the socioeconomic factors in the income of both genders. The coefficient of the adoption decision was positive and momentous in affecting the income of both genders. This agrees with several studies on the adoption of technology (e.g., Asfaw *et al*., 2012; Koledoye and Deji, 2015; Olutumise *et al*., 2020), where they also established a positive relationship between income and adoption decisions. The probable reason might be the benefits accrued by food crops and tree plants in the long run. The results of FIW showed that adoption decisions increased inequality among male farmers by 1.5% and increased inequality among female farmers by 0.2%. The rise in inequality shares of adoption decisions could be attributed to the statement of Anwar *et al*. (2017) that the more investment in agroforestry, the more the farmers earn income. These results tally with the findings of Shita *et al*. (2020) that adoption decisions increase income inequality.

Access to information on agroforestry was directly and statistically noteworthy in influencing the income of male and female farmers by 5.8% and 7.5%, respectively. The result is comparable with the results of Koledoye and Deji (2015), who also reported a direct association between income and source of information. It was further revealed that access to agroforestry information increases the inequality by 1.3% apiece for both genders among the adopters. This implies that access to agroforestry information significantly contributes to increasing income inequality between adopters and non-adopters. The farmer's age significantly increased the female farmers' income but reduced inequality by 1%. This is contrary to the findings of Saira and Anther (2016), who stated that age contributes to inequality and favours high-income earners. Formal education increases the income of both male and female farmers by 1.9% and 2.1%, respectively. The result supports the findings of Olutumise *et al*. (2022), who reported a significant and direct relationship between education and income among Nigeria's non-timber forest product gatherers. It was also noted that education reduced inequality by 10.8% and 14.5% for male and female farmers, respectively. Even though education was the highest contributor to reducing inequality, the magnitude of the female farmer is about 4% higher than their male counterparts. A similar result was reported by Saira and Anther (2016), where primary education decreased inequality compared with non-educated individuals, but secondary and tertiary education increased inequality. The result on education also supports the claim of Costa (2019), who stated that income inequality is more among female households than among their male colleagues.

Again, the household size coefficient significantly increased the female farmers income. The inequality contribution (FIW) is about a 4.3% increase. This implies that the larger the number of households, the greater the inequality among the female farmers. Farm size was not statistically significant, but it increased inequality by 3.2% and 1.9% for male and female farmers, respectively. The experience of the farmer significantly increased the income of both genders. The values of FIW show that farming experience reduced inequality by 11.9% and 7% for male and female farmers, respectively. It means that the more experience a farmer has, the more generates income to bridge the inequality in crop production. Being non-credit constrained increased income by 30.8% and 27.5% for male and female farmers, respectively. The outcomes of the inequality contribution showed that being non-credit constrained increased inequality by 14.1% and 12.6% for male and female farmers, respectively. The rise in inequality shares due to credit constraints indicated that non-credit-constrained farmers accrued more income than credit-constrained ones, leading to income inequality. Cooperative society membership was significant in affecting the income of the male farmers and made a positive contribution to the inequality. This implies that being a member will increase inequality by 10.3% compared to a non-member of a cooperative society.

It is, therefore, concluded that credit constraints (14.1%), experience (11.9%), and education (10.8%) had the highest contributions to inequality among male farmers, while education (14.5%) and credit constraints (12.6%) had the highest contributions among their female counterparts.

It can be deduced from the results that any farmer, male or female, who has adopted agroforestry technology, has access to correct agroforestry information, is educated and experienced, and has no restriction on accessing credit or a loan, will bridge income inequality. However, young female farmers with a considerable household size could have an edge over their older counterparts, who have larger households, in bridging income inequality. Likewise, male farmers that belong to cooperative societies could also have an edge over their male counterparts who are not members in reducing income inequality. The study has been able to identify gender-specific factors in reducing income inequality, especially among rural farming households.

Conclusions and Recommendations

This study examined the effect of agroforestry technology adoption on income inequality across gender among arable crop farmers in Southwest Nigeria. The study concluded that adoption of agroforestry technology increased income inequality among male and female crop farmers. The level of income inequality difference between adopters and non-adopters of agroforestry technology among female arable crop farmers is greater than what was obtained among male arable crop farmers. Income inequality among female arable crop farmers was greater than that of male arable crop farmers. More male arable crop farmers adopted agroforestry technology than their female counterparts. Credit constraints, experience, and education had the highest contributions to inequality among male farmers, while education and credit constraints had the highest contributions among their female contemporaries.

As a result, policy measures targeted at promoting the adoption of agroforestry technology, especially among female arable crop farmers, should be put in place. For example, policies that make more productive resources that aid the adoption of agroforestry technology (such as farmland) available to farmers equally, either male or female, should be encouraged. The wider income inequality difference between the female adopters and non-adopters of agroforestry technology could be attributed to the significant difference in the rate of agroforestry technology adoption between higher-income and lower-income arable crop farmers. Therefore, government and other stakeholders should intensify efforts on improving agroforestry technology adoption by lower-income arable crop farmers through the provision of incentives such as access to affordable credit, access to planting materials, secure land ownership, access to information on agroforestry technology, and so on. If the existing income inequality is to be reduced, there should be an improvement in the credit condition and an investment in the education of the farmers since credit constraints and education contributed to income inequality among the respondents. Having seen cooperative membership significantly influencing adoption of agroforestry technology, arable crop farmers are encouraged to join cooperative society in order to benefit from the cooperative advisory services, financial supports, and information sharing. Finally, it is suggested that further studies that consider adoption of various agroforestry technology strategies and income inequality among crop farmers which cover larger areas and sample size should be carried out.

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Novelty Statement

This study examined agroforestry technology adoption and level of income inequality across gender, which is very scarce in the literature because agroforestry technology adoption and level of income inequality may vary significantly across gender. Also, the effect of agroforestry technology adoption is clearly shown in this study, unlike other studies which did not give clear information on the effect of agricultural technology on income inequality. This study's evidence will assist policymakers and other stakeholders in formulating policies that engender sustainable development in Nigeria.

Author's Contribution

Lawrence Olusola Oparinde is the lead researcher and designed the research.
Lawrence Olusola Oparinde and Adewlae Isaac Olutumise analysed data and wrote the report.
Ademola Adegoroye collected data used for the study.

Conflict of interest
There are no conflicts of interest indicated by the authors.

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