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Income inequality in phezukomkhono mlimi farming households: A case study of Nkomazi Local Municipality, South Africa

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ABSTRACT
The South African government has developed several policies and intervention programmes to address food insecurity, poverty, and income inequality. One such programme is the Phezukomkhono Mlimi (PKM) initiative. However, empirical evidence demonstrating the impact of government programmes like the PKM on poverty and income inequality remains limited. This study examined income inequality and its determinants. A structured questionnaire was used to collect data from 230 respondents. The data were analyzed using descriptive statistics, the Gini coefficient, and a quantile regression model. The results indicated a high level of income inequality, with a Gini coefficient of 0.48. The majority (60.87%) of households derived their income from farming activities. Other sources of income included retirement funds (10.43%) and salaries (7.39%). The findings suggested a high unemployment rate within the study population. Age, education, household size, and farm size were identified as determinants of income inequality in the study area. Although the income inequality observed was lower than provincial and national levels, government intervention through the PKM programme has not significantly impacted income inequality in the study area. Considering this, policy interventions to improve equitable access to education, family planning, and farm size are recommended.

Contribution/Originality: There is a dearth of studies that investigate income inequality and its determinants among rural farming households in South Africa. This is the first study to quantify the level of income inequality among PKM farming households and to identify predictors of income inequality among farming communities in a rural setting.

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1. INTRODUCTION

Goal 1 of the Sustainable Development Goals of the United Nations is to eliminate poverty in all its forms everywhere by 2030 (Rahman, 2017; United Nations, 2015). However, many rural areas, especially in developing countries, remain vulnerable to income inequality and poverty, and as a result, there is a need to help rural farmers diversify and sustain production for increased social, economic, and environmental benefits (Akpan, Okon, Udo, & Akpakaden, 2020; Kadigi, 2021; Sambo, 2021). This is especially crucial for smallholder farmers in rural areas because it can enhance their food supply, income, and wealth (Akpan et al., 2020). The significant gap in income inequality between rural and urban populations in developing countries has been attributed to the dependence of rural societies on low-paid agricultural activities (Waris, Khan, Urrahman, Hronec, & Suplata, 2023). Inequality is responsible for several problems such as uneasiness, violence, and corruption. Given the high income inequality in South Africa, the government has been preoccupied with the fight against poverty and inequality. As a result, the government has developed several policies and intervention programmes to help combat poverty and its impact on society, especially the formally disadvantaged groups. One such programme is the Phezukomkhono Mlimi (PKM) programme, introduced in 2005 (Sambo, Oguttu, & Mbombo-Dweba, 2025; Sambo, 2021). Available evidence on the PKM programme shows that the programme has had an impact on food security among the participating households. Particularly, it has been able to decrease the severity of food insecurity (Sambo, 2021). Based on this, it is hypothesized that the PKM programme has the potential to ameliorate inequality in the local population.

However, empirical evidence showing the impact of government support programmes on poverty and income inequality is lacking, more so in the context of programmes like the PKM. Such evidence is needed by policymakers and other stakeholders to formulate suitable policies, plans, and strategies to achieve sustainable development in these areas. It is worth noting that the levels of income inequality in farming households may vary significantly between farming households, the size of agricultural land, and the farmers' economic characteristics (Akpan et al., 2020; Rahman, 2017). To the best of our understanding, these characteristics have not received adequate attention among scholars. Furthermore, studies that employ cross-sectional data while focusing on small-scale sites and locations, such as the Nkomazi Local Municipality (NKLM), are lacking. In addition, where cross-sectional data is applied, most researchers tend to ignore the effects of variation in household, farming, and economic characteristics as well as the existing transforming structures and processes. Moreover, available evidence suggests that extremely skewed income inequality is one of the major sources of, and positively correlates with, poverty (Akpan et al., 2020). Since the South African government views agriculture as one of the major instruments in fighting poverty, it is important to understand the extent of income disparity and poverty levels as well as the factors that influence the manifestation of poverty among farmers who benefit from the PKM programme. Unfortunately, there is no evidence of studies that have investigated income inequality in PKM farming households in the NKLM. Hence, this study investigates the nature and determinants of income inequality in PKM farming households in the NKLM, South Africa.

2. MATERIALS AND METHODS

2.1. Study Area

The study was carried out in the NKLM, the smallest of the four municipalities within the Ehlanzeni District Municipality of the Mpumalanga Province, South Africa. The NKLM is bordered by the City of Mbombela Local Municipality (to the west), Kruger National Park (to the north), Mozambique (to the east), and the Kingdom of Eswatini (to the south). It is linked with Mozambique via the national road, the N4, while two provincial roads, the R570 and R571, connect it with the Kingdom of Eswatini. The NKLM covers an area of 4,785 km² and is inhabited by approximately 591,928 people (Statistics South Africa, 2022). Agriculture, mining, and tourism are the major contributors to the economy of the NKLM. The number of households practicing agriculture and the unemployment level are also high in the study area (Statistics South Africa, 2011).

2.2. The Target Population

A list of farming households (N=543) that benefited from the PKM programme during the 2018/19 production season (i.e., April 2018 to March 2019) in the study area was requested from the Department of Agriculture, Rural Development, Land and Environmental Affairs (DARDLEA). The 543 farming households constituted the target population.

2.3. Sampling Method and Sample Size

A random sample of 230 respondents was drawn from the sample frame of 543 farming households that benefited from the PKM programme using simple random sampling. The 230 respondents were determined using the formula described by Adam (2020) for determining sample size from a finite population, as described below.

$$n = \frac{N}{1+N(e^2)} \qquad (1)$$

Where: n = sample size; N = target population; e = margin error set at 0.05.

Thus, $n = \frac{543}{1+543(0.05^2)} = \frac{543}{1+543(0.0025)} = \frac{543}{1+1.36} = \frac{543}{2.36} = 230.08 \approx 230$

2.4. Study Design and Data Collection

A cross-sectional, questionnaire-based study design was adopted to achieve the objectives of this study. Quantitative data were collected between 1 February and 24 March 2020 using a structured questionnaire, which was administered during face-to-face interviews by four trained enumerators. The questionnaire solicited demographic and socio-economic information from the respondents.

2.5. Data Analysis

The data were inputted into Microsoft Excel and subsequently transferred to the Statistical Package for the Social Sciences (SPSS version 28) for further analysis. Descriptive statistics, the Gini coefficient, and the quantile regression model were employed to analyze the data.

2.5.1. Descriptive Statistics

The socio-economic characteristics of the respondents were summarized and presented as tables and figures.

2.5.2. Gini Coefficient

The Gini coefficient was used to measure income inequality among the farming households in the study area. The Gini coefficient is a tool widely used to measure inequality, particularly income or wealth distribution. It helps to understand how income or wealth is distributed across a population, providing insight into the level of fairness or disparity in a society. The closer the Gini coefficient is to 0, the more equal the distribution of wealth, and the closer it is to 1, the more unequal the distribution of wealth (Bellu & Liberati, 2006). According to Gini (2005), the Gini coefficient can be presented as the area between the line of equality and the Lorenz curve divided by the total area under the line of equality in the graphical presentation of the Lorenz curve. Furthermore, it can be expressed or specified mathematically using the following equation.

$$G = 1 - \sum_{i=1}^{n}(W_i - W_{i-1})(Z_i + Z_{i-1}) \quad (2)$$

Where, G is the Gini coefficient, W_i is the cumulated proportion of the population variable, for $i = 0..., n$, with $W_0 = 0$, $W_n = 1$ and Z_i is the cumulated proportion of the income variable, for $i = 0....n$, with $Z_0 = 0$, $Z_n = 1$. W_i and Z_i should be arranged in an increasing order such that $W_i > W_{i-1}$ and $Z_i > Z_{i-1}$, respectively.

2.5.3. Quantile Regression Model

The quantile regression model was employed to identify the determinants of income inequality among the PKM farming households in the study area. Quantile regression is an alternative to linear regression when the assumptions for linear regression are not met. This statistical modeling method has recently gained significant attention in income inequality and poverty analysis studies (Debebe & Zekarias, 2020; Garza-Rodriguez, Ayala-Diaz, Coronado-Saucedo, Garza-Garza, & Ovando-Martinez, 2021). This method provides a more detailed view of how variables affect various parts of the population (Cook & Manning, 2013). Quantile regression is particularly useful because it describes how explanatory variables (or predictors) affect different parts of the distribution of the dependent variable in this case, income. Instead of just indicating how a variable impacts the average (as is the case in traditional regression), it shows how these variables influence the outcomes at different quantiles such as the 10^{th} percentile and the 50^{th} percentile (median) (Xu, 2023). This is useful because the effect of the predictor variables can vary across the income spectrum, providing a more complete picture of the data and capturing subtle distributional effects that would otherwise be missed in standard analysis (Cook & Manning, 2013). Based on the equation described by Garza-Rodriguez et al. (2021), the quantile regression model is specified as follows:

$$\mathrm{Qln}(Yi|Xi) = \sum_{i:Yi\geq X\prime\beta}^{N} q|Y_i - X'_i\beta q| + \sum_{i:Yi\leq X\prime\beta}^{N}(1-q)|i - X'_i\beta q| \quad (3)$$

Q(ln(Yi)|Xi): This represents the quantile of the log of total income per adult equivalent (the dependent variable, Yi) for the i^{th} household, conditional on the values of the explanatory variables (X).

Where:

Xi: Represents a column vector of realizations for k^{th} explanatory variables (predictors such as age, education, farming experience, or household size, etc.) that may influence the household's income.

β: A column vector of unknown parameters corresponding to the explanatory variables, which the model seeks to estimate. These parameters represent the effect of each predictor at the specified quantile of the income distribution.

$0\leq q\leq 1$: The quantile of interest. For instance, q=0.5 would represent the median, while q=0.25 would represent the 25^{th} percentile.

The quantile regression was applied to assess relationship between the dependent variable and explanatory variables at the 10th, 25th, 50th, 75th, and 90th quantiles of the income distribution. Quantile regression is well-suited for this purpose as it examines the distribution of income at different points instead of focusing solely on the mean (Bottai et al., 2014). In this case, the quantiles used in regression allow for insight into the factors that influence income at the extremes of the income distribution, in addition to those at quantiles between those extremes (Leeds, 2014). Quantile regression differs from ordinary linear regression in the sense that it does not involve any supposition about the distribution of the regression residuals. Quantile regression is not affected by outliers or skewness in the distribution of the outcome variable, giving more statistical efficacy when outliers exist. Moreover, inference on quantiles can allow transformation of the outcome variable without the glitches experienced in ordinary linear regression (Bottai et al., 2014; Leeds, 2014).

2.5.4. The Conceptual Framework

Table 1 graphical representation of the dependent, independent, and presumed relationships with the independent/explanatory variables included in the quantile regression model.

Table 1. Description, measurement, and hypotheses of explanatory variables used in the quantile regression model.

Variables	Type of variable	Measurements	Hypothesis
Age	Continuous	Years	-
Years of schooling	Continuous	Years	-
Household size	Continuous	Years	+
Farming experience	Continuous	Years	-
Gender	Dummy	Male/Female	±
Living with disability	Dummy	Yes/No	±
Marital status	Dummy	Married/Otherwise	+
Participating in off-farm activities	Dummy	Yes/No	-
Farm size	Dummy	≤3ha / 4-5ha / 6-8ha / >8ha	±

2.6. Ethical Consideration

Prior to the commencement of the data collection exercise, approval to conduct this study was obtained from the DARDLEA and the Ethics Committee of the College of Agriculture and Environmental Science at the University of South Africa (Ref #: 2019/CAES_HREC/178).

3. RESULTS

3.1. Socio-Economic Characteristics of the Respondents

The socio-economic characteristics of the respondents presented in Table 2 indicate that most of the farmers were above 56 years of age (66.96%) and were females (61.30%). The highest proportion was married (46.52%), followed by single (11.74%), divorced (6.96%), and widowed (34.78%). Slightly more than half (53.48%) had a household size of 3 to 6 people. Up to 13.48% of the respondents had disabilities. Regarding education, just under half (48.70%) of the respondents did not attain Grade 12, and just above one-third (39.13%) had no formal education. Very few had attained Grade 12 (7.83%) and tertiary (4.35%) education. Most respondents had smaller farms of three hectares or less in size (61.74%), and had access to extension services (70.87%) and did not participate in off-farm activities (62.61%).

Table 2. Socio-economic characteristics of the respondents (n=230).

Variables	Frequency (F)	Percentage (%)
Age in years		
≤35	10	4.35
36-45	17	7.39
46-55	49	21.30
56-65	54	23.48
> 65	100	43.48
Gender		
Male	89	38.70
Female	141	61.30
Persons with disability		
Yes	31	13.48
No	199	86.52
Marital status		
Married	107	46.52
Single	27	11.74
Divorced	16	6.96
Widowed	80	34.78
Household size		
< 3	79	34.35
3-6	123	53.48
> 6	28	12.17
Level of education		
No formal education	90	39.13
Less than grade 12	112	48.70
Grade 12	18	7.83
Tertiary education	10	4.35
Farming experience		
<25 years	125	54.65
≥25 years	105	45.35
Farm Size (Hectares)		
≤3	142	61.74
4-5	58	25.22
6-10	21	9.13
>10	9	3.91
Participation in off-farm activities		
Yes	86	37.39
No	144	62.61
Access to extension services		
Yes	163	70.87
No	67	29.13

3.2. The Different Sources of Income for the Farming Households that participated in the study

Table 3 presents the different sources of income for the respondents. The majority (60.87%) of the households derived their income from farming activities such as sales of farm produce, leasing of land, and leasing of farm equipment and machinery. Other sources of income included receiving social grants (56.52%) and receiving pension payouts (10.43%). A mere 7.39% of the respondents earned wages and salaries, suggesting a high unemployment rate in the study area. Only 37.39% of the respondents generated income from other non-farming activities.

Table 3. Sources of income of the respondents.

[1]Source of income	Frequency (F)	Percentage (%)
Farm income	140	60.87
Social grant	130	56.52
Retirement funds	24	10.43
Wages and salaries	17	7.39
Remittances	23	10.00
Other non-farming activities	86	37.39

Note: [1]Mutiple responses were possible.

3.3. Income Distribution and the Gini Coefficient of the Study Population

Table 4 presents the income distribution of households in the study area. The results indicate that the majority (90.43%) of households had a per capita monthly income of less than R1,500.00, which accounts for 50.11% of the total income. This was followed by an equal proportion (4.35%) of households earning a per capita monthly income of R1,501.00 to R2,500.00 and R2,501.00 to R5,000.00. However, the latter income bracket (R2,501.00 to R5,000.00) contributed a higher percentage (18.22%) to the total income than the former income bracket (R1,501.00 to R2,500.00), which contributed 15.95%. The proportion of households with an annual income of R5,001.00 to R10,000.00 and those earning above R10,000.00 were both 0.43%, but the contribution of the latter income bracket to the total income was twice as high (10.02%) compared to the former (5.69%).

Table 4. Income distribution of households (n=230).

Per capita income per month	Number of households (F)	Percentage of distribution (%)	Percentage of income contribution (%)
Less than R1 500	208	90.43	50.11
R1 501-R2 500	10	4.35	15.95
R2 501-R5 000	10	4.35	18.22
R5 001-R10 000	1	0.43	5.69
Above R10 000	1	0.43	10.02
Total	**230**	**100**	**100**

Table 5 shows the determination of the Gini coefficient based on the formula derived by Gini (2005). The results show that the study population had a Gini coefficient of 0.48, which indicates some degree of inequality.

Table 5. Measurement of the Gini coefficient of households.

Income distribution	Cumulative % of population	Cumulative % of income	(W_i-W_{i-1})	(Z_i+Z_{i-1})	$(W_i-W_{i-1})(Z_i+Z_{i-1})$
0	0	0	0.00	0	**0.00**
Less than R1 500	0.98	0.50	0.98	0.50	**0.49**
R1 501-R2 500	0.99	0.66	0.00	1.16	**0.01**
R2 501-R5 000	0.99	0.84	0.00	1.50	**0.01**
R5 001-R10 000	1.00	0.90	0.00	1.74	**0.01**
Above R10 000	1.00	1.00	0.00	1.90	**0.01**
$G = 1 - \sum_{i=1}^{n}(W_i - W_{i-1})(Z_i + Z_{i-1})$=1-0.52=0.48					**Total = 0.52**

Figure 1 presents the determination of the Gini coefficient based on the Lorenz curve. The Lorenz curve was plotted based on the cumulative percentage of the population (on the X-axis) and the cumulative percentage of income (on the Y-axis). Graphically, the Gini coefficient (0.48) is reflected as the quotient of the area (A), which is between the Lorenz curve and the line of equality, and the total area under the line of equality (A+B).

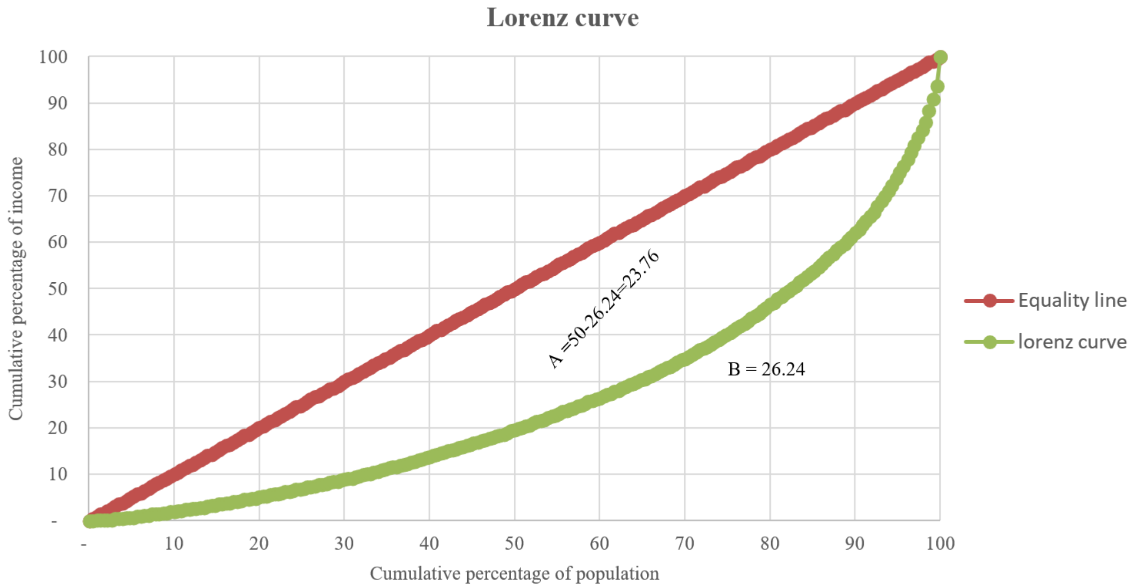

Figure 1. Lorenz curve.

3.4. Determinants of Income Inequality Among the Households

Table 6 shows the results of the quantile regression analysis. Variables such as age, education, household size, and farm size had a statistically significant effect on income inequality in this study. The direction and magnitude of the effect of the predictor variables on the outcome variable (per capita income) are shown by the coefficients of the quantile regression analysis.

The age of the household head had a negative effect on the per capita income of the household in almost all quantiles, but it was significant at the median (50^{th}) and 75^{th} quantiles. Meanwhile, education had a positive impact on the income level of households at all quantiles except the 10^{th} quantile. However, the impact of education was only significant at the 25^{th} quantile. Furthermore, the magnitude of the impact of education increased with the increase in the quantile levels.

Household size had a negative and significant effect on income across all quantiles. Its magnitude also increased with the increase in quantile levels. Regarding farm size, a positive effect on household income was observed across all quantiles except the 10^{th} quantile in the first two levels of farm size, namely, in three (3) or fewer hectares and between 4 and 5 hectares. However, their association was only significant at the 25^{th} quantile. The third level of farm size (6-8 hectares) had a positive effect on household income across all quantiles, but was only significant at the 25^{th} and 50^{th} quantiles. The magnitude of the effect increased with higher quantiles in all farm size levels.

Table 6. Quantile regression analysis of the determinants of income inequality among households.

Variables	10th Quantiles			25th Quantiles			50th Quantiles			75th Quantiles			90th Quantiles		
	Coe[1]	t[2]	p[3]	Coe	t	p	Coe	t	p	Coe	t	p	Coe	t	p
Age	-0.02	-0.04	0.97	0.48	0.81	0.42	-5.18	-2.16	0.03*	-14.02	-2.50	0.01*	-5.10	-0.52	0.60
Years of schooling	-2.13	-1.56	0.12	6.83	4.18	0.00*	11.72	1.80	0.07	29.28	1.92	0.06	41.19	1.55	0.12
Household Size	-53.97	-31.67	0.00*	-51.67	-25.38	0.00*	-54.49	-6.69	0.00*	-88.68	-4.67	0.00*	-143.30	-4.33	0.00*
Farming experience	-0.25	-0.73	0.47	-0.63	-1.56	0.12	-0.84	-0.52	0.60	0.77	0.21	0.84	-9.66	-1.47	0.14
Gender (Male)	19.96	1.72	0.09	-7.20	-0.52	0.60	70.97	1.28	0.20	77.41	0.60	0.55	292.61	1.30	0.20
Disabled (Yes)	-1.47	-0.10	0.92	-18.29	-1.02	0.31	-61.17	-0.85	0.40	-72.23	-0.43	0.67	-42.23	-0.14	0.89
Married (Yes)	-10.47	-0.91	0.36	6.73	0.49	0.63	22.90	0.42	0.68	171.92	1.34	0.18	64.99	0.29	0.77
Farm size (≤3 ha)	-8.56	-0.30	0.76	78.31	2.32	0.02*	237.03	1.76	0.08	436.30	1.39	0.17	572.33	1.04	0.30
Farm size (4-5ha)	-1.64	-0.06	0.96	78.28	2.23	0.03*	243.02	1.73	0.08	482.82	1.48	0.14	763.19	1.34	0.18
Farm size (6-8ha)	42.87	1.38	0.17	129.70	3.49	0.00*	469.72	3.16	0.00*	531.33	1.54	0.13	766.34	1.27	0.21
POFA[4] (Yes)	10.63	0.99	0.32	-0.46	-0.04	0.97	89.51	1.74	0.08	98.87	0.82	0.41	308.65	1.48	0.14

Note: [1]Coefficient.
[2]t-ratio.
[3]Statistically significant p-value.
[4]Participation on off-farm activities.
*Statistically significant at p=0.05.

4. DISCUSSION

Widening income inequality among households is a concern for most governments (Teka, Woldu, & Fre, 2022), policy makers and the research community (Anyiam et al., 2023). In this study, the total Gini index was 0.48, which indicates high inequality in the study population. This is concerning given the association between income inequality and poverty, food insecurity (Abdulsalam, Abdulwahab, Zakari, & Adamu, 2024; Haini, Musa, Wei Loon, & Basir, 2023), and the fact that income inequality is a deterrent to overall economic growth (Sulla, Zikhali, & Cuevas, 2022). Among farming communities in particular, income inequality compromises livelihoods and farming activities (Abdulsalam et al., 2024).

With regard to the existence of income inequality in farming households, the results of the current study are consistent with previous studies (Dib, Alamsyah, & Qaim, 2018; Kadigi, 2021; Priscilla, Singh, & Vatta, 2021; Teka et al., 2022). However, in comparison, previous studies reported higher Gini coefficients of more than 50% (Kadigi, 2021; Priscilla et al., 2021; Teka et al., 2022). Furthermore, the Gini coefficient reported here is also lower than the provincial income inequality and the national level. According to the Mpumalanga Provincial Treasury (2024), the Gini coefficient in the Mpumalanga Province, where this study was conducted, was 0.59 in 2022. The observed difference could be attributed to variations in household characteristics across these studies. For example, the present study included only rural farming households, whereas the determination of the provincial Gini coefficient encompassed households with a variety of characteristics. Reports have shown that, in general, rural areas (Sulla et al., 2022) and smaller cities (Alimi, Maré, & Poot, 2018) have lower inequalities when compared to urban areas. While the income inequality registered in this study is considerably lower than the provincial rate, it is still a cause for concern. This is because, according to previous studies (Abdulsalam et al., 2024; Luebker, 2010; Zantsi, Greyling, & Vink, 2019), a Gini coefficient of 0.35 is considered high.

It is noteworthy to mention that this Gini coefficient is comparable to the one observed in a study conducted in the Eastern Cape, South Africa, among emerging farmers, where a Gini coefficient of 0.48 was also observed (Zantsi et al., 2019). This confirms the findings of previous studies, which concluded that while income inequality exists in rural areas, it tends to be lower than that observed in urban areas (Sulla et al., 2022).

Age had a negative effect on income inequality and was significant at the 50th and 75th quantiles. This suggests that an increase in the proportion of the population with a higher age results in a decrease in income inequality. This finding contrasts with the findings by Debebe and Zekarias (2020), who demonstrated that income among households in southern Ethiopia increased with age, thus decreasing the income gap. Similarly, Liu, Ibrahim, and Chin (2025) observed a negative relationship between population aging and income inequality. In support of this, Abdulsalam et al. (2024) argue that as household members get older, they can find income sources which ultimately contribute to the overall income of the household. In the case of agricultural households, the observed trend could be explained by the fact that, generally, agriculture among smallholder farmers is labor-intensive; therefore, productivity may be negatively affected due to age.

An increase in the number of years of schooling corresponds with a higher education level. Education was expected to play a significant role in reducing income inequality in this study. However, an increase in the number of years of schooling of the household head translated into an increase in income inequality in this study. Previous studies have found the relationship between education and income inequality to be ambiguous at times. For instance, Nabassaga, Chuku, Mukasa, and Amusa (2020) found a non-linear, inverted U-shape relationship between education and income inequality. In another study, Moyo, Mishi, and Ncwadi (2022) found that the effect of education on income inequality may be either positive or negative, depending on equal access to education. The results of the present study are comparable with the findings of other studies. For example, in Nigeria, Aminu, Wei, Arowolo, and Ibrahim (2021) found that education had an increasing effect on income inequality among smallholder arable crop farmers. In Nekemte Town, Ethiopia, Teshome, Sera, and Dachito (2021) found that variations in education contributed negatively to income inequality. This could be attributed to the fact that household heads who have attained higher education levels are more likely to adopt better farming practices and hence earn more than households with lower education. Therefore, it is not surprising that in a study population like the one observed in this study, where there are wide discrepancies in education, there are variations in income, thus resulting in high income inequality. Similar assertions were made by Aminu et al. (2021), who attributed this to the fact that education augments the skills base and consequently positively influences income-earning capacity. Thus, increasing the income gap if there is inequality in access to education (Moyo et al., 2022).

The fact that household size had a statistically significant negative effect across all quantiles is consistent with findings of previous studies, which demonstrated that the size of the household is significantly associated with income inequality (Nebebe, & Appa Rao, 2016; Shin, 2020; Waris et al., 2023). Therefore, the findings reported here imply that having many large households contributes to a decrease in income inequality in the area. Some studies have reported similar results. For example, it has been noted that an increase in the size of the family is likely to lead to more income earners per household, thereby increasing the overall income of the household (Debebe & Zekarias, 2020; Rahman, 2017). Therefore, the effect of household size on income inequality might be informed by the dependency ratio or working-age group in the households and the area where the study is conducted. For example, in cities and towns where jobs are more readily available compared to rural areas, household size might significantly decrease income inequality. In support of this, Abdulsalam et al. (2024) argue that in a large-sized household where the dependency ratio is low, most of its members can find income sources, which ultimately contribute to the overall income of the household.

Farm size was another significant determinant of income inequality. In this study, farm size was captured as a categorical variable with three levels: ≤3ha, 4-5ha, and 6-8ha. All three levels of farm size had a positive association with income inequality, except for the first quantile of the ≤3ha and 4-5ha levels. The magnitude of the impact of farm size increased with the increase in the quantiles. This shows that an increase in farm size positively impacts income. This implies that households with smaller farms have lower incomes than those with larger farms, increasing the gap between the poor and rich households, hence higher inequality within those lower categories. This could be attributed to the fact that households with larger cultivated lands tend to improve their earning capacity (Aminu et al. (2021).

5. CONCLUSION AND RECOMMENDATIONS

The study examined the extent and determinants of income inequality among farming households using the Gini Coefficient and quantile regression model. The Gini coefficient in this study area was higher than 0.35, indicating that income inequality persists despite the participation of farming households in the PKM program.This situation has the potential to predispose farming households to adverse effects such as food insecurity, poverty, and weakened livelihoods. Age, education, household size, and farm size were identified as factors with a significant impact on income inequality among respondents. Therefore, policies aimed at reducing income inequality among farming households should consider these key factors. Strategies to promote equitable access to education are necessary. For example, educational support programs targeting disadvantaged children and children with uneducated parents should be prioritized. Other equity strategies include providing free and mandatory primary and secondary education for all children, ensuring access for excluded groups and learners with special educational needs, increasing resource allocation to schools, and creating equitable learning and teaching environments. Providing comprehensive sexual and reproductive health education to both adults and school-going adolescents could aid in family planning, thereby reducing large family sizes. The positive impact of farm size in this study emphasizes the need for larger agricultural lands as a means to increase the earning capacity of agricultural households. Successful implementation of land reform programs and leasing vacant productive land could help increase farm size and production, directly contributing to reducing poverty and income inequality. However, agricultural land alone is insufficient; support for agricultural households from both public and private sectors to maximize land use is also essential.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
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