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Farm Income Determinants Among Agricultural Households in Tanzania: The Impact of Pre-Harvest Losses

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ABSTRACT

Agriculture remains central to Africa's development aspirations as outlined in Agenda 2063 and the Sustainable Development Goals, particularly in eradicating poverty and hunger. In Tanzania, despite efforts to enhance productivity, farm incomes remain low, with limited empirical focus on pre-harvest losses, a critical yet underexplored constraint. This study investigates the impact of pre-harvest losses on farm income among maize and paddy farming households in Tanzania, using data from the 2019/2020 National Panel Survey (NPS Wave 5). Guided by the Agricultural Household Model (AHM), the study employed a Robust Linear Mixed Effects Regression Model to account for data heterogeneity, outliers, and hierarchical structure. The response variable, farm income, was proxied by the log-transformed value of crop harvests. Key explanatory variables included pre-harvest loss, agronomic practices, and household-level characteristics, with soil type, crop type, and location (strata) modeled as random effects. Findings reveal a significant negative association between pre-harvest losses and maize income, highlighting the adverse effects of inadequate crop management during production. While the effect on paddy income was statistically insignificant, the overall trend underscores the importance of addressing losses before harvest. Mechanization, inorganic fertilizer use, and improved seeds were positively associated with higher farm income, while hired labor showed a negative association, suggesting inefficiencies in labor use. Intercropping and organic fertilizer use had mixed or marginal effects depending on the crop. Based on the study findings, the study concludes that reducing pre-harvest losses is vital for improving farm incomes and recommends integrated strategies involving improved agronomic practices, access to quality inputs, targeted extension services, and investment in efficient irrigation and labor-saving technologies. These insights provide a critical foundation for agricultural policy reform focused on enhancing productivity and rural livelihoods in Tanzania.

1. Background to the research problem

Africa's Agenda 2063 "The African We Want", among others, envisions ending poverty and achieving inclusive growth and sustainable development. The notable strategy for achieving the aspirations includes modernizing agriculture, which to date remains a core economic activity on the continent (FAO, 2018; FAO *et al*., 2020). Agriculture contributes to about 16% of the continent's GDP, and employs nearly two-thirds of the continent's population, with the majority of them being in rural areas and reliant on subsistence farming (United Nations, 2019a). Apart from registering its relevance in achieving the aspirations documented in Africa's 2063 agenda, agriculture remains crucial in achieving the global development goals, particularly SDG 1 and SDG 2, which focus on ending poverty in all its forms and ending hunger, achieving food security, and improving human nutrition.

Parallel to the continental and global aspirations where agriculture remains central, FAO, (2018) show that the world's population is projected to reach 9.7 billion by 2050, an increase that goes hand in hand with an increase in food demand. Statistics from the United Nations (2019b) show that 8.5 billion tons of food will be required to feed the globe by 2030 and 9.7 billion tons by 2050. For this to be achieved, FAO estimates food production for human consumption to increase by at least 50 percent and yields by 35 percent (FAO, 2018). Nevertheless, FAO (2017, 2018) documents that about one-third of the food produced in the world annually, equivalent to 1.3 billion tons, is lost before it reaches the final consumers. Quantitatively, the losses reduce the amount of food available for human consumption, whereas, from an economic point of view, losses are attributed to reduced farmers' income.

Food loss occurs at different stages of the agricultural value chain. In developing countries, much of the losses are usually documented during production, crop handling, and storage stages (Rockefeller, F, 2015). Loss that occurs during production, technically referred to as Pre-harvest losses, denotes a reduction in expected yield before harvest. The losses are often driven by several factors, including pests, diseases, poor agronomic practices, weather variability, and limited use of inputs such as fertilizers, pesticides, and irrigation. Despite the losses undermining food availability and farmer income, they remain less documented even in national agricultural strategies. This argument remains valid even in Tanzania. While the government, through the Ministry of Agriculture, has made substantial efforts to address post-harvest losses as documented in the national strategies, such as the Post-harvest Loss Management Strategy 2019–2029, similar attention has not been given to losses that occur before harvests. Equally, the second phase of the Agricultural Sector Development Programme (ASDP-II), while emphasizing agricultural productivity and resilience, does not exhaustively document loss-preventive measures, particularly those occurring during crop production.

Although they remain less explored and empirically undocumented, the unmanageable losses are linked to a reduction in the amount of agricultural produce, thus likely to harm productivity and subsequently, income derived from farming activities. For instance, evidence from Searchinger *et al*. (2018) shows that food loss leads to a 15 percent loss in small-scale farmers' income and results in approximately 1 trillion USD in global economic losses. In Tanzania, citing specific documentation, maize and paddy are among the key staples necessary for both urban and rural livelihoods. Notwithstanding their utility importance, national average yields remain low, with 1.8 and 2.2 tons/ha, respectively (NBS, 2023), well below the FAO's estimates of potential yields of 6–10 tons/ha for maize and 3–6 tons/ha for paddy (Senkoro *et al*., 2018). This discrepancy denotes a critical reduction in production, which, despite having no empirical documentation on the same, is equally associated with reduced farmer income.

This study, therefore, addresses a critical yet less-investigated aspect of agricultural development in Tanzania: the impact of pre-harvest loss on farm income among maize and paddy farming households. While existing literature, such as studies by Abass et al. (2014), Ismail and Changalima (2019), Chegere (2018a,b), Chegere *et al*. (2020, 2022), has discussed post-harvest issues, empirical evidence detailing the economic impacts of pre-harvest losses, particularly on farm income, remains limited.

The current study, therefore, contributes to the literature by evaluating the extent to which pre-harvest loss impacts farm income among maize and paddy farming households in Tanzania. Our analysis is guided by the Agricultural Household Model (AHM), which provides an integrated perspective on farm production and household welfare decisions (Singh *et al*,1986). The theory is based on the assumption that *"households are price-takers for every commodity, including labor, that is both produced and consumed by the household"*. The model integrates production and consumption decisions within a single decision-making unit, the household. Unlike neoclassical models that treat production and consumption separately, AHM acknowledges that in smallholder farming systems, these decisions are interdependent. Singh et al. (1986) argue that for any production cycle, the household is assumed to maximize a utility function:

$$U = f(\chi_a, \chi_m, \chi_l) \quad (1)$$

Where, the commodities are an agricultural staple (χ_a), a market-purchased good (χ_m), and leisure (χ_l).

The AHM provides a comprehensive lens for understanding how farm households in Tanzania allocate resources toward crop production, manage risks such as pre-harvest loss, and ultimately experience outcomes related to income. In the context of this study, while captureing heterogeneity in household characteristics such as age, gender, and farming experience, which can shape both production behavior and responsiveness to innovations, it allowed for a holistic examination of how farm households make decisions regarding crop management practices, experience of pre-harvest losses, and the subsequent effects on farm income. Since income in the AHM is endogenously determined by household production outcomes, any factor that negatively impacts production, such as crop loss, also limits the household's ability to meet its consumption needs, including food. This was evidently backed by the tudy findings that evidenced a ngative influence of crop loss on farim icnome, such that, pre-harvest losses diminish the amount of crop available for sale, thereby reducing household income.

2. Materials and Methods

2.1.Source of Data

The secondary data used, notably, the dataset from the fifth wave of the 2019/2020 National Panel Survey (NPS 5). The data were sourced from the National Bureau of Statistics (NBS), a government agency mandated with the sole role of collecting, organizing, compiling, and disseminating official statistics within the United Republic of Tanzania.

2.2.Description and Measurement of Variables

2.2.1. Response variable

The response variable was Farm Income, which relates to returns in the form of financial gains generated from farming operations. Literature depicts various ways of measuring farm income, among others being the valuation of agricultural output. In this light, the current study proxied farm income from the monetary value of harvests. In the 2020/21 NPS, information on the actual value of the harvest was collected from households that reported they had harvested crops. The response variable was therefore quantitative and continuous, valued at the prevailing market prices.

2.2.2. Explanatory variables

Pre-harvest loss was the key explanatory variable; it was a binary, coded 1 if the household experienced crop loss and 0 otherwise. Other explanatory variables included different farming practices, and input use, such as the use of herbicides, pesticides, organic fertilizers, inorganic fertilizers, animal traction, mechanized farming, soil erosion control and water management mechanisms, intercropping, and type of seeds. These were indicator variables, with code 1 if the household adopted a particular farming practice in the production of either maize or paddy and 0 otherwise. For seeds, the variable was code 1 if the household used improved seeds and 0 otherwise. In the context of the current study, these were considered as farm technology-related variables. Additionally, the study used household and farm-related variables that are likely to influence the decision of a household to adopt and use a particular farming technology. They are: Household headship, and farming Experience proxied by the Age of the head of household and access to credit.

2.3.Estimation techniques

The study used the *rlmerf()* function available under the robustlmm package in R to fit a Robust Linear Mixed Effect Regression Model. The choice of this model was motivated by the nature of the response variable. In this analysis, the actual data points of the response variables (value of harvests) indicated signals of heterogeneity and the existence of outliers, which are common distributional properties for most economic variables. Despite a log transformation being made to normalize and stabilize variance across observations, the use of a robust regression model remained relevant as it does not consider the distributional properties as well as the assumption of the grouping structure of the data (Koller, 2016).

Apart from using pre-harvest loss, agronomic, and technology variables as predictors, the dataset includes both household-level variables and grouping factors such as soil type, crop type, and geographical location. These hierarchical data structures were likely to introduce potential correlation among observations within the same group, thus violating the independence assumption of standard regression models (Schielzeth et al., 2020). In this light, the use of a robust mixed-effects model was appropriate, among others, to allow the estimation of random intercepts for each group of the baseline values of harvests to vary across groups while reducing the influence of such outliers and improving the reliability of the estimates.

In estimation, the explanatory variables were grouped into two: random effects as well as fixed effects. While pre-harvest loss, technology adoption, and some selected household and farm characteristics variables constituted the fixed effects, soil type, crop type, and strata were treated as grouping variables. In the context of the current study, strata are a location variable, specifying rural and urban settings in each region.

The robust linear mixed-effects model was estimated using an iterative re-weighting algorithm, which down-weights the influence of outliers on parameter estimation (Koller, 2016). The model diagnostic was made by fitting the residuals and fitted values, as well as Normal Q-Q plots. The plots were examined to assess residual variability as well as model fit. Equally, the random effects variances were examined to investigate the relevance and contribution of each grouping factor.

Let Y denote a response variable, X a vector of fixed effects, with regression coefficient β, and U a possible random intercept. Then, borrowing from Schielzeth *et al*. (2020), the current study developed the estimation equation as:

$$Y = X^T\beta + U + \epsilon \tag{2}$$

The response variable, value of harvests was heterogeneous, with notable skewed distribution. To reduce variability, it was log-transformed. Letting Y_{ijks} denote the log-transformed value of harvests for household i, crop j, and in strata k, and soil s; X_{ijks} be a vector fo fixed-effects covariates, U^{soil}, U^{crop}, and U^{strata} represent random intercepts soil, crop and strata respectively, and ϵ_{ijks} stand for an error term, equation 2 was modified to equation 3:

$$Y_{ijks} = X_{ijks}^T\beta + U_s^{soil} + U_j^{crop} + U_k^{strata} + \epsilon_{ijks} \tag{3}$$

Such that

$$U_s^{soil} \sim N(0, \sigma_{soil}^2) \qquad U_j^{crop} \sim N\left(0, \sigma_{crop}^2\right) \qquad U_k^{strata} \sim N(0, \sigma_{strata}^2) \quad \epsilon_{ijks} \sim N(0, \sigma^2)$$

3. Results and Discussion

3.1. Value of harvests by crop type and technology adoption status

Table 1 presents descriptive statistics for the outcome variable (value of harvests) by technology adoption status. For maize, farmers who adopted at least one technology reported an average harvest value of 257,296.6 TZS, while non-adopters had a significantly lower average of 119,609.3 TZS. However, the trimmed mean, which reduces the influence of extreme values, is noticeably lower for both groups: 150,442.9 TZS for adopters and 74,421.01 TZS for non-adopters. This suggests that the mean value of harvests is possibly inflated by a few large-scale farmers, highlighting the influence of outliers.

The median value of harvests for technology adopters is 120,000 TZS, compared to 50,000 TZS for non-adopters. Since the median is less affected by extreme values, it provides a more representative measure of central tendency. This means that at least 50 percent of the adopters harvested crops worth up to 120,000 TZS, while 50 percent of non-adopters had harvest values of 50,000 TZS or lower. These results reinforce the notion that farmers who adopt at least one farming technology generally achieve higher harvest values.

For Paddy, the average value of harvests for farmers who adopted at least one technology is 1,122,777, which is almost three times higher than the 377,710.5 recorded for non-adopters. However, the trimmed mean for technology users is 588,841.3, while for non-users, it is 283,228.3. This substantial difference suggests that even after adjusting for extreme values, farmers who adopt technology still achieve notably higher harvest values. The results highlight the relevance of technology adoption on paddy productivity, possibly due to improved input use.

The median value of harvests for technology users is 420,000, while for non-users, it is 210,000. This result reinforces the argument that technology adoption is associated with higher paddy harvests, as at least 50% of technology users earn above 420,000 compared to just 210,000 for non-users. The fact that the median is substantially lower than the mean suggests a right-skewed distribution, meaning that while most farmers have moderate harvest values, a few large-scale farmers pull up the mean.

Table 1: Mean and Median values of harvets by crop type and technology adoption status

Description	**Maize**		**Paddy**	
	Used at least one technology	Did not use any technology	Used at least one technology	Did not use any technology
Mean	257,296.6	119,609.3	1,122,777	377,710.5
trimmed	150,442.9	74,421.01	588,841.3	283,228.3
Median	120,000	50,000	420,000	210,000

3.2. Value of harvests by crop type and crop loss status

Summary statistics for the estimated value of harvests by crop type and pre-harvest loss status are presented (Table 2). For Maize, farmers who experienced pre-harvest losses reported an average harvest value of 173,416.7 TZS, which was lower than the 503,508.0 TZS recorded by those who did not experience pre-harvest loss. The trimmed mean, which mitigates the influence of extreme values, shows a similar trend, with 105,081.1 TZS for farmers affected by pre-harvest loss and 337,804.7 TZS for those who were not. This suggests that pre-harvest loss substantially reduces harvest values, even after adjusting for outliers. The median harvest value for farmers who experienced preharvest loss is 80,000 TZS, compared to 270,000 TZS for those who did not. Since the median is less sensitive to extreme values, this confirms that the typical farmer facing preharvest losses tends to have significantly lower harvests.

For paddy farmers, those who experienced preharvest loss reported a mean harvest value of 770,896.4 TZS, lower than half of the 1,805,914 TZS recorded for those without preharvest losses. The trimmed mean, at 414,641.5 TZS for affected farmers and 1,008,032 TZS for non-affected farmers, suggests that crop loss significantly reduces productivity, and extreme values skew the mean upward. The median harvest value for farmers who experienced preharvest loss is 300,000 TZS, while for those unaffected, it was 900,000 TZS. This significant gap suggests that paddy farmers who manage preharvest losses tend to achieve substantially higher harvest values. The results reinforce the crucial role of crop loss management measures in securing agricultural output and livelihoods.

Table 2: Mean and Median values of harvests by crop type and crop loss status

Description	Maize		Paddy	
	Experienced crop loss	Did not experience crop loss	Experienced crop loss	Did not experience crop loss
N	1,782	474	519	143
Mean	173,416.7	503,508.0	770,896.4	1,805,914
trimmed	105.081.1	337,804.7	414,641.5	1,008,032
Median	80,000	270,000	3.0×10^5	9.0×10^5

3.3.Value of harvests by crop type, technology adoption, and crop loss status

The study examined the value of harvests (in Tanzanian Shillings) as reported by the survey respondents by crop type, technology adoption status, and whether they experienced preharvest losses. Table 3 presents the findings for maize farming households. Evidence as reported shows that, for non-adopters, those who did not experience crop loss had an average harvest value of 349,136 TSH, with a median of 143,000 TSH. The positive skewness (2.26) indicates that some farmers achieved significantly higher harvest values than the average. Nevertheless, among non-adopters who experienced crop loss, the mean harvest value was lower (96,232 TSH), with a median of 45,000 TSH. The value of skewness (4.59) was high compared to those who did not experience loss; this suggests that, despite experiencing preharvest losses, some farmers attain relatively high harvest values.

For technology adopters, those who did not experience preharvest loss had the highest harvest values, with a mean of 511,022 TSH and a median of 282,500 TSH. However, the skewness (5.46) indicates a wide variation in harvest values, with some farmers reporting exceptionally high production. On the contrary, adopters who suffered preharvest losses recorded a decline in harvest values, with a mean of 184,063 TSH and a median of 89,000 TSH. Notably, the value of skewness (19.6) highlights that while most farmers experienced losses, a small fraction had high harvests, and accordingly, higher values.

Table 3: Summary statistics of the value of harvests by technology adoption and pre-harvest loss status - Maize.

Crop	**Used at least one farming technology**		**Did not use any farming technology**	
	Experienced crop loss	**Did not experience crop loss**	**Experienced crop loss**	**Did not experience crop loss**
N	1,566	452	216	22
Mean	184,063	511,022	96,232	349,136
Median	89,000	282,500	45,000	143,000
Skewness	19.6	5.46	4.59	2.26

For paddy farmers, the trend is similar, with technology adopters consistently outperforming non-adopters (Table 4). Among non-adopters who did not experience crop loss, the mean harvest value was 708,727 TSH, with a median of 539,000 TSH. The skewness (1.07) was relatively low, indicating a more symmetric distribution of harvest values. However, non-adopters who experienced crop loss recorded a reduction in earnings, with a mean of 342,359 TSH and a median of 200,000 TSH. The higher skewness (4.28) suggests that, despite crop loss, a few farmers had considerably high harvest values.

For adopters, those who did not experience crop loss had the highest earnings among all groups, with a mean harvest value of 1,897,346 TSH and a median of 960,000 TSH. However, the high skewness (8.86) suggests that some farmers had higher values of harvests. Even among adopters who experienced crop loss, the mean harvest value remained relatively high at 877,001 TSH, with a median of 339,500 TSH. The high value of skewness (17.1) indicates that some farmers still managed to achieve strong harvest values despite experiencing crop loss.

Table 4: Summary statistics of the value of harvests by technology adoption and pre-harvest loss status - Paddy.

Description	**Used at least one CSM technology**		**Did not use any CSA technology**	
	Experienced crop loss	Did not experience crop loss	Experienced crop loss	Did not experience crop loss
N	416	132	103	11
Mean	877,001	1,897,346	342,359	708,727
Median	339,500	960,000	200,000	539,000
Skewness	17.1	8.86	4.28	1.07

Overall, the findings of the current study show the relevance of technology adoption on agricultural productivity, as adopters consistently report higher harvest values than non-adopters across both maize and paddy crops. Correspondingly, evidence shows that preharvest loss reduces the value of harvests, with non-adopters being more severely affected. On the other hand, statistics for skewness suggest that a small proportion of farmers achieve relatively high harvest values, likely due to favorable farming conditions or better farm management practices. On the other hand, the findings showed that paddy farmers (particularly technology adopters) reported higher harvest values than maize farmers. This could be attributed to differences in crop profitability, market demand, and/or production conditions.

3.4.Power transformation of the response variable

In this study, a power transformation was applied to the value of maize harvests to reduce variability in the original data. Specifically, the study employed the Box-Cox transformation, primarily to reduce the impact of extreme values (outliers) while making the distribution of the variable more symmetric and suitable for regression analysis. Figure 1 presents a violin plot that illustrates the distribution of the power-transformed value of maize harvests across two key factors: technology adoption and crop loss (preharvest loss) status. The overall shape of the violin plot after transformation appears relatively symmetric, indicating that the transformation improved the distributional properties of the outcome variable.

While some extreme values (outliers) are still observed, their influence has been minimized, confirming the effectiveness of the transformation in reducing their impact. The figure shows that technology adoption is associated with higher harvest values. While preharvest losses negatively influence harvest values, farmers who adopt technologies tend to have better returns than non-adopters. These findings provide valuable insights into the role of technologies in mitigating the adverse effects of crop losses, reinforcing the importance of promoting their adoption among farmers.

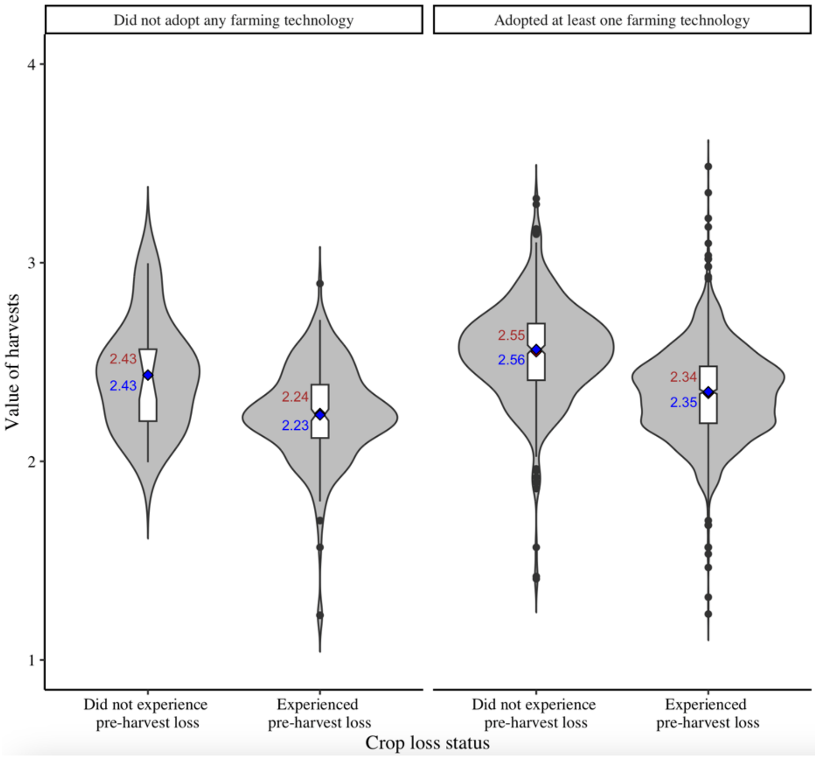

Figure 1: Distribution of the response variable - Maize

For paddy, Figure 2 illustrates the distribution of the value of harvest after power transformation. As depicted, compared to non-adopters, the adopters exhibit a higher central tendency, implying that technology adoption is associated with improved harvest values. Similarly, for farmers who experienced crop loss, the median and mean values of the adopters remain higher than their non-adopted counterparts. This suggests that although preharvest losses still reduce harvest values, technology adoption may help mitigate these losses. That is, while preharvest losses negatively impact returns, adopters tend to experience better outcomes than non-adopters

The application of the power transformation has resulted in a more symmetric distribution, reducing the original right-skewed nature of the data. Despite the transformation, some extreme values (outliers) remain visible, particularly among the technology adopters. These outliers suggest that while some farmers achieve significantly higher harvests, there is considerable variability in productivity, likely due to differences in management practices, resource access, or external environmental factors.

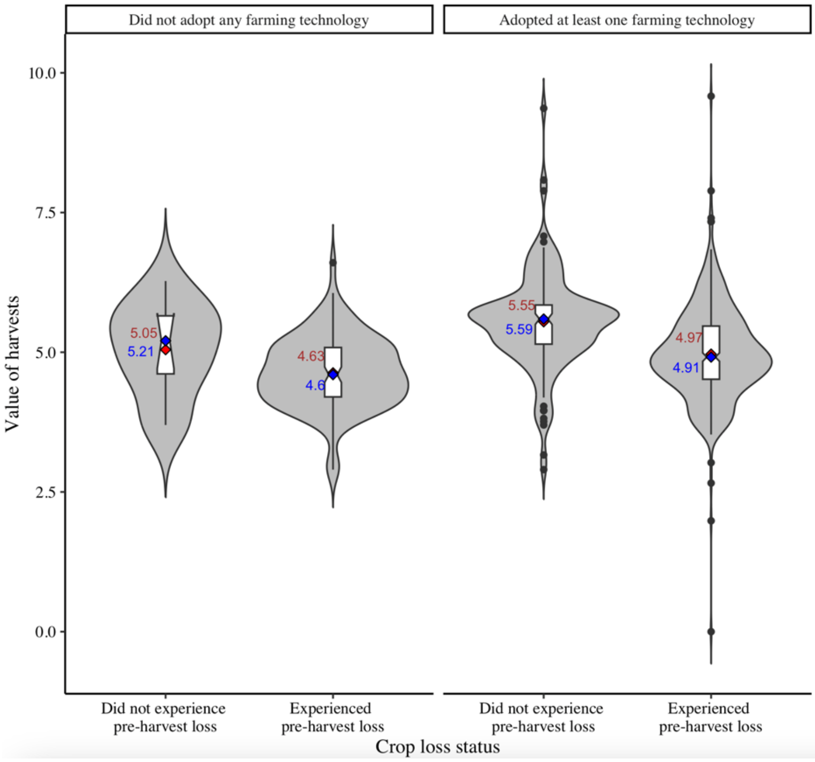

Figure 2: Distribution of the response variable - Paddy

3.5.Histogram

To further explore the distribution of the response variable, particularly the normality of the data, a histogram was made for both crops. Figure 3 illustrates the distribution of the log-transformed value of harvests for maize and paddy. As shown, both distributions appear approximately normal, with the maize dataset exhibiting a nearly symmetric shape and minimal skewness. The mean and median are closely aligned, indicating a well-centered distribution. In contrast, the paddy dataset shows a slight right skew with a longer tail, suggesting the presence of a few extreme values. Despite this, the transformation has effectively reduced skewness in both cases, making them suitable for statistical modeling.

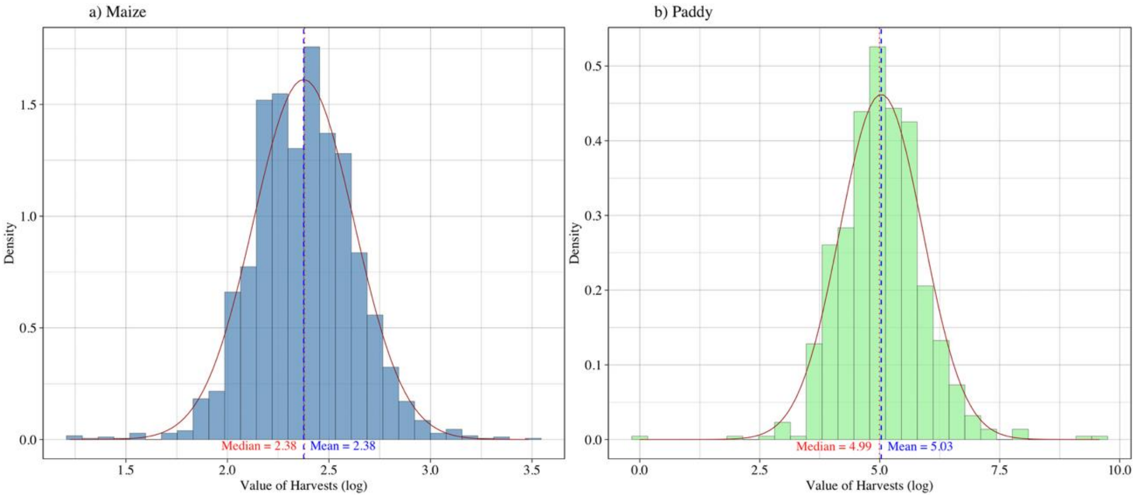

Figure 3: Distribution of the response variable for both crops

3.6.Model Performance

Table 5 presents the survey findings on model performance, indicating the proportion of variance in farm income (harvest values) explained by both fixed and random effects. As depicted, the conditional R^2 is 72 percent, indicating that, considering both crops, the model explains about 72 percent of the variation in the outcome variable. Similarly, for maize, it accounts for about 65.2 percent, while for paddy, explanatory variables explain about 59.2 percent of the variation in the value of harvests.

Considering marginal effects, the marginal R^2, which stands for the proportion of variance explained by the fixed effects only, was 63.9 percent for maize and 53.1 percent for paddy. The proportion of variance explained by explanatory variables for maize is relatively high, suggesting that fixed effects are better determinants of the value of harvests for maize farmers. Similarly, for paddy, fixed effects explain a significant portion of the variance, though to a slightly lesser extent than for maize.

Table 5: Model Performance.

Description	Conditional R2	Marginal R2
Maize	0.652	0.639
Paddy	0.592	0.531

3.7.Random Effects

Table 6 presents the estimated random effects, which provide insights into the variability of farm income across different levels of stratification, particularly concerning location and soil type. For maize, the variance attributed to StrataID is estimated at 0.01332 (SD = 0.1154), suggesting that differences in location contribute only marginally to the variation in farm income. Conversely, the variance associated with Soil type is slightly higher at 0.02150 (SD = 0.1466), indicating that soil characteristics exert a relatively greater influence on farm income compared to location.

For paddy, the variance due to StrataID is 0.3445 (SD=0.5869), indicating that location exerts a much stronger influence on paddy farm income compared to maize. This suggests that rice farming outcomes are more location-sensitive, potentially due to differences in irrigation infrastructure, climate conditions, or access to markets. Similarly, the variance associated with Soil type for paddy is 0.19714 (SD=0.440), reinforcing the importance of soil conditions in determining farm productivity and income.

The findings of the current study indicate that soil type has a more pronounced impact on maize farm income variability than location, while paddy farm income is more sensitive to location-based factors. Among others, the findings of the study suggest that future policy interventions aiming to improve farm income should consider soil suitability assessments, targeted agricultural support based on crop type, and enhanced market access strategies.

Table 6: Estimation output of the Restricted generalized linear model - Random Effects.

Description	Groups	Name	Variance	Std.Dev
Maize	StrataID	(Intercept)	0.01332	0.1154
	Soil type	(Intercept)	0.0215	0.1466
Paddy	StrataID	(Intercept)	0.34459	0.5869
	Soil type	(Intercept)	0.19714	0.4440

3.8.Fixed Effects

Table 7 presents estimation output for the fixed effects of the restricted generalized linear model. Overall, the findings of the study preharvest loss impacts farm income negatively and is thus linked with the reduction of farm income. This remains valid for estimation outputs from the crop-specific analysis, thus necessitating interventions such as improved storage, pest control, and timely harvesting to reduce losses.

A general view of farming technologies indicates that mechanization and inorganic fertilizers significantly improve farm income, suggesting the need for policies that promote access to modern farming technologies. On the contrary, the use of hired labor imposes a negative impact on farm incomes, implying the need for improved labor management strategies. While factors like access to credit, irrigation, and soil conservation are positively associated with farm incomes, their effects are not statistically significant.

Table 7: Estimation output of the Restricted generalized linear model - Fixed Effects.

Variable	**Maize**			**Paddy**		
	Coefficient	**Std.Error**	**P-value**	**Coefficient**	**Std.Error**	**P-value**
Intercept	2.4488	0.0278	<0.001	12.2505	0.2624	<0.001
Preharvest loss: Yes	-0.1917	0.00092	<0.001	-0.0766	0.0965	0.4272
Herbicides: Yes	0.0129	0.0152	0..2966	0.2325	0.1412	0.0997
Pesticides: Yes	0.0108	0.0102	0.1548	0.2310	0.1864	0.2151
Inorganic Fertilizer: Yes	0.2031	0.0568	0.0003	0.0372	0.1416	0.7925
Organic Fertilizer: Yes	0.0487	0.0517	0.3466	-0.3241	0.1427	0.0231
Main seeds: Traditional	-0.1660	0.0441	0.0001	-0.1374	0.1150	0.2320
Mechanization: Yes	0.3168	0.0751	<0.001	0.3290	9.1551	0.0340
Animal traction: Yes	0.3755	0.0489	<0.001	0.3759	0.1014	0.0002
soil water control: Yes	0.0356	0.0780	0.6482	0.0396	0.1193	0.0709
Intercropping: Yes	-0.0316	0.0415	0.6661	-0.2689	0.1530	0.07887
Irrigation: Yes	0.1653	0.2503	0.509	0.2123	0.2433	0.3829
Hired Labor: Yes	-0.2320	0.0460	0.001	-0.2482	0.0812	0.0023
Area Harvested	0.4047	0.0091	<0.001	0.2697	0.0175	<0.001
Farming Experience	-0.0006	0.0014	0.6852	0.0024	0.0027	0.3681
Household head: Male	0.1174	0.0474	0.0132	0.2117	0.0946	0..0253
Location: Urban	0.1351	0.0741	0.0683	0.2489	0.1640	0.1291

Variable	Maize			Paddy		
	Coefficient	**Std.Error**	**P-value**	**Coefficient**	**Std.Error**	**P-value**
Access to credit: Yes	-0.0849	0.1641	0.1694	-0.4930	0.5693	0.3865

Confining the analysis to variable specific, the coefficient of preharvest loss for maize was negative (−0.1917) and significant (p-value < 0.001), implying that pre-harvest loss is associated with a 19.17 percent reduction in the value of maize harvests, such that farmers who experience loss, the value of their harvests is likely to 19.2 percent lower as compared to those without losses. For paddy, the coefficient was −0.0766 and insignificant (p-value < 0.001) at all conventional levels, implying that farmers prone to pre-harvest loss their farm income is 7.66 percent lower than those without; nevertheless, the effect is not statistically significant.

The findings of the study indicated that the use of Inorganic fertilizer imposes a positive and significant effect on the value of harvests for both maize and paddy. For maize, the coefficient was 0.2031, implying that the value of maize harvests is 20.31 percent higher for farmers using inorganic fertilizer as compared to the non-users. For paddy, the coefficient is 0.0372; however, insignificant (p-value = 0.7925). The insignificant coefficient for paddy depicts that, although the use of inorganic fertilizer evidences an increase in the value of harvest, its influence remains insignificant. On the contrary, the use of organic fertilizer revealed diverse effects. For Maize, the effect was positive (0.0487), however insignificant (p-value = 0.3466), while for Paddy, the effect was negative (−0.3241) and significant (p-value = 0.0231). The findings suggest that the application of organic fertilizer is associated with an increase in the value of maize harvests; however, the effect lacks statistical justification. For paddy, the effect is negative and statistically justified, with adopters likely to register a reduction of at least 31.4 percent in the values of harvests.

The use of either traditional or improved seeds was also found to influence the value of the harvests. For maize, the coefficient was negative (−0.1660) and significant (p-value <0.001), while for Paddy, the coefficient was also negative (−0.1373); however, insignificant (p-value = 0.2320). These findings imply that the use of traditional seeds in the production of maize is associated with a reduction in farm income, with the estimated value of harvests for those using traditional seeds being 16.6 percent lower as compared to those using modern seeds. For Paddy, the influence is relatively lower than that of maize (13.74 percent); nevertheless, insignificant.

Considering Mechanization framing, evidence showed its significance in enhancing the value of harvests for both crops. For maize, the coefficient was 0.3168, indicating that the use of mechanization in farming leads to a 31.68 percent increase in the value of maize harvests. For paddy, the coefficient was 0.3290, reflecting a 32.90 percent increase in paddy harvest value. The comparable effects for maize and paddy suggest that mechanization benefits farmers likely by reducing labor costs, increasing efficiency, and minimizing crop losses. As with mechanization, the use of animal traction in farming also stood out as a prominent determinant of farm income. For maize, the findings predicted a positive (0.3755) and significant coefficient (p-value < 0.001), while for paddy, a similar effect is observed, with a marginal difference in coefficients (0.3759) and a probability value of 0.0002. These findings imply that the use of animal traction in the production of maize and paddy is likely to scale up farm income by 37.55 and 37.59 percentage points, respectively.

The use of hired labor indicated a negative impact on the value of harvests across all crop categories; for maize was −0.2320 (p-value < 0.001), and for paddy was - 0.2482(p-value = 0.0023). The findings imply that using hired labor in the production of crops is associated with a 23.20 and 24.82 percent reduction in the value of harvests for maize and paddy, respectively. The negative effect of hired labor can be referenced from several standpoints, among others being inefficiencies in farm management or high wage costs that may exceed the additional output generated.

The study investigated the influence of soil erosion control and water harvesting facilities on farm income and found diverse effects across crops. The regression coefficients for both crops were positive (0.0356 for maize and 0.0396 for paddy); however, insignificant for maize (p-value < 0.6482) and marginally significant for paddy (p-value < 0.0709). These findings confirm that, while the presence of soil erosion controls and water harvesting facilities contributes to improved soil fertility and moisture retention, the immediate impact on harvest values is not substantial in the production of maize and is marginally pronounced in the case of paddy. Despite its level of significance, the findings confirm that the presence of soil erosion controls and water harvesting facilities in the production of paddy is associated with scaling up the value of harvests by 3.96 percentage points.

Reading intercropping, the findings of the study did not show a significant effect on the value of harvests for maize. For Paddy, the coefficient was negative (−0.2689) and marginally significant (p-value = 0.07887). The negative regression coefficient paddy indicates that, despite its relevance in improving land use efficiency and biodiversity, intercropping is, however, associated with a reduction the the value of paddy harvests by 26.89 percent. The same effect is observed in the case of maize; however, the insignificant coefficient could be coupled with several reasons, among others being the challenge of managing multiple crops simultaneously or competition of crops for nutrients, thus resulting in the reduction of the harvests, and accordingly, their value.

Considering irrigation, its influence on scaling up the value of harvests was insignificant. The regression coefficient was positive, suggesting that irrigation is linked to increased farm income, such that farmers using irrigation in the production of maize and rice are more likely to have higher returns than those without. However, the lack of statistical significance implies that the effectiveness of irrigation in the production of maize and paddy can be attributed to several factors apart from water availability, including but not limited to available irrigation technologies.

3.9.Model Diagnostic

Figure 4 presents the residual versus fitted values plot. It provides insights into the performance of the robust linear mixed-effects model applied to maize and paddy production data. For a well-fitted/specified model, residuals are required to be randomly scattered around zero. In this analysis, most of the residuals are concentrated around zero, signaling a well-specified model. Nevertheless, some residuals exhibit some slight dispersion at lower fitted values, suggesting potential heteroskedasticity.

The color gradient represents the weights assigned to residuals, with lighter blue points indicating higher weights and darker blue points representing lower weights. The findings indicate that residuals with higher weights are concentrated around zero, and those with lower weights are more at extreme values, particularly in the lower range of fitted values. This pattern suggests that the robust estimation method gave greater importance to the observations with higher weights when estimating coefficients, thus enhancing the robustness of the findings while reducing the undue influence of outliers. Since the influence of the extreme values is minimized on the final estimates, the current estimation outputs remain valid for interpretation, as the model has effectively accounted for variations and potential outliers in the data.

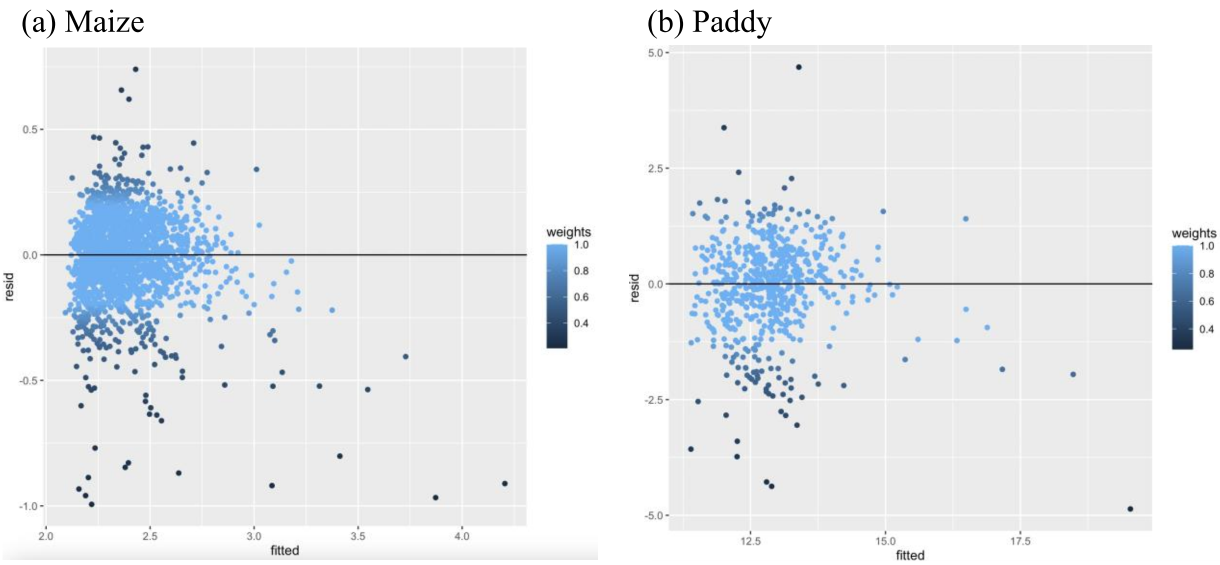

Figure 4: Distribution of the residuals: residual-fitted plot

3.10. Discussion of findings

The study's findings offer important insights into the dynamics of farm income among Tanzanian households, especially with pre-harvest losses, input use, mechanization, labor practices, and socio-demographic characteristics. Drawing from the Tanzania National Panel Survey, the analysis reveals several critical observations with real-life implications for agricultural policy and rural livelihoods.

Conforming to the findings of Tatlid et al. (2005), a striking result is the consistent negative effect of pre-harvest losses on the value of crop harvests, particularly maize. Farmers experiencing such losses see a significant drop in their income, underscoring the widespread and detrimental effects of inadequate preharvest management practices. Although the effect is statistically insignificant for paddy, the general pattern confirms that minimizing pre-harvest loss remains relevant in improving farm incomes in Tanzania.

Consistent with Tabo et al. (2007) and Martey et al. (2019), the use of inorganic fertilizer significantly enhances maize productivity, which aligns with national agricultural input support programs that have encouraged its use. This positive association is not as strong for paddy, potentially due to an inefficient application or soil conditions less responsive to inorganic inputs. Conversely, organic fertilizers, despite being environmentally friendly, show inconsistent results. For maize, they provide a marginal but statistically insignificant benefit, while for paddy, they appear to reduce the value of harvests. Despite the findings of the current study being in line with Li et al. (2024), they, however, contradict the findings of Martey (2018). This might reflect challenges in sourcing quality organic matter or the need for longer-term applications to realize benefits.

In conformity with existing theoretical and empirical findings, the analysis depicted that the use of traditional seeds is associated with lower harvest values for maize and, to a lesser extent, paddy. The findings of the current study are in line with studies by Addison et al. (2022), Awotide et al. (2011), and Akanbi et al. (2024). The findings reflect the continued productivity gap between improved and local seed varieties, which has a corresponding influence on farm incomes.

Among the robust findings of the study are the positive and significant impacts of mechanization and animal traction. In line with empirical evidence as documented among others by Verma (2006) and Peng et al. (2022), mechanized farming offers critical labor-saving and efficiency-enhancing benefits. Despite that the findings of the current study contradict Jansen (1993) and Lawrence et al. (1997) regarding the positive and significant coefficient on the use of animal traction, the findings showed that the application of these technologies in both maize and paddy farming offers an indispensable contribution to increasing the value of harvests. These findings further stand firm in validating the relevance of investing in mechanized farming as well as promoting access to machinery services.

Regarding the use of hired labor in production, the current study evidenced that it is associated with a reduction in the value of harvests for both maize and paddy. The findings of the current study could emanate from several instances, such as management inefficiencies, inadequate supervision, or high wage burdens outweighing productivity gains. The findings suggest that while labor is essential, its impact depends heavily on the quality and structure of labor deployment on farms. Based on these findings, improving labor management skills or shifting toward more efficient labor efficiency, as well as labor-saving technologies, could accordingly improve productivity outcomes.

Though the effect of soil erosion control and water harvesting facilities is minimally registered, their potential cannot be undermined. The benefits of water retention structures are reflected in the borderline significance coefficient for paddy. This is likely backed by the fact that paddy is grown in a waterlogged environment, and thus, having properly managed water systems as well as soil erosion control mechanisms matters the most. Thus, proper integration of these practices into farming could improve productivity and, subsequently, increase the value of harvests.

With intercropping, the findings of the study depicted negative and marginally significant effects, particularly in paddy production. While intercropping is often promoted for its ecological and risk-diversifying benefits, the findings of the current study suggest that the practice may not necessarily translate into higher farm incomes. This could be associated with several factors, including farm management practices and competition of crops for air, nutrients, and moisture. Based on these findings, evaluating existing intercropping strategies in cereal production remains relevant to ensure economic as well as agronomic viability.

Irrigation, often touted as a key to resilience, shows positive yet statistically insignificant effects. This could reflect the variability in irrigation quality, coverage, or inefficiencies in water use. Expanding access to affordable, well-managed irrigation schemes, especially in semi-arid regions, could unlock productivity potential, provided it's supported by complementary inputs and extension.

4. Conclusions and Recommendations

4.1. Conclusion

Based on the study findings, the study concludes that pre-harvest loss impacts farm income negatively. Reducing pre-harvest losses is therefore not merely a technical concern but a critical pathway toward enhancing household farm income, particularly in maize production systems. However, this depends on aligning loss-reduction strategies with broader improvements in input use, seed quality, agronomic practices, as well as careful attention to how technologies interact with labor dynamics, ecological conditions, and crop-specific requirements. Given this, the study finds that meaningful income gains from farming demand an integrated approach, one that combines modern technologies, efficient labor use, and ecosystem-smart practices tailored to the realities of smallholder agriculture.

4.2. Recommendations

The study proposes mitigating pre-harvest losses through improved agronomic practices. This can be achieved by: firstly, strengthening extension services though establishing robust extension services to educate farmers on best practices for pest, disease, and drought management, and secondly, promoting use of pest-resistant crops by encourage the adoption of pest-resistant seed varieties and provide subsidies or incentives for their purchase, particularly in areas highly affected by pest infestations.

On the other hand, enhancing seed quality and access to improved seed varieties. This can be realized by providing subsidies for the purchase of high-quality, improved seed varieties that are pest-resistant, drought-tolerant, and suited to local soil conditions. On the other hand, strengthening seed distribution networks remains relevant to allow more efficient seed distribution networks to ensure that farmers have access to improved seeds. This may include establishing seed banks and community-based seed systems to make seeds more accessible and affordable.

Additionally, advocacy on the use of both inorganic and organic fertilizers to improve soil fertility should be in place. However, the application should be based on proper soil testing and tailored recommendations to ensure effectiveness. Where necessary, fertilizer use should be linked to agronomic training to avoid over-application or improper use. Parallel to this, while intercropping can enhance ecological resilience, it should be strategically planned to ensure economic viability. Where necessary, studies to assess the best intercropping combinations for enhancing both farm productivity and income, while reducing competition between crops for resources like water and nutrients, should be conducted.

Furthermore, investing in affordable and efficient irrigation systems remains critical for mitigating the impacts of irregular rainfall and enhancing productivity, particularly for paddy farmers. Focus on expanding irrigation coverage in semi-arid and drought-prone regions, where water management can directly impact crop yields. In areas with limited water resources, promote water-saving technologies such as drip irrigation and rainwater harvesting. Training farmers on these technologies and providing subsidies can help ensure their adoption.

5. Conflicts of Interest

The author declares that no conflict of interest appeared to influence the work reported in this paper.

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