The Impact of Agronomic Practices on Pre-harvest Losses Among Maize and Paddy Farming Households in Tanzania: Evidence from the 2019/2020 National Panel Survey

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Abstract
This study investigates the impact of agronomic practices and technology adoption on the extent of pre-harvest losses among maize and paddy farming households in Tanzania. Using data from the fifth wave of the 2019/2020 Tanzania National Panel Survey, we estimate pre-harvest loss as the difference between expected and actual production and construct a binary indicator that takes the value 1 if a household experienced crop loss and 0 otherwise. To assess the impact, we employ two estimation techniques: Propensity Score Matching (PSM) and the Generalized Additive Model (GAM). Results from the PSM reveal a negative and significant Average Treatment Effect (ATE), with marginal probabilities indicating that adopters of agricultural technologies have an approximately 15 percent lower predicted probability of experiencing pre-harvest losses compared to non-adopters. In the GAM analysis, intercropping, the use of organic and inorganic fertilizers, herbicides, mechanization, animal traction, and improved seeds are found to influence maize pre-harvest losses, with intercropping being the only practice associated with increased losses. For paddy, the use of organic fertilizer shows a positive association with pre-harvest losses, while animal traction, pesticides, and irrigation are associated with reductions in losses. Based on these findings, it is essential to promote the widespread adoption of effective technologies through targeted extension programs. In addition, training on the appropriate use of these technologies, coupled with government subsidies to support adoption, could play a critical role in reducing pre-harvest losses and enhancing food security.

Key words: Agronomic practices; Potential Yield; Pre-harvest loss; Technology adoption; GAM; Animal traction

JEL Classification Codes: E23, D24, Q12, Q18

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1.0 Introduction

The persistence of global hunger and food poverty amid rising population growth presents a profound economic and development challenge. The 2030 Agenda for Sustainable Development, among others, identifies the eradication of poverty and hunger as central to global well-being. With the world population projected to reach 8.5 billion by 2030 and 9.7 billion by 2050 (United Nations, 2019b), ensuring sustainable food systems is essential not only for human welfare but also for economic stability. Achieving these objectives depends significantly on the productivity and sustainability of the agricultural sector. However, this initiative is undermined by systemic inefficiencies, including pre-harvest losses, that reduce food availability and depress households' farm incomes, thereby perpetuating poverty and inefficiency in food markets.

According to the Food and Agriculture Organization (FAO, 2017, 2018b), an estimated 1.3 billion tons of food are lost annually across the global value chain. This represents not only a waste of calories and nutrients but also a substantial loss of income and productivity, especially in developing economies where agriculture accounts for a significant share of GDP and employment. In sub-Saharan Africa (SSA), the majority of food losses occur during the production, handling, and storage stages (Searchinger *et al*., 2018), and approximately 35% of food produced never reaches the consumer (Sethi *et al.*, 2020).

In Africa, and Tanzania in particular, pre-harvest losses are poorly documented, which limits the potential for scalable solutions (FAO, 2018b, 2019). The challenge is visible in persistently low yields. Citing specific documentation for maize and paddy, the major staple foods in the country, the FAO estimates potential yields at 6–10 tons for maize and 3–6 tons for paddy per hectare (Senkoro et al., 2018). However, actual national averages remain at 1.8 and 2.2 tons per hectare, respectively (NBS, 2023). This gap underscores inefficiencies in production, much of which stems from poorly documented and under-addressed pre-harvest losses. The losses represent an often-overlooked form of production inefficiency and have received inadequate empirical attention (Fekadu & Andarege, 2024; Nkwain et al., 2022).

Additionally, while Tanzania has developed national strategies on post-harvest loss management (URT, 2019a, b) and broader sector plans such as the Agricultural Sector Development Program Phase II (ASDP II), pre-harvest lacks comparable policy visibility and remains absent from formal monitoring systems. This neglect reflects a lack of empirical evidence, diagnostic capacity, and investment in early-stage loss reduction. Consequently, decision-makers lack the information needed to design effective interventions, and farmers continue to operate below their production frontier. To fill this empirical and policy gap, this study poses the following research questions: [1] What is the extent of pre-harvest losses in maize and paddy production in Tanzania? [2] To what extent does the adoption of technology mitigate pre-harvest losses? [3] How do specific agronomic practices influence pre-harvest losses in maize and paddy systems?

These questions are directly motivated by the need to enhance farm-level efficiency, boost agricultural incomes, and improve food system resilience. By linking losses to technology and agronomic decisions, the study seeks to identify scalable solutions rooted in both economic theory and practical relevance. It also contributes to the literature by focusing on pre-harvest dynamics, a relatively underexplored dimension of the yield gap discourse. The study is theoretically framed by three complementary perspectives that inform its analytical approach. The Production Function Theory conceptualizes agricultural output as a function of key inputs such as land, labor, fertilizer, and technology (Taherdoost, 2018). Pre-harvest loss is understood as a deviation from the potential output frontier, reflecting inefficiency. The Diffusion of Innovation Theory (Rogers, 1995), which explains how technologies spread through farmer communities, emphasizing the role of communication channels, social systems, and perceived benefits. The Unified Theory of Acceptance and Use of Technology (Lai, 2017, 2020), which identifies behavioral and structural factors affecting technology uptake, including performance expectancy, effort expectancy, and facilitating conditions.

Together, these theories enable a holistic investigation of pre-harvest loss and technology adoption. By embedding these theories in the Tanzanian context, this research offers insights into both the technical and behavioral determinants of pre-harvest losses. It positions technology adoption not merely as a technical fix but as an economic behavior shaped by expectations, constraints, and institutional support**.** This framing supports the design of policies aimed at reducing losses, enhancing efficiency, and promoting sustainable agricultural transformation

The remainder of this study is organized as follows. Section 2 reviews the literature on technological adoption in agricultural production and management. Section 3 depicts the study area, sampling methodology, sample size, measurement of variables, and analytical methods. Section 4 presents the study findings, and Section 5 rests on conclusions and recommendations.

2.0 Literature review

2.1 Theoretical Framework

The present study integrates multiple theoretical lenses to investigate pre-harvest losses and technology adoption among smallholder farmers. First, the Production Function Theory posits that agricultural output is a function of key inputs, land, labor, capital, seeds, fertilizer, and technology (Taherdoost, 2018). In this framework, pre-harvest loss is conceptualized as a form of production inefficiency, representing deviations from the optimal input-output frontier. This theoretical stance provides a basis for modeling inefficiencies that arise due to constraints in technology, agronomic practices, or knowledge.

Second, the Diffusion of Innovation Theory (Rogers, 1995) describes how innovations are adopted over time within a social system. It identifies five attributes influencing adoption: relative advantage, compatibility, complexity, trialability, and observability. In agriculture, this theory is critical in understanding how innovations such as improved seeds or mechanization spread among farmers and how social structures mediate adoption. Third, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Lai, 2017; 2020) brings in behavioral and contextual considerations, performance expectancy, effort expectancy, social influence, and facilitating conditions as key predictors of technology adoption. Although originally developed in information systems literature, UTAUT is increasingly used in agricultural contexts, especially where behavioral, institutional, and infrastructural barriers influence adoption.

Furthermore, the study is informed by concepts from agricultural economics, particularly models of adoption under risk and uncertainty, as well as stochastic frontier analysis, which conceptualizes inefficiency as a gap between observed and potential output. This grounding allows the current research to assess pre-harvest losses as a measurable inefficiency problem and connect theoretical constructs to empirical estimation strategies. Theoretical frameworks applied here enable an integrated analysis of both technical and behavioral sources of pre-harvest losses. The study positions inefficiency as an economic issue, explained not only by input constraints but also by adoption behavior, institutional conditions, and farmer perceptions.

2.2 Empirical Literature

2.2.1 Determinants of technology adoption

Numerous studies examine the drivers of agricultural technology adoption in Sub-Saharan Africa. For instance, Mumah et al. (2024) used an endogenous switching regression model in Kenya to assess the adoption of chisel harrows. They found farm size, credit access, gender, and extension contact positively associated with adoption, while age and market distance had negative effects. Similarly, Mdoda et al. (2022) employed PSM to assess mechanization adoption and found similar socioeconomic influences; however, the study had limited generalizability due to its small sample size.

In Uganda, Pan *et al*. (2018) employed a regression discontinuity design to demonstrate that households in eligible villages were more likely to adopt improved, cost-effective agricultural inputs, underscoring the catalytic role of extension services. A complementary perspective is provided by Bundi *et al*. (2020), who examined the adoption of pre-harvest practices (PHPs) among mango farmers. Their use of multivariate and ordered probit models revealed that adoption was influenced by farming experience, income from off-farm sources, mango sales, number of mango trees, access to inputs, and farmer perceptions.

Collectively, these studies highlight the significance of access to inputs, market participation, and extension services in promoting adoption. However, they often stop short of linking technology adoption to outcomes such as loss mitigation or efficiency gains. Furthermore, behavioral and cognitive dimensions, such as perceptions of effort, risk aversion, and attitudes, remain underexplored, pointing to the potential value of integrating frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT).

2.2.2 Estimation and Measurement of Losses

Accurately measuring pre-harvest losses remains a methodological challenge. Most studies rely on recall-based data with limited methodological frameworks or spatial resolution, thus raising concerns about reliability. While global assessments such as those by FAO (2019) and Abass et al. (2018) have developed general loss profiles, they rarely provide empirical, peer-reviewed evidence grounded in representative field data.

For example, Shah (2014) assessed soybean losses in Maharashtra and estimated that 14–16% of total production was lost across pre-harvest to post-harvest stages. However, like many studies, the estimates were based on farmer-reported losses. Similarly, Alemayehu et al. (2018) used descriptive and regression techniques to assess fruit loss in Northwestern Ethiopia. They found total losses of 44.8%, with pre-harvest losses accounting for 20.7%. Factors such as income source, pesticide use, and organic input application were significant predictors of loss levels. Nevertheless, the study lacked specific documentation on how losses were measured.

However, innovative approaches are emerging. For instance, Yamada et al. (2025) introduced a novel methodology using computer vision and deep learning to detect and quantify pre-harvest losses in soybean and wheat. Leveraging advanced imaging technologies such as Mask RCNN, YOLOX, DETR, and a modified YOLOv8-p2, they achieved high precision and recall, with the best model yielding an F1 score of 0.710 for soybean and 0.698 for wheat. Despite these advancements, integrating such technologies with socioeconomic surveys remains limited.

2.2.3 Technology use and pre-harvest losses

While the yield-enhancing effects of technology adoption are well-documented (see, for instance, Sheahan & Barrett, 2017), evidence specifically linking technology use to reductions in pre-harvest losses is limited. For instance, Darfour and Rosentrater (2022) reported that over 93% of maize farmers in Ghana experience pre-harvest losses caused by rodents, birds, and lodging. Similarly, Kirigia et al. (2017) identified several causes of pre-harvest losses, such as drought stress, unfertile soils, pest infestation, and poor harvesting techniques, emphasizing production risks in SSA. Despite the contribution of the studies to the literature, they relied heavily on self-reported data, with limited methodological rigor.

From a more technological angle, Kumari et al. (2023) highlighted the role of mechanization in improving the quality and safety of horticultural produce. They noted that pre-harvest mechanization, when adequately powered and economically viable, significantly reduces losses and enhances produce quality. In Tanzania, Mlyashimbi *et al*. (2022) conducted field simulations and found higher rodent-induced seedling damage in clay soils. Despite offering biological insights, this study lacked socioeconomic integration, limiting its policy relevance. Also, there remains a limited number of empirical studies that rigorously quantify how specific technologies affect pre-harvest losses across varied farming systems.

2.2.4 Synthesis and Gaps in the Literature

Despite the extensive literature on agricultural technology adoption, few studies explicitly link these technologies to reductions in pre-harvest losses. Much of the existing work is descriptive, lacks rigorous identification strategies, and is often based on small or region-specific samples. Therefore, measurement of pre-harvest losses remains inconsistent, with few studies leveraging large-scale representative data or integrating agronomic and socioeconomic dimensions.
In Tanzania specifically, an absence of data-driven evaluations and minimal literature on pre-harvest loss quantification and its linkage to agronomic or technological interventions. Existing policy strategies prioritize post-harvest losses, leaving a significant evidence gap for pre-harvest inefficiencies. This underscores a critical gap in evidence-based policy formulation for reducing pre-harvest losses through targeted technological interventions.

This study fills these gaps by combining economic, behavioral, and agronomic lenses to evaluate how technology adoption and farming practices affect pre-harvest losses. By leveraging nationally representative data and advanced econometric methods, it offers context-specific, policy-relevant insights for enhancing agricultural efficiency in Tanzania.

3.0 Materials and Methods

3.1 Data types and sources

The study used secondary data from the fifth wave of the 2019/2020 Tanzania National Panel Survey (NPS-5). The data were sourced from the National Bureau of Statistics (NBS).

3.2 Measurement of study variables

In this study, the outcome variable was pre-harvest loss. The study borrowed computational methodology from FAO (2018a) and thus computed preharvest losses by considering the difference between expected production and effective production (1). After the computation of actual and relative losses, the study created an indicator variable, carrying a value of 1 if a household had experienced crop loss and 0 otherwise.

$$LpreH = Qexp - Q = (Aplant \times Yexp) - (Aharv \times Yeff) \qquad (1)$$

Where *Qexp* refers to expected production, which was computed by taking the product of planted area (*Aplant*) and expected yield (*Yexp*); and Q is the effective production, computed by taking the product of harvested area (*Aharv*) and effective yield (*Yeff*).

To get the expected Yield, first, the study computed the actual yield as a ratio of the quantity harvested (Q) to the area harvested. After computing the actual yield, the data were grouped by crop type and domain, and then the expected yield was estimated as the *80^{th}* percentile of effective farm yield, FAO (2018a). Accordingly, the expected production was computed by taking the product of the expected yield and the area planted.

The main predictor variables for this study were application of herbicides, pesticides, organic fertilizers, inorganic fertilizers, mechanized farming, use of animal traction, soil erosion control and water management mechanisms, and intercropping. 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. Also, the type of seeds used constituted a list of predictors, with code 1 if the household used improved seeds and 0 otherwise. 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. Other variables relating to determining accessibility to farms, such as distance from the farm to the main road and from the farm to home, were also used.

3.3 Estimation techniques

To achieve the intended study objectives, the two approaches were employed in the analysis: [1] the Propensity Score Matching technique and [2] the Generalized Additive Model (GAM).

3.3.1 Propensity Score Matching (PSM)

The current study adopted a computational approach as proposed by Gertler et al. (2010) and Zhao *et al*. (2021). The study defined the propensity, $e(x)$, as the conditional probability of a household to adopt a particular production technology, $p(T)$, given a set of covariates, x. Propensity scores were estimated in the framework suggested by Rosenbaum and Rubin (1983) as :

$$e(x) = Pr(T = 1|x) = F(h|x) = E(T = 1|x) \qquad (2)$$

Where F (.) is a cumulative distribution function of the probability of being treated, and X is a vector of observable pre-treatment characteristics. In the context of the current study, the technology adoption (*techAdoption*) referred to the use of at least one modern technology-related farming practice and was computed by aggregating (summing) the values of ten (10) variables and then creating an indicator variable with code 1 for households that adopted at least one technology (sum of *techAdoptionScore*> 0) and 0 otherwise (sum of *techAdoptionScore* = 0).

After computing the propensity scores, the units in the treated group were matched to the pool of control units. Full matching was found appropriate for this study as it matches one treated unit to one or more control units, it uses all the available information (no loss of sample size), and reduces bias as well as the distance between control and treated units (Harris and Horst, 2016). Balance was then assessed by comparing the means of both treated and control units (Caliendo and Kopeinig, 2008) and treatment effects were estimated using a Generalized Linear Model with a logit link, (Wooldridge, 2013, 2015).

To gain insightful knowledge about the effect of technology adoption on pre-harvest losses, the study computed marginal effects which according to Norton et al. (2019) and Lüdecke (2018), are useful in measuring the extent to which the predicted probability of the outcome variable (pre-harvest losses) changes given that the household adopts a particular farming technology without taking into account the non-linear influence of other predictors.

3.3.2 Generalized Additive Model

The Generalized Additive Model (GAM) is a class of models that extends the usual collection of likelihood-based regression models in a method for its estimation (Hastie and Tibshirani, 1986). GAM was used to allow variable-specific estimation, thus relevant in presenting a granular understanding of specific farming practices that drive the impact and how their impact varies by crop type. Learning from Hastie and Tibshirani (1986), GAM generalizes a logistic binary model

$$\log\left(\frac{p(x)}{1+p(x)}\right) = \delta_0 + x\delta \tag{3}$$

to smooth a function defined by :

$$log\left(\frac{p(x)}{1+p(x)}\right) = \delta_0 + \sum_{j=1}^{l} s_j x_j + \sum_{i,j} te(x_i, x_j) + \sum_{j=1}^{p} \delta_j x_j \tag{4}$$

where;

- sj(xj) are smooth functions for continuous predictors *farmExp*, *distMainRoad* and *distHome*. These variables are expected to have a non-linear relationship with the outcome variable.
- The tensor products $te(x_i, x_j)$ for interaction capture the extent to which the specified predictor variables jointly influence the outcome variable.
- $\delta_p x_p$ are linear terms for categorical predictors: *herbicides, pesticides, OrganicFert, InOrganicFert, Mechanization, animalTraction, SoilWaterControl, intercropping, MainSeeds, hhHead*. These variables are included as fixed effects and are not expected to have nonlinear effects on the outcome variable.

Therefore, substituting the smooth effects and tensor product smooths in the estimation equation (8), the estimation equation used in this study is as presented in (9)

$$\begin{aligned} log\left(\frac{p(x)}{1+p(x)}\right) = {} & \delta_0 + s\ (farmExp) + \ s\ (distHome) + \ s\ (distMainRoad) \\ & + te(farmExp, distMainRoad) + \ te(farmExp, distHome) \\ & + te(distHome, distMainRoad) \ + \sum_{j=1}^{p} \delta_j x_j \end{aligned} \tag{4}$$

4.0 Results and Discussion

4.1 Crop Loss

Table 1 presents a summary of the statistics on the status of crop loss by crop type. Among the total households reported to engage in Maize and Paddy production, 75.7 percent experienced preharvest losses while 24.3 percent did not. Across crops, statistics indicate minimal variation, with proportion of househsehold that expericnced loss being marginally higher in paddy farming households (76.0 percent) as compared to Maize farming households (75.7 percent).

Table 1: Number and Percent of households experienced pre-harvest loss

Crop type	Did not Experienced Loss		Experience Loss	
	Count	Percent	Count	Percent
Maize	573	24.3	1782	75.7
Paddy	164	24.0	519	76.0
Total	**737**	**24.3**	**2301**	**75.7**

4.2 Mean, Median, and Percentage Loss

The current study computed the loss percentage as well as the mean and median loss of crops by crop type. As depicted (Table 2), the loss percentage of Maize and Paddy crops aggregated to 35.3 percent and 38.8 percent, respectively. Further, statistics show the losses of Maize and Paddy averaging 514 tons and 1230 tons, with median values of 409 and 760 tons, respectively. The findings depict that preharvest losses are more pronounced in Paddy than in Maize, both in terms of absolute values and relative losses. The possibility of some households having exceptionally higher losses is also evidenced by higher values of the mean over the median.

Table 2: Mean, Median, and Percentage losses of Maize and Paddy before harvests

Crop	Mean	Median	Percent
Maize	514	409	35.3
Paddy	1203	760	38.8

4.3 Farming experience, proximity to farm, and crop loss

The study used the variable age as a proxy for farming experience, distance to home, and distance to market, hypothesizing that these variables are likely to impact the decision of a farmer to adopt a particular technology and subsequently influence crop loss.

For maize crops (Table 3), statistics show that households that heads of households that did not experience loss their mean and median age was less than those that experienced crop loss. Similarly, the average distance to home and the average distance to the main road were less for households that did not register losses as compared to those that had their crops lost during production. From this we draw several insights, including: [1] farmers experiencing crop loss are on average older than those without losses; [2] Farmers whose farms are far from residences are more vulnerable to preharvest losses; and [3] Preharvest loss of maize is marginally low to farms located close to main road than those far away.

Table 3: Number, Mean, Median, Maximum, and Minimum values of key variables by pre-harvest loss status - Maize

Variable description	Did not experience loss			Experienced loss		
	Age	Distance to home	Distance to road	Age	Distance to home	Distance to road
N	1743	1743	1743	635	635	635
Mean	48.6	4.2	1.8	50.7	5.0	2.0
Median	47.0	0.01	0.5	50.0	1.5	1.0

For the Paddy (Table 4), the findings depict that loss was registered to households with younger household heads than those with older heads. This could be translated to a lack of commendable farming experience or inadequate technical know-how on managing farm challenges and risks. Concerning distance to home, there is no notable difference in the average distance. However, the median for those who had losses is slightly higher, suggesting that paddy farms located far away from homes are prone to registering losses. This could be attributed to the nature of paddy farms, which require constant monitoring to prevent them from being invaded by animals, particularly birds. On the contrary, evidence shows that farms located further away from the main road had a reduction in exposure to losses. Losses were common to paddy farms that are relatively close to the main road.

Table 4: Number, Mean, Median, Maximum, and Minimum values of key variables by pre-harvest loss status – Paddy

Variable description	Did not experienced loss			Experienced loss		
	Age	Distance to home	Distance to road	Age	Distance to home	Distance to road
N	528	527	528	157	157	157
Mean	48.9	10.7	2.8	47.0	10.7	2.7
Median	48.0	3.0	1.5	46.0	4.0	1.0

4.4 Technology adoption

Descriptive statistics (Table 5) indicate that farming households have relatively low adoption rates of modern agricultural technologies. For maize-cropping households, intercropping and the use of improved seeds were the most adopted farming practices. The use of animal traction and organic fertilizer was minimal, and practices such as soil and water conservation and irrigation were lastly adopted. For paddy cropping households, the most adopted practice is the use of animal traction, and practices such as soil erosion control and water conservation, and intercropping were minimally adopted.

Table 5: Percentage distribution of households applying or using selected farming practices

Farming practice	Maize	Paddy
Herbicides	06.6	12.4
Pesticides	17.6	6.40
Organic Fertilizer	20.4	7.90
Inorganic Fertilizer	19.7	12.4
Mechanization	09.1	12.0
Animal Traction	35.5	55.8
Soil and water conservation	07.3	11.37
Intercropping	50.4	7.40
Irrigation	0.80	3.80
Improved main seeds	44.2	14.5

Table 6 depicts the study findings on the overall technology adoption and crop type. As indicated, 89.2 percent of households that engaged in maize production adopted at least one technology, while 10.8 percent did not. Similarly, 82.8 percent of households that engaged in paddy production were able to adopt at least one technology, whereas 17.2 percent did not. Technology adoption was, therefore, relatively higher in maize-farming households as compared to paddy-farming households.

Table 6: Distribution of Agricultural households by technology adoption status and crop type

Description	Maize		Paddy	
	Count	Percent	Count	Percent
Used at least one technology	2122	89.2	567	82.8
Did not use any technology	256	10.8	118	17.2

4.5 Production, technology adoption, and preharvest

Table 7 presents the mean and median values of harvests by crop type, technology adoption status, and whether the household experienced pre-harvest loss. The results indicate that, on average, both the mean and median harvest values are consistently higher for households that adopted modern farming technologies and did not experience pre-harvest losses. Moreover, even among non-adopters, households that did not experience pre-harvest loss reported higher harvests than their counterparts who faced losses.

Table 7: Mean and Median values of harvests (in tons) by Crop Type, technology adoption status, and whether the household experienced pre-harvest losses

Description			Mean	Median
Maize	Adopters	Experienced preharvest loss	427	240
		Did not Experience loss	1845	666
	Non-Adopters	Experienced preharvest loss	211	100
		Did not Experience loss	640	50
Paddy	Adopters	Experienced preharvest loss	1114	700
		Did not Experience loss	2631	2100
	Non-Adopters	Experienced preharvest loss	621	300
		Did not Experience loss	1204	900

4.6 PSM Estimation output

4.6.1 Summary of Balance for Matched Data

As indicated (Table 8), the balance diagnostics from the propensity score matching show that the balance was equally achieved. Statistics on the standardized mean differences are close to zero, with smaller systematic differences between groups on observed characteristics after matching. For distance to main road, despite its means being similar among the two groups, its variance ratio was a relatively higher, signaling residual imbalance. However, the findings indicate an overall good balance, enough for estimating the treatment effects.

Table 8: Summary of Balance for Matched Data

Variable	Means treated	Means control	STD.Mean Diff	Var.Ratio	eCDF Mean
Distance	0.87	0.87	0.0149	1.2001	0.0058
Age	48.97	48.27	0.0469	0.8179	0.0224
Hhhead: male	0.73	0.72	0.0421	-	0.0191
Hhhead: female	0.26	0.28	-0.0421	-	0.0191
Distance to home	5.88	5.34	0.0239	8.4962	0.0346
Distance to main road	2.07	2.38	-0.0825	1.3475	0.0265
Location: rural	0.85	0.84	0.0261	-	0.009
Location: urban	0.15	0.16	-0.0261	-	0.009

4.6.2 Average Treatment Effect (ATE)

Table ***9*** presents the Average Treatment Effect (ATE). For the maize, the ATE is negative (-0.161) and significant (p-value < 0.01). Similarly, the ATE for paddy is also negative (-0.150) and significant (p-value < 0.01). The findings indicate that technology adoption during production imposes a negative impact on pre-harvest loss, such that technology adopters are less likely to experience pre-harvest loss than non-adopters. Accordingly, adopting technology in production, on average, reduces preharvest losses of maize and paddy by 16.1 and 15.0 percentage points, respectively.

Table 9: Estimates of the Average Treatment Effect (Odds) on the probability scale by crop type.

Term	Estimate	Std. Error	Z Value	Prob.	2.5%	97.5%
Maize	-0.161	0.0318	-5.05	<0.001	-0.223	-0.0985
Paddy	-0.150	0.0369	-4.08	<0.001	-0.223	-0.0781

4.6.3 Average Comparisons

Table 10 presents the predicted probabilities of crop loss for technology adopters and non-adopters. As depicted, the predicted probabilities of experiencing pre-harvest losses in maize are higher for non-adopters (90.1 percent) as compared to adopters (74.4 percent). Equally, from paddy farming households, adoptors had a 73.8 percent predicted probability of experiencing pre-harvest losses as opposed to the 88.8 percent of the non-adoptors.

Table 10: Estimates of the average predicted probability of pre-harvest loss by levels of technology adoption scale and crop type.

Tech. Adoption	Estimate	Std. Error	Z Value	Prob.	2.5%	97.5%
Maize						
Adopters	0.744	0.0111	66.8	<0.001	0.722	0.766
Non-adopters	0.905	0.0299	30.3	<0.001	0.846	0.964
Paddy						
Adopters	0.738	0.0150	49.3	<0.001	0.708	0.767
Non-adopters	0.888	0.0355	25.0	<0.001	0.818	0.958

4.7 Generalized Additive Model

4.7.1 Parametric regression output

The Generalized Additive Model (GAM) enabled analysis of the effect of individual technology adoption variables on pre-harvest loss. The results, based on odds ratios, indicate that farmers who intercrop maize with other food crops are 57 percent more likely to experience pre-harvest losses. In contrast, the use of organic and inorganic fertilizers reduces the probability of pre-harvest loss by 25 and 44 percentage points, respectively. The application of herbicides is associated with a 35 percent reduction in the likelihood of pre-harvest loss, while mechanization lowers the probability of loss by 28 percent. Similarly, the use of animal traction is linked to a 43 percentage point reduction in the probability of experiencing pre-harvest losses. Furthermore, the adoption of improved seeds reduces the likelihood of pre-harvest loss by 46 percent, meaning farmers who use improved seeds have a 0.46 lower probability of incurring losses.

In the case of paddy production, pre-harvest losses were significantly influenced by the use of organic fertilizers, animal traction, pesticides, and irrigation. The findings suggest that irrigation is associated with a 68 percent reduction in pre-harvest losses, while the use of pesticides and animal traction reduces the likelihood of loss by 48 percent, each. In contrast, the use of organic fertilizers increases the likelihood of pre-harvest loss, with farmers applying organic fertilizers being 2.17 times more likely to experience such losses compared to non-users.

Table 11: Parametric Regression outputs of the Generalized Additive Model

Descriptio	*Maize*			*Paddy*		
	Coeff.	*Std.Error*	*Pr(|z|)*	*Coeff.*	*Std.Error*	*Pr(|z|)*
(Intercept)	2.0141	0.2548	< 0.001	1.8662	0.2647	< 0.001
Household headship:Male	-0.2833 [0.75]	0.1245	0.0228	-0.1803 [0.84]	0.2365	0.4260
Herbicides:Yes	-0.4333 [0.65]	0.1942	0.0257	-0.1880 [0.83]	0.3015	0.5327
Pesticides:Yes	0.1262 [1.13]	0.1374	0.3584	-0.6565 [0.52]	0.3972	0.0984
Inorganic Fertilizer:Yes	-0.5751 [0.56]	0.1262	< 0.001	-0.3277 [0.73]	0.3277	0.3302
Organic Fertilizer: Yes	-0.2874 [0.75]	0.1257	0.0222	0.7737 [2.17]	0.4098	0.0590
Main seeds:Improved	-0.6236 [0.54]	0.1052	< 0.001	-0.1176 [0.89]	0.2704	0.6636
Mechanization:Yes	-0.4728 [0.62]	0.1668	0.0046	-0.4710 [0.62]	0.3198	0.1409
Animal traction:Yes	-0.5663 [0.57]	0.10731	< 0.001	0.6478 [0.52]	0.2142	0.0025
Soil & water control:Yes	-0.0250 [0.98]	0.1073	0.8938	0.0501 [1.05]	0.2915	0.8436
Intercropping:Yes	0.4480 [1.57]	0.1874	< 0.001	0.1134 [1.12]	0.3910	0.7717
Irrigation:Yes	0.5265 [1.69]	0.1032	0.3858	-1.1473 [0.32]	0.4841	0.0178

4.7.2 Smooth terms and tensor interaction effects

Considering interaction terms, the tensor products of farming experience and distance to home were significant (p-value = 0.0432) at five percent, similar to the interaction of Distance to home and distance to main road (p-value = 0.0292). These findings confirm that, the combined experience of farming experience and distance to home and that of Distance to home and distance to main road are important in determining preharvest losses.

Table 12: Approximate significance of smooth terms for Maize

Description	**edf**	**Ref.df**	**Chi.sq**	**Pr(> |z|)**
s(FarmingExp)	1.0002	1.000	4.120	0.0424
s(Distance to home)	2.7190	3.343	1.574	0.8354
te(Distance to main road)	1.0022	1.004	0.832	0.3642
te(Farming Experience ,Distance to home)	1.0014	1.003	4.070	0.0432
te(Farming Experience ,Distance to main road)	0.0004	20.00	0.000	0.6114
te(Distance to home ,Distance to main road)	9.8552	15.00	17.430	0.0292

For paddy, distance to home was the only univariate smooth term that had a significant influence (at the 10 percent level) on the outcome variable, while farming experience, proxied by age of the head of household and distance to main road, showed a non-significant effect at all conventional levels. For tensor interactions, the effect of farming experience and distance to home, as well as distance to home and distance to main road, was not significant. However, the study found the significant influence of the interaction effect of farming experience and distance to the main road on paddy pre-harvest losses.

Table 13: Approximate significance of smooth terms for Paddy

Description	edf	Ref.df	Chi.sq	Pr(> |z|)
s(FarmingExp)	1.0000	1.000	1.383	0.2397
s(Distance to home)	1.0001	1.000	2.807	0.0939
te(Distance to main road)	1.0000	1.000	0.020	0.8877
te(Farming Experience, Distance to home)	1.0000	1.000	1.310	0.2524
te(Farming Experience, Distance to main road)	0.7576	8.000	1.645	0.0940
te(Distance to home, Distance to main road)	2.0684	15.000	3.203	0.15714

5.0 Conclusions and Recommendations

Based on the survey findings, analysis from the PSM model confirms that the adoption and use of technologies are critical in reducing pre-harvest losses. The study, therefore, concludes that households that use modern agronomic practices or mechanization have a lower likelihood of experiencing such losses. Equally, based on the insights from the GAM, the study concludes that the impact of agricultural practices on pre-harvest losses is not uniform: it is subject to and responsive to crop type, as well as the nature of the technology applied.

Based on the findings, the study recommends promoting farming technologies such as herbicides, mechanization, improved seeds, and fertilizers, all of which significantly reduce pre-harvest losses when properly applied. The study emphasizes the importance of crop-specific interventions: for maize, the focus should be on herbicides, mechanization, and inorganic fertilizers, while for paddy, irrigation, animal traction, and effective pest control should be prioritized. Additionally, the use of organic fertilizers should be guided by crop-specific recommendations, as their benefits vary depending on soil and water conditions. Improved irrigation infrastructure and training on water-saving techniques are particularly crucial for paddy cultivation to address water management challenges. The study also calls for a re-evaluation of intercropping practices, as these may inadvertently increase losses in maize farming if not properly managed.

6.0 References

Abass, A. B., Awoyale, W., Alenkhe, B., Malu, N., Asiru, B. W., Manyong, V., & Sanginga, N. (2016). Can food technology innovation change the status of a food security crop? A review of cassava transformation into “bread” in Africa. *Food Reviews International*, *34*(1), 87–102.

Adediran, J., *et al*, (2005). Application of organic and inorganic fertilizer for sustainable maize and cowpea yields in Nigeria. *Journal of plant nutrition*, 27(7):1163–1181.

Alemayehu, M., Abera, M., & Bizuayehu, S. (2018). Determinants and extent of pre-and postharvest losses of fruits in Northwestern Ethiopia. *International Journal*, *5*(4), 68-75.

Bundi, A., Mburu, J., Mbogoh, S. G., & Ambuko, J. L. (2020). Factors influencing the adoption of pre-harvest practices among mango farmers in Embu and Machakos counties, Kenya. *International Journal of Postharvest Technology and Innovation*, 7(1), 56-72.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1):31–72.

Darfour, B. and Rosentrater, K. A. (2022). Pre-harvest and post-harvest farmer experiences and practices in five maize growing regions in Ghana. *Frontiers in Nutrition,* 9:725815.

Fahad, S., Nguyen-Thi-Lan, H., Nguyen-Manh, D., Tran-Duc, H., and To-The, N. (2023). Analyzing the status of multidimensional poverty of rural households by using sustainable livelihood framework: policy implications for economic growth. *Environmental Science and Pollution Research,* 30(6):16106–16119.

FAO (2017). *The future of food and agriculture: Trends and challenges*. Fao.

FAO (2018a). Guidelines on the measurement of harvest and post-harvest losses: Recommendations on the design of a harvest and post-harvest loss statistics system for food grains (cereals and pulses).

FAO (2018b). World food and agriculture—statistical pocketbook.

FAO (2019). *The state of food and agriculture 2019: Moving forward on food loss and waste reduction*. UN.

Fekadu, A. and Andarege, B. (2024). Analysis of the pre-harvest factors that influence the postharvest quality attributes of tomatoes (Lycopersicon esculentum mill.): A systematic review. *Scientia Horticulturae*, 337:113460.

Gertler, P., Martinez, S., Premand, P., Rawlings, L. B., and Vermeersch, C. M. (2010). Impact evaluation in practice: A new guide.

Harris, H. and Horst, S. J. (2016). A brief guide to decisions at each step of the propensity score matching process. *Practical Assessment, Research & Evaluation*, 21(4):n4.

Hastie, T. and Tibshirani, R. (1986). Generalized additive models. *Statistical science,* 1(3):297–310.

Kirigia, D., Kasili, R., & Mibus, H. (2017). African leafy vegetables pre-harvest and post-harvest constrains and technologies for losses reduction along the field to consumer chain. *African Journal of Horticultural Science*, *12*, 51-60.

Kumari, A., Singh, S., VP, A., Joshi, P., Chauhan, A. K., Singh, M., & Hemalatha, S. (2023). Mechanization in pre-harvest technology to improve quality and safety. In *Engineering*

Aspects of Food Quality and Safety (pp. 93-114). Cham: Springer International Publishing.

Kumar, D. and Kalita, P. (2017). Reducing postharvest losses during storage of grain crops to strengthen food security in developing countries. *Foods*, 6(1):8.

Lai, H.-J. (2020). Investigating older adults' decisions to use mobile devices for learning, based on the unified theory of acceptance and use of technology. *Interactive Learning Environments*, 28(7):890–901.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, 14(1):21–38.

Lüdecke, D. (2018). ggeffects: Tidy data frames of marginal effects from regression models. *Journal of open source software*, 3(26):772.

Mdoda, L., Mdletshe, S., Dyiki, M., and Gidi, L. (2022). The impact of agricultural mechanization on smallholder agricultural productivity: Evidence from Mnquma Local Municipality in the Eastern Cape Province. *South African Journal of Agricultural Extension*, 50(1):76–101.

Mlyashimbi, E. C., Kimaro, D. N., Tarimo, A. J., Machang'u, R. S., Isabirye, M., and Makundi, R. H. (2022). Pre-harvest loss assessment of maize crop in semi-arid areas in Tanzania due to rodent pests. *African Journal of Agricultural Research*, 18(6):414–420.

Mumah, E., Chen, Y., Hong, Y., and Okello, D. (2024). Machinery adoption and its effect on maize productivity among smallholder farmers in western Kenya: Evidence from the chisel harrow tillage practice. *Research on World Agricultural Economy*, 5(1):1–18.

NBS (2023). Annual agriculture sample survey. Technical report, National Bureau of Statistics.

Nkwain, K., Odiaka, E., Ikwuba, A., Fatty, L., and Gam, A. (2022). Pre-harvest losses of Musa spp. and food security situation of households in sub-Saharan Africa. *Asian J. Adv. Res. Rep*, 16:28–40.

Norton, E. C., Dowd, B. E., and Maciejewski, M. L. (2019). Marginal effects—quantifying the effect of changes in risk factors in logistic regression models. *Jama*, 321(13):1304– 1305.

Rockefeller, F (2015). Perspectives on Reducing Post-harvest Losses of Agricultural Products in Africa. Technical report, United Nations Economic Commission for Africa, Ethiopia.

Rogers, E. M. (1995). Diffusion of innovations: modifications of a model for telecommunication. *Die diffusion von innovationen in der telekommunikation*, pages 25–38.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Sahin, I. (2006). Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory. *Turkish Online Journal of Educational Technology-TOJET*, 5(2):14–23.

Searchinger, T., Waite, R., Hanson, C., Ranganathan, J., Dumas, P., and Matthews, E. (2018). Creating a sustainable food future.

Senkoro, C. J., Tetteh, F. M., Kibunja, C. N., Ndungu-Magiroi, K. W., Quansah, G. W., Marandu, A. E., Ley, G. J., Mwangi, T. J., and Wortmann, C. S. (2018). Cassava yield and economic response to fertilizer in Tanzania, Kenya and Ghana. *Agronomy Journal*, 110(4):1600–1606.

Sethi, G., Bedregal, L., Cassou, E., Constantino, L., Hou, X., Jain, S., Messent, F., Morales, X., Mostafa, I., Pascual, J., et al. (2020). Addressing food loss and waste: A global problem with local solutions.

Shah, D. (2014). Empirical assessment of pre- and post-harvest losses of soybean crop in Maharashtra. *Artha Vijnana*, 56(3):307–317.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia manufacturing*, 22:960–967.

United Nations (2019a). *World Food and Agriculture - Statistical Pocketbook 2018*. United Nations (2019b). *World population prospects 2019*. Number 141. New York.

URT (2019a). National postharvest management strategy (2019-2029). Technical report, Ministry of Agriculture, Dodoma - Tanzania.

URT (2019b). Postharvest management strategy implementation plan (2019-2024). Technical report, Ministry of Agriculture, Dodoma - Tanzania.

Wooldridge, J. M. (2002). Introductory econometrics: A modern approach (south. Wooldridge, J. M. (2013). *Introductory Econometrics* 5th ed.

Yamada, W., Francis, J., Jewison, J., Runge, T., & Digman, M. (2025). Pre-harvest loss quantification in grain crops. *Computers and Electronics in Agriculture*, *236*, 110405.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Cengage learning.

Zhao, Q.-Y., Luo, J.-C., Su, Y., Zhang, Y.-J., Tu, G.-W., and Luo, Z. (2021). Propensity score matching with r: conventional methods and new features. *Annals of translational medicine*, 9(9):812.