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# Impact of Northern Tanzania Potato System Improvement Project on Income and Food Security of Smallholder Farmers in Arusha District, Tanzania

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**Abstract:** *Potatoes are a staple crop with substantial potential to enhance the income and food security of smallholder farmers in Tanzania. This study assesses the impact of the Northern Tanzania Potato System Improvement (NTPSI) project on smallholder farmers in Arusha District, focusing on both economic and food security outcomes. Using a cross-sectional survey of 192 farmers, comprising both participants and non-participants of the NTPSI project, the study applied Propensity Score Matching (PSM) to address selection bias and ensure robust comparison. Key outcome indicators included Gross Margin (GM) for income, Household Dietary Diversity Score (HDDS), and Household Food Insecurity Access Scale (HFIAS) for food security. The results reveal that participation in NTPSI significantly improved economic returns and food security. Specifically, the Average Treatment Effect on the Treated (ATT) showed that participants had a mean gross margin increase of TZS 512,000 per acre compared to non-participants ($p < 0.01$). Moreover, the HDDS score increased by an average of 2.4 points ($p < 0.01$), indicating better household dietary diversity, while the HFIAS score decreased by 3.7 points ($p < 0.05$), suggesting reduced food insecurity. These statistically significant findings confirm the effectiveness of the NTPSI project in enhancing smallholder livelihoods. The study underscores the transformative potential of integrated agricultural interventions, such as improved seed distribution, farmer training, and access to extension services, on rural incomes and nutrition. The evidence supports scaling similar programs across potato-producing regions in Tanzania to contribute to achieving SDGs 1 (No Poverty) and 2 (Zero Hunger).*

**Keywords:** *Smallholder Farmers, Food Security, Propensity Score Matching, Gross Margin, Potato System Improvement*

## 1. Background Information

Potato production has emerged as a high-potential agricultural enterprise for smallholder farmers in Tanzania, particularly in the Northern Highlands. As a staple and income-generating crop, potatoes offer substantial nutritional and economic benefits, making them a strategic commodity for enhancing food security and household welfare. Agriculture remains the backbone of Tanzania's economy, employing approximately 65.5% of the population, mostly smallholder farmers (FAO, 2023). Despite this critical role, the sector faces persistent structural and operational challenges, including low productivity, limited access to quality inputs, and poor market infrastructure (Bjornlund *et al.*, 2020). These bottlenecks continue to trap smallholders in cycles of poverty and food insecurity, with over 14 million people experiencing food shortages annually (Integrated Food Security Phase Classification, 2023; Anker Research Network, 2020).

The potato subsector in Northern Tanzania, particularly in Arusha District, has considerable potential but remains underutilized due to traditional farming methods, low input use, and a lack of institutional support. The introduction of the Northern Tanzania Potato System Improvement (NTPSI) project sought to address these barriers by enhancing farmer access to high-quality seed, promoting good agronomic practices, and strengthening extension support systems (RECODA, 2019). While previous interventions have mainly concentrated on the Southern Highlands, where most research has been conducted, there remains a critical empirical and knowledge gap in evaluating the effects of similar interventions in the Northern Highlands, which contribute about 30% of national potato output (Groot *et al.*, 2020).

Across East Africa, the potato sector has attracted various donor-funded initiatives that target different nodes of the value chain. For example, projects like the EAC-GIZ Seed Potato Project have worked to enhance regional seed potato trade through capacity building and implementation of sanitary and phytosanitary (SPS) measures, equipping National Plant Protection Organisations (NPPOs) with technical resources (EAC, 2022). In Uganda, Turyasingura *et al.* (2022) examined sustainability constraints in potato value chain projects, emphasising the need for local ownership, post-project support, and stakeholder engagement. Similarly, Jan *et al.* (2022) highlighted the critical shortage of certified seed potatoes, less than 1% of demand is met through formal systems, proposing farmer-based innovations like Seed Plot Technology (SPT) and Positive Selection Techniques (PST) to overcome this supply bottleneck.

The NTPSI project is distinctive in its integrative approach, combining lessons from regional interventions with tailored strategies that respond to the socio-economic and agro-ecological realities of Northern Tanzania. By equipping farmers with productive inputs and practical knowledge through RIPAT (Rural Initiatives for Participatory Agricultural Transformation) groups, NTPSI empowers local stakeholders to take ownership of production systems. This contrasts with externally driven interventions that often face sustainability issues once project funding ceases. The project's design aligns with principles from the High Payoff Input Model, which theorises that strategic investments in productivity-enhancing inputs, like improved seed, technical training, and information, can transform subsistence agriculture into a commercially viable sector (Ruttan, 1977).

The High Payoff Input Model also underscores the importance of research institutions and technological development in driving yield improvements. However, the High Payoff Input Model overlooks the constraints faced by smallholders, including limited access to inputs, dependency on external resources, and environmental degradation linked to synthetic inputs (Udemezue & Osegbue, 2018). These limitations are especially pertinent in regions like Arusha, where infrastructural deficits and climate vulnerability shape farmer decision-making. The study underlying this research therefore adopts the High Payoff Input Model to evaluate the impact of NTPSI participation on farmer income, measured by Gross Margin (GM), and household food security, assessed via the Household Dietary Diversity Score (HDDS) and the Household Food Insecurity Access Scale (HFIAS).

This study thus seeks to fill a crucial empirical gap by assessing the outcomes of NTPSI in Northern Tanzania, answering the core research question: *What is the impact of the Northern Tanzania Potato System Improvement project on the income and food security of smallholder farmers in Arusha District?* Therefore, by comparing participants and non-participants, the study isolates the effect of the intervention while controlling for selection bias. In doing so, it provides actionable insights for policymakers and development practitioners on how targeted agricultural interventions can drive rural transformation. The findings help shape future programs aimed at enhancing agricultural productivity, boosting rural incomes, and addressing persistent food insecurity challenges in Tanzania and beyond.

## 2.0 Theoretical Framework

The High Payoff Input Model (Ruttan, 1977) provides a foundational theoretical lens for understanding the transformation of subsistence farming systems into productive, market-oriented enterprises through the application of high-yield technologies. Central to the model is the assumption that the adoption of high payoff inputs, such as improved seed varieties, fertilisers, pesticides, irrigation, and mechanisation, substantially increases agricultural productivity, income, and ultimately, food security. The model also assumes that three pillars must align for this transformation to succeed: (i) research institutions that generate relevant agricultural innovations, (ii) effective delivery systems that disseminate these technologies, and (iii) capable farmers willing and able to adopt the innovations. The success of the model has been historically demonstrated through the Green Revolution, where significant public investment in research and technology diffusion resulted in remarkable yield increases in countries such as Mexico (wheat) and the Philippines (rice), validating the model's assumptions (Ruttan, 1988).

Despite its strengths, the High Payoff Input Model has faced substantial criticism for its limitations, especially in the context of smallholder agriculture in developing countries. Critics argue that the model is input-intensive and capital-dependent, creating a barrier for resource-constrained smallholder farmers who may not afford continuous input use (Udemezue & Osegbue, 2018). This often leads to unequal benefit distribution, with wealthier or larger-scale farmers gaining more from the technologies than their poorer counterparts. Furthermore, the model is criticised for promoting chemical-dependent agriculture, which can result in negative environmental impacts such as soil degradation, reduced biodiversity, and water pollution. Another major concern is its limited integration of indigenous knowledge systems and traditional ecological practices. The model tends to favour uniform technology packages, making farming systems vulnerable to climate variability, market shocks, and policy changes. Additionally, inadequate training, weak extension services, and poor rural infrastructure in many developing countries hinder the practical implementation and sustainability of the model's assumptions.

In the context of this study, the High Payoff Input Model is highly relevant for assessing the impact of the Northern Tanzania Potato System Improvement (NTPSI) project on smallholder farmers' income and food security in Arusha District. The NTPSI project aligns closely with the model by providing high-yield seed varieties, training, and extension services, core high-payoff inputs, to participating farmers. The study hypothesises that farmers who access these inputs through NTPSI are better positioned to increase productivity and income, thereby enhancing household food security. The model also helps in identifying the enabling factors that influence input effectiveness, such as access to markets, credit, and agro-climatic suitability (e.g., Arusha's moderate temperature and rainfall). As such, by integrating socio-economic variables like education, household size, and farming experience into the Propensity Score Matching framework, the study evaluates the theory's applicability in real-world smallholder contexts. Ultimately, the model provides a structured theoretical foundation to explain the mechanisms through which input-based interventions like NTPSI can lead to transformative outcomes in rural livelihoods.

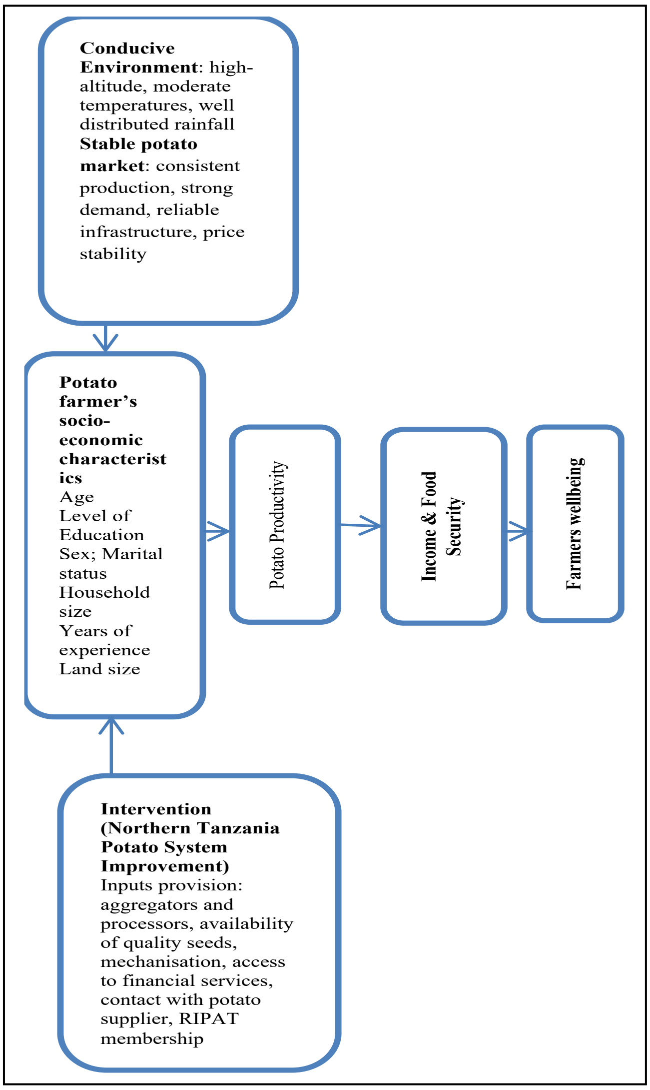


**Figure 1: High payoff Input model (Adapted from Ruttan, 1977).**

## 3.0 Methodology

### 3.1 Description of the study area

The study was conducted in the Arusha district of Northern Tanzania. The district is located between latitudes 2°14' to 5°2' south and longitudes 35°12' to 36°0' east. The district borders Kenya to the north (Peligal, 1999). Arusha district has over 449,518 people (Government of Tanzania, 2022). Arusha's high-altitude climate is ideal for potato farming, with cool temperatures, sufficient rainfall, and fertile volcanic soils (Olarinoye *et al.*, 2023). The district comprises the Northern highlands, which produce 30% of the total Tanzania potato output, making it a strategic location to leverage existing farming practices and improve yields through innovative systems. Also, RECODA aimed to evaluate the impact of the Northern Tanzania Potato System Improvement Project within the Arusha District, focusing on its outcomes and contributions to smallholder farmers' wellbeing (RECODA, 2019).

### 3.2 Research design and data collection

The study employed a cross-sectional design for data collection and analysis. The design was selected because it provided a practical and cost-effective approach to assess the project's outcomes at a specific time. Given the time, resources and lack of baseline data constraints, this design allowed for collecting data from a diverse group of smallholder farmers (Booth *et al.*, 2021; Hunziker & Blankenagel, 2024). However, to address the design limitation in determining causal effect, the study employed PSM to create a statistically comparable control group, thereby improving the robustness of impact attribution. Moreover, the study integrated qualitative data to provide deeper insights into the factors behind the changes. Primary data was collected using a semi-structured questionnaire applied to 192 potato producers, household heads and an observation guide.

### 3.3 Sample and Sampling Procedures

The study employed the multi-stage sampling technique, and Arusha district was purposely chosen as it served as the primary implementation site of the Northern Tanzania Potato System Improvement Project (RECODA, 2019). The study included Engutoto, Imbibia, and Engalaoni as treated villages and Olkokola, Sambasha, Bangata, Shiboro, and Uldonyosambu as control villages. Thereafter, purposive sampling was used to select the potato farmers. The treatment group comprised project participants actively involved in the NTPSI (Rahman *et al*, 2022). The control group was selected using stratified random sampling to identify farmers with similar characteristics to those in the treatment group. Key factors considered included socio-economic status, farming experience, geographic location, and agricultural practices. The approach ensured that the control group mirrored the treatment group in relevant baseline conditions, enabling a meaningful comparison of outcomes between the two groups. This method also mitigates the lack of baseline data that directly restricts the ability to measure pre-intervention conditions. The sample size was determined using the Krejcie & Morgan (1970) formula, resulting in 96 respondents for the control group and 96 for the treatment group, providing a statistically representative sample for the analysis. The study used gross margin indicators to measure potato farming operations' profitability. To obtain the income results from the difference between the total revenue from selling potatoes and the operational costs of producing them (Mbaga *et al.*, 2024). The food security was measured using the HDDS and HFIAS. HDDS assess the variety of foods consumed by a household over a reference period. It serves as a proxy indicator for a household's nutritional quality and food access (Chegere & Kauky, 2022). HFIAS measures the access dimension of household food insecurity, whether a household had enough food and could obtain it over a specific reference period, usually the past 30 days (Nicholson *et al.*, 2021; Safari& Mandara, 2022).

### 3.4 Data Analysis

Data analysis was conducted using STATA (version 17), whereby descriptive (i.e., means, standard errors, and frequencies) and inferential statistics were determined. An LSD test was done to compare the means between treatment and control groups (Mehmetoglu & Jakobsen, 2022). The study utilised the Propensity Score Matching (PSM) to account for potential selection bias and compared household income proportion from potato sales between participants and non-participant groups using the gross margin for income and HDDS and FIAS for food security (Kane et al., 2020). The PSM approach involved matching participants and non-participants based on covariates like access to credit, extension services, and market access to estimate the treatment effect more accurately by using the difference in expectation of Average Treatment Effects on the Treated (ATT) between the participants and non-participants presented as ATT as well as other measures including ATU and ATE. To estimate the propensity score, the binary logistic regression analysis was conducted as shown in the equation (Leuven & Sianesi, 2018):

$$logit\left[\frac{p(Y=1)}{P(Y=0)}\right] = \beta0+\beta1(\text{Sex}) + \beta2(\text{farming experience})+\beta3(\text{Household Size})+\beta4(\text{Education level}) +\beta5(\text{Access to market information}) + \beta6(\text{Number of Season growing}) + \beta7(\text{Distance from the market}) +\beta8(\text{age})+ \beta8(\text{Access to extension service})+ \beta9(\text{Access to credit}) \ldots\ldots\ldots\ldots\ldots \text{ eqn (i)}$$

Whereby $logit\left[\frac{p(Y=1)}{P(Y=0)}\right]$, represents the likelihood of someone to participate in the project.

Further, the ATT was calculated using the difference expected in the Gross Margin, HDDS and HFIAS scores between the participants and non-participant groups, expressed in equations ii, iii, and iv, respectively.

$$ATT_{GM} = E(GM_1) - E(GM_0) \ldots\ldots \text{eqn (ii)}$$

Whereby: $ATT_{GM}$ is the Average Treatment Effect on the Treated for the outcome variable Gross Margin; E ($GM_1$) is the expected mean of GM for the participant; E ($GM_0$) is the expected mean of GM for the non-participant group.

$$ATT_{HDDS} = E(HDDS_1) - E(HDDS_0) \ldots\ldots \text{eqn (iii)}$$

Whereby: $ATT_{HDDS}$ is the Average Treatment Effect on the Treated for the Household Dietary Diversity Score (HDDS); E ($HDDS_1$) is the expected mean of HDDS for the participant group; and E ($HDDS_0$) is the expected mean of HDDS for the non-participant group

$$ATT_{HFIAS} = E(HFIAS_1) - E(HFIAS_0) \ldots\ldots \text{eqn(vi)}$$

Whereby: $ATT_{HFIAS}$ is the Average Treatment Effect on the Treated for the HFIAS (Household Food Insecurity Access Scale); E ($HFIAS_1$) is the expected mean of HFIAS for the participant group, and E ($HFIAS_0$) is the expected mean of HFIAS for the non-participant group.

### 3.6 Ethical Considerations

Prior to data collection, informed consent was obtained from all participants. The study maintained strict confidentiality and anonymity, and participation was voluntary. Ethical clearance was granted by the appropriate institutional review board at Sokoine University of Agriculture (SUA) and President's Office - Regional Administration and Local Government in Tanzania (TAMISEMI).

## 4.0 RESULTS AND DISCUSSION

### 4.1 Socio-economic characteristics of respondents

Study findings (Table 1) highlight a slight female majority among the sample, with 53.1% and 55.2% of non-participants. The finding contradicts the results by Leavens *et al.* (2019), who reported that women are less likely to lead agricultural activities. Age-wise, a larger proportion (76%) of non-adopters fall within the 36-65 age range compared to adopters (63.5%), indicating that non-adopters might be slightly older on average, aligning with the results by Namwata *et al.* (2010) who observed that older farmers may rely more on traditional practices and be more resistant to change, leading to lower adoption rates. This suggests that older individuals are more conservative and less likely to adopt new agricultural practices, thus affecting their incomes. In terms of education, a higher percentage of non-participants have primary education (59.4%) compared to participants (46.9%), while participants have a higher percentage with no formal education (35.4% vs. 24.0%). The study results contradict the results of Kinuthia and Mabaya (2017), who suggest that Farmers with higher levels of education are more likely to adopt new technologies because they have a better understanding of the benefits and application processes. This might suggest that those with lower educational attainment may be more inclined to adopt certain practices, possibly due to external influences such as community leaders or incentives rather than educational background.

The household size is similarly distributed across both groups, with the majority having between 3 and 10 members, though participants have a slightly higher representation in the 5-10 member category (47.9%). The research results align with the findings of Manda et al. (2024) and Mutungi et al. (2023), who agree that larger household sizes often mean greater availability of labour, which can facilitate the adoption of labour-intensive technologies and more family members also make it easier to experiment with new practices without significantly disrupting regular activities. This could indicate a potential association between household size and adoption, where larger households might have more labour resources to engage in farming activities. Additionally, participants tend to have more farming experience (21.9% with over 10 years) compared to non-participants (11.5%), aligning with the results by Lasway *et al.* (2021). The result suggests that experience might play a role in adopting new practices, possibly due to greater familiarity with agricultural trends. Farm size distributions show that non-participants are likelier to have larger farms (32.3% with below 1 hectare), contradicting the results by Mugula *et al.* (2023) that suggest larger farm sizes were positively associated with higher adoption intensity. This might influence their decisions regarding adoption, as smaller-scale farmers might be more adaptable to changes or innovations in farming practices.

**Table 1: Respondents' socio-economic characteristics (n=192)**

| Variables | Category | Participants | | Non-participants | | Total | |
|---|---|---|---|---|---|---|---|
| | | Freq | Per (%) | Freq | Per (%) | Freq | Per (%) |
| *Sex of respondent* | Female | 51 | 53.1 | 53 | 55.2 | 104 | 54.2 |
| | Male | 45 | 46.9 | 43 | 44.8 | 88 | 45.8 |
| *Age category* | 18 – 35 | 26 | 27.1 | 19 | 19.8 | 45 | 23.4 |
| | 36 -65 | 61 | 63.5 | 73 | 76.0 | 134 | 69.8 |
| | Above 65 | 9 | 9.4 | 4 | 4.2 | 13 | 6.8 |
| *Marital Status* | Single | 86 | 89.6 | 82 | 85.4 | 168 | 87.5 |
| | Married | 1 | 1.0 | 4 | 4.2 | 5 | 2.6 |
| | Widow/Widower | 9 | 9.4 | 10 | 10.4 | 19 | 9.9 |
| *Education level* | No formal education | 34 | 35.4 | 23 | 24.0 | 57 | 29.7 |
| | Primary education | 45 | 46.9 | 57 | 59.4 | 102 | 53.1 |
| | Secondary education | 15 | 15.6 | 13 | 13.5 | 28 | 14.6 |
| | Tertiary education | 2 | 2.1 | 3 | 3.1 | 5 | 2.6 |
| *Household size category* | Below 3 | 4 | 4.2 | 3 | 3.1 | 7 | 3.6 |
| | 3 – 5 | 42 | 43.8 | 48 | 50.0 | 90 | 46.9 |
| | 5 – 10 | 46 | 47.9 | 45 | 46.9 | 91 | 47.4 |
| | Above 10 | 4 | 4.2 | 0 | 0.0 | 4 | 2.1 |
| *Farming experience* | Below 3 | 11 | 11.5 | 8 | 8.3 | 19 | 9.9 |
| | 3 – 5 | 31 | 32.3 | 37 | 38.5 | 68 | 35.4 |
| | 5 – 10 | 33 | 34.4 | 40 | 41.7 | 73 | 38.0 |
| | Above 10 | 21 | 21.9 | 11 | 11.5 | 32 | 16.7 |
| *Farm size category* | Below 1 | 26 | 27.1 | 31 | 32.3 | 57 | 29.7 |
| | 1 – 3 | 46 | 47.9 | 55 | 57.3 | 101 | 52.6 |
| | 3 – 5 | 15 | 15.6 | 9 | 9.4 | 24 | 12.5 |
| | Above 5 | 9 | 9.4 | 1 | 1.0 | 10 | 5.2 |

## 4.2 Production of Potatoes, cost and gross margins across treatment categories

Study findings (Table 2) show the significant differences in potato production, costs, and gross margins between participants and non-participants. Participants achieve a substantially higher mean total harvest (24.36 tons/acre) compared to non-participants (15.87 tons/acre), thus aligning with the results by Amin *et al.* (2022) that concluded that the adoption of agricultural technologies has a positive impact on farm profitability. Generally, farmers who adopt modern technologies, such as improved seeds, fertilisers, and mechanisation tools, experience higher yields, which leads to increased farm income and profitability.

**Table 2: Production of Potatoes, cost and gross margins across treatment category (n=192)**

| Variable | Participation status | Mean ± SE | Minimum | Maximum |
|---|---|---|---|---|
| *Total harvest (kg/acre)* | Participant | 24.36 ± 6.22a | 0 | 550 |
| | Non-participant | 15.87 ± 1.39b | 0 | 65 |
| *Total Cost (TZS)* | Participant | 62,946.81 ± 1,683.72b | 0 | 100,000 |
| | Non-participant | 103,750.18 ± 19,269.6a | 0 | 1,600,000 |
| *Total Revenue (TZS)* | participant | 686,536.54 ± 139,981.23a | 0 | 10,930,000 |
| | Non-participant | 333,152.48 ± 24,584.55b | 0 | 1,347,000 |
| *Gross margin (TZS)* | participant | 632,388.38 ± 142,498.31a | 10,000 | 10,845,000 |
| | Non-participant | 229,402.3 ± 28,758.75b | 1,000,000 | 1,247,000 |

Interestingly, despite having lower total costs on average (TZS 62,946.81 for participants against TZS 103,750.18 for non-participants), participants generate significantly higher total revenue (TZS 686,536.54) than non-participants (TZS 333,152.48). This difference is reflected in the gross margins, where participants enjoy a much larger average margin (TZS 632,388.38) than non-participants (TZS 229,402.30). The GM difference can be attributable to the use of multi-season potato production reported by the project participants during the observation guide. The study findings conform to the results of the study by Arslan *et al.* (2022), which suggest that adopting improved technologies enhances productivity and improves profitability and economic benefits.

## 4.3 Factors influencing behaviour across potato farmers

The binary logistic regression results presented in Table 3 offer insights into the factors influencing the likelihood of adopting practices that could impact the household income from potato sales (Harrell & Harrell, 2015). Among the variables tested, education level, farming experience, and household size category are statistically significant predictors of adoption, as indicated by their p-values ($p<0.05$). Specifically, the positive coefficient for education level (0.062) suggests that a higher education level increases the likelihood of adopting relevant agricultural practices. This implies that better-educated farmers may be more open to adopting new practices due to their greater access to information or ability to understand and implement innovations. Similarly, the positive coefficient for farming experience (0.135) indicates that more experienced farmers are more likely to adopt, potentially due to their familiarity with agricultural challenges and confidence in trying new methods. Household size also positively influences adoption, with a coefficient of 0.715, suggesting that larger households may have more labour resources, making them more capable of adopting labour-intensive practices.

**Table 3: The binary logistic regression results for predicting pscore for impact assessment (n=192)**

| Variable | Coef. | St. Err. | t-value | p-value | 95% Conf | Interval |
|---|---|---|---|---|---|---|
| *Sex of respondent* | 0.058 | 0.307 | 0.190 | 0.849 | -0.543 | 0.659 |
| *Age category* | 0.391 | 0.347 | 1.130 | 0.260 | -0.289 | 1.072 |
| *Marital Status* | -0.168 | 0.282 | -0.600 | 0.551 | -0.721 | 0.385 |
| *Education level* | 0.062 | 0.030 | 2.090 | 0.037* | 0.004 | 0.120 |
| *Farm size category* | -0.003 | 0.122 | -0.020 | 0.980 | -0.242 | 0.236 |
| *Farming experience* | 0.135 | 0.042 | 3.220 | 0.001* | -0.217 | -0.053 |
| *Household size category* | 0.715 | 0.341 | 2.100 | 0.036* | -1.383 | -0.047 |
| *_cons* | 0.476 | 1.067 | 0.450 | 0.655 | -1.614 | 2.567 |
| *Mean dependent var* | | 0.339 | **SD dependent var** | | | 0.021 |
| *Pseudo r-squared* | | 0.045 | **Number of obs** | | | 192 |
| *Chi-square* | | 22.32 | **Prob > chi2** | | | 0.0022 |

** Indicate that the coefficient is significant at the 0.05 level of significance (p<0.05)*

Despite these significant predictors, other variables like the respondent's sex, age category, marital status, and farm size category do not significantly influence the likelihood of adoption, as their p-values are above the 0.05 threshold. The Pseudo-R-squared value of 0.045 suggests that while the model does provide some predictive power, it explains only a tiny portion of the variability in adoption behaviour. The Chi-square value (22.32, p = 0.0022) indicates that the model is statistically significant, meaning that the included variables collectively contribute to predicting adoption.

## 4.4 Estimating propensity score and balancing check of smallholder farmers

The provided descriptive statistics for the pscore were calculated for the 192 observations in the study. The mean pscore is 0.3385, with a standard deviation of 0.1553, indicating that, on average, the probability of adopting the practices under investigation is about 33.85%, with some variability across the sample. The minimum pscore is 0.0189, and the maximum is 0.6824, showing a wide range of adoption probabilities among the respondents. This range suggests that while some individuals are doubtful about adopting the practices (with scores close to 0), others have a relatively high probability of adoption (with scores nearing 0.7).

Table 4 presents the results of the balance check for hypothesis testing between treatment categories, comparing unmatched and matched samples. The balance check assesses whether the propensity score matching (PSM) process effectively equated the participant and treatment groups across various socio-economic variables (Benedetto *et al.,* 2018). In the unmatched samples, there are noticeable biases in several variables, particularly education level, household size, and farming experience, which show biases of -17.9%, 19.8%, and 24.1%, respectively.

**Table 4: Balance check for the hypothesis testing treatment categories (n=192)**

| Variable | Unmatched / Matched | Mean: Participant | Mean: Non-participant | Bias: % | Bias: %reduction | T-test: t-value | T-test: P-value | V(P)/V(N-P) |
|---|---|---|---|---|---|---|---|---|
| **Sex** | U | 1.457 | 1.448 | 1.9 | | 0.130 | 0.896 | 1.00 |
| | M | 1.462 | 1.387 | 15 | -689.8 | -1.760 | 0.081 | 1.02 |
| **Age category** | U | 1.819 | 1.844 | -4.6 | | -0.320 | 0.749 | 1.58* |
| | M | 1.817 | 1.731 | 16.2 | -249.7 | 0.530 | 0.596 | 1.31 |
| **Marital status** | U | 1.202 | 1.250 | -7.8 | | -0.540 | 0.592 | 0.89 |
| | M | 1.183 | 1.430 | -40.2 | -416.6 | -0.820 | 0.413 | 0.85 |
| **Education level** | U | 1.830 | 1.958 | -17.9 | | -1.230 | 0.219 | 1.05 |
| | M | 1.828 | 2.032 | -28.4 | -58.9 | 0.210 | 0.830 | 1.35 |
| **Household size** | U | 1.702 | 1.563 | 19.8 | | 1.370 | 0.174 | 1.27 |
| | M | 1.710 | 1.430 | 39.7 | -100.2 | 1.810 | 0.072 | 1.46 |
| **Farm size** | U | 2.149 | 2.083 | 4.9 | | 0.340 | 0.734 | 0.87 |
| | M | 2.129 | 1.957 | 13 | -162.2 | 2.280 | 0.024 | 1.10 |
| **Farming experience** | U | 8.266 | 6.927 | 24.1 | | 1.670 | 0.097 | 1.92* |
| | M | 8.032 | 6.989 | 18.8 | 22.1 | -0.810 | 0.418 | 1.04 |

** If variance ratio outside [0.66; 1.51] for U and [0.66; 1.51] for M*

## 4. 5 Common support

The results for the common support test in Table 5 show the distribution of treated and untreated observations that fall within the region of common support, which is crucial for ensuring a valid comparison between the two groups in the propensity score matching analysis (Caliendo & Kopeinig, 2008). Out of 192 total observations, 190 (98.96%) are on support, meaning their propensity scores fall within a range that allows for a meaningful comparison between participants and non-participant groups. Specifically, 94 non-participants and 96 participants are within this common support region, ensuring that most samples can be effectively matched and compared.

**Table 5: Results for common support of test for treatment categories (n=192)**

| Treatment | Support | | Total |
|---|---|---|---|
| | Off support | On support | |
| Non-participants | 2 | 94 | 96 |
| Participants | 0 | 96 | 96 |
| Total | 2 | 190 | 192 |

Only two non-participant observations are off-support, indicating that their propensity scores are outside the treatment group's range, making them unsuitable for comparison.

The high level of common support suggests that the PSM has successfully identified comparable groups, thereby enhancing the reliability and validity of the subsequent impact analysis.

## 4.6 Treatment effect assessment across treatment categories

Table 6 provides the results for the Average Treatment effect on the Treated (ATT) and Average Treatment effect on the Untreated (ATU) regarding the gross margin from potato sales. For the unmatched sample, the gross margin for treated farmers is significantly higher (TZS 632,388.38) compared to controls (TZS 229,402.30), with a substantial difference of TZS 402,986.08 and a t-statistic of 2.80, indicating a significant effect before matching. After matching, the ATT shows that participants' farmers have a gross margin of TZS 635,338.79, while non-participants have TZS 275,162.84, with a reduced but still significant difference of TZS 360,175.96 and a t-statistic of 2.37. The research result endorses the findings of Chami (2020), who noted that smallholder farmers who adopt improved seeds, fertilisers, and modern farming techniques are more likely to achieve higher yields and better profit margins.

Conversely, the ATU reveals that non-participant farmers have a higher gross margin (TZS 498,669.44) than participant farmers, with a difference of TZS 269,267.14. However, this result is not directly quantified with a t-statistic. The Average Treatment Effect (ATE) of TZS 298,523.09 summarises the overall impact of participation gross margins, reflecting a positive treatment effect across the sample. Table 3.7 presents the results for the Average Treatment Effect (ATE) and Average Treatment Effect on the Treated (ATET) concerning gross margins from potato sales, comparing participants and non-participants. The ATE of TZS 298,523.1, with a standard error of TZS 128,236.9 and a z-value of 2.33, is statistically significant (p=0.020), indicating that, on average, the adoption of practices leads to a substantial increase in gross margins compared to non-adoption. The 95% confidence interval ranges from TZS 47,183.34 to TZS 549,862.8, reflecting a robust positive impact with some variability. The ATET is slightly higher at TZS 328,401.5, with a standard error of TZS 141,854.6 and a similar z-value of 2.32, also statistically significant (p=0.021). This suggests that the impact on gross margins is even more pronounced among those who participated in the project, with the confidence interval spanning from TZS 50,371.52 to TZS 606,431.5. Both measures confirm that participation in the NTPSI project significantly improves gross margins, with the ATET highlighting a more substantial effect for participants compared to the general average treatment effect, as shown in Figure 2.

**Table 6: Results for ATE and ATET on Gross margin result on income from potato farmers (n=192)**

| Variable | Sample | Treated | Controls | Difference | S.E. | T-stat |
|---|---|---|---|---|---|---|
| Gross margin | Unmatched | 632388.38 | 229402.30 | 402986.08 | 1439 62.6 | 2.80 |
| | ATT | 635338.79 | 275162.84 | 360175.96 | 151897.4 | 2.37 |
| | ATU | 229402.30 | 498669.44 | 269267.14 | | |
| | ATE | | | 298523.09 | | |

## 4.7 Prevalence of food security based on indicators by treatments.

Table 7 compares food security status between participants and non-participants in the Northern Tanzania Potatoes System Improvement project based on the Household Dietary Diversity Score (HDDS) and Household Food Insecurity Access Scale (HFIAS). The findings indicate significant differences in food security outcomes between the two groups, as evidenced by the highly significant Chi-square tests ($p < 0.05$). Among the participants, a majority (59.4%) exhibited high dietary diversity, reflecting a more varied and nutritionally adequate diet than non-participants, where only 21.9% fell into this category. Conversely, a substantial proportion of non-participants (46.9%) reported the lowest dietary diversity, suggesting limited access to various foods, a key indicator of poor nutritional outcomes. The data strongly imply that participation in the NTPSI project is associated with improved dietary diversity and food security.

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**Table 7: Chi-Square Results of Farming Households Food Security Based on HDDS and HFIAS Indicators (n=192)**

| Food security indicators | Classification criterion | Non-participants |  | Participants |  | Pearson Chi-Square Tests |  |  |
|---|---|---|---|---|---|---|---|---|
|  |  | Freq | Per (%) | Freq | Per (%) | Chi-square | df | Sig. |
| HDDS | Lowest dietary diversity | 45 | 46.9% | 6 | 6.3% | 46.582 | 2 | 0.000* |
|  | Medium dietary diversity | 30 | 31.3% | 33 | 34.4% |  |  |  |
|  | High dietary diversity | 21 | 21.9% | 57 | 59.4% |  |  |  |
| HFIAS | Food secure | 5 | 5.2% | 29 | 30.2% | 91.95 | 3 | 0.000* |
|  | Mildly Food insecure | 22 | 22.9% | 62 | 64.6% |  |  |  |
|  | Moderately Food insecure | 46 | 47.9% | 5 | 5.2% |  |  |  |
|  | Severe Food insecurity | 23 | 24.0% | 0 | 0.0% |  |  |  |

** Indicate significance at 0.05 significance level (p<0.05)*

Table 7 compares food security status between participants and non-participants in the Northern Tanzania Potatoes System Improvement project based on the Household Dietary Diversity Score (HDDS) and Household Food Insecurity Access Scale (HFIAS). The findings indicate significant differences in food security outcomes between the two groups, as evidenced by the highly significant Chi-square tests ($p < 0.05$). Among the participants, a majority (59.4%) exhibited high dietary diversity, reflecting a more varied and nutritionally adequate diet than non-participants, where only 21.9% fell into this category. Conversely, a substantial proportion of non-participants (46.9%) reported the lowest dietary diversity, suggesting limited access to various foods, a key indicator of poor nutritional outcomes. The data strongly imply that participation in the NTPSI project is associated with improved dietary diversity and food security.

**Table 8: Describing food security index scores of HDDS and HFIAS**

| Food security index | Non-participants |  |  | Participants |  |  |
|---|---|---|---|---|---|---|
|  | Mean | S. D | Standard Error | Mean | S. D | Standard Error |
| HDDS | 4.20 | 1.92 | .20 | 7.61 | 3.13 | .32 |
| HFIS | 8.69 | 3.39 | .35 | 3.58 | 3.10 | .32 |

Participants in the NTPSI project have a notably higher mean HDDS (7.61) compared to non-participants (4.20), with the error bars indicating that this difference is statistically meaningful. This suggests that participants have access to a more diverse and nutritionally adequate diet. Conversely, the HFIAS score, which indicates food insecurity levels, is much lower for participants (3.58) than for non-participants (8.69). This indicates that participants are experiencing significantly less food insecurity. The error bars on the HFIAS scores also show a meaningful difference, reinforcing the positive impact of project participation on reducing food insecurity, as shown in Figure 2.

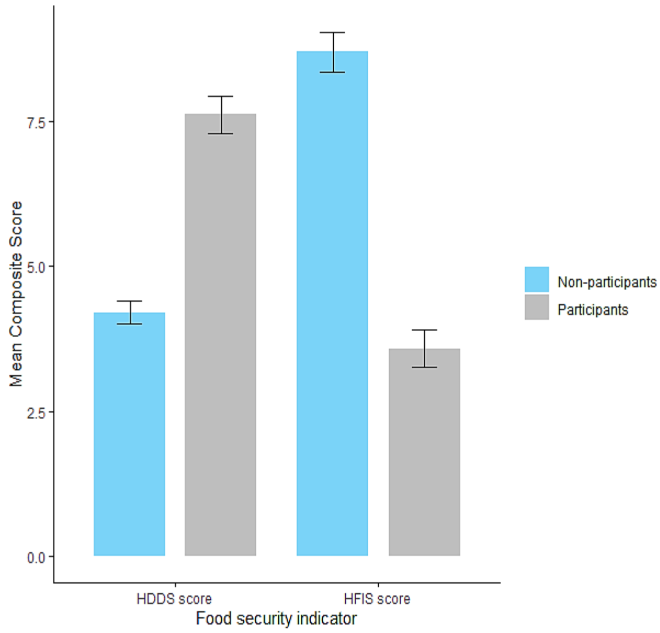


**Figure 2: Comparison of HDDS and HFIAS Scores by Participation in the NTPSI Project**

The results show the observed differences in food security outcomes when integrating the findings from Table 10 on common support for participants' categories. Of the 96 non-participant households, all are on support, meaning they were not matched for treatment, indicating they do not share similar characteristics with the participant group within the common support range. However, 27 participant households are off support, implying they differ significantly from the non-participant group in characteristics that influence food security outcomes.

**Table 10: Common support for treatment categories (n=192)**

| Treatment | Support |  | Total |
|---|---|---|---|
|  | Off support | On support |  |
| Non-participants | 0 | 96 | 96 |
| Participants | 27 | 69 | 96 |
| Total | 27 | 165 | 192 |

The 69 participants' households on support are more comparable to the 96 non-participant households, and these treated households likely benefited from the NTPSI project, leading to improved HDDS and reduced HFIAS scores. This suggests that the positive outcomes observed in Figure 3 can be attributed to the treatment effect, as those on support are similar in characteristics to the untreated group, yet show significantly better food security outcomes due to their participation in the project.

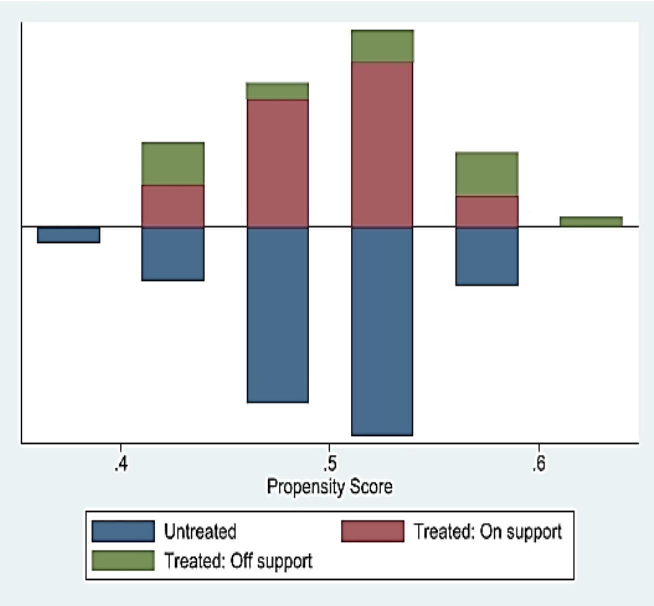


**Figure 3: PSM score distribution across treatment.**

## 4.8 ATT and ATE comparison across participation categories and Food index

Table 11 presents a comparison of the Average Treatment Effect on the Treated (ATT) for the Household Food Insecurity Access Scale (HFIAS) and Household Dietary Diversity Score (HDDS) across matched and unmatched samples. For the HFIAS, the unmatched sample shows that treated households (participants in the NTPSI project) have a significantly lower food insecurity score (3.583) compared to control households (8.688), with a difference of -5.104. This sizeable negative difference, coupled with a highly significant t-statistic (-10.88), indicates that participants experience much lower food insecurity. When considering the ATT, which focuses on matched households, the difference becomes even more pronounced (-5.870) and remains statistically significant (t-statistic of -9.75). This suggests that participation in the NTPSI project has a strong, positive effect on reducing food insecurity, even after accounting for other factors through matching.

Similarly, for HDDS, the unmatched comparison shows that participant households have a significantly higher dietary diversity score (7.615) compared to non-participants (4.198), with a difference of 3.417 and a highly significant t-statistic (9.12). When analysing the ATT, the difference slightly decreases to 3.275 but remains significant (t-statistic of 6.36). This result indicates that participation in the NTPSI project substantially improves dietary diversity, and this effect persists even after controlling for differences between participant and non-participant groups through matching. The robustness of these results across both unmatched and matched samples suggests that the NTPSI project effectively enhances food security and dietary diversity among participants, underscoring its importance in improving the well-being of smallholder farmers in the district.

**Table 3.11: Comparison of ATT across matched and unmatched categories (n=192)**

| Variable | Sample | Participants | Non-participants | Difference | S.E. | T-stat |
|---|---|---|---|---|---|---|
| HFIS | Unmatched | 3.583 | 8.688 | -5.104 | 0.469 | -10.88* |
| | ATT | 3.507 | 9.377 | -5.870 | 0.602 | -9.75* |
| HDDS | Unmatched | 7.615 | 4.198 | 3.417 | 0.375 | 9.12* |
| | ATT | 7.783 | 4.507 | 3.275 | 0.515 | 6.36* |

** Indicate significance at 0.05 significance level (p<0.05)*

Table 12 further reinforces the significant impact of the NTPSI project by comparing the Average Treatment Effect (ATE) between participants and non-participants. The negative ATE coefficient of -6.255 for HFIS, coupled with a highly significant z-value of -13.17 ($p < 0.000$), indicates that participants in the project experience substantially lower food insecurity than non-participants.

**Table 12: ATE comparison between participants and non-participants (n=192)**

| ATE | Coefficient | std. errs. | Z | P>z |
|---|---|---|---|---|
| Participants vs non-participants | -6.255208 | 0.474229 | -13.17 | 0.000* |
| Participants vs non-participants | 3.411458 | 0.3867442 | 8.82 | 0.000* |

** Indicate significance at 0.05 significance level (p<0.05)*

Conversely, the positive ATE coefficient of 3.411 for HDDS, with a significant z-value of 8.82 ($p < 0.000$), confirms that participants have significantly higher dietary diversity than non-participants. These results highlight the NTPSI project's effectiveness in improving productivity, which resulted in higher income for project participants. The project participants experienced food security and dietary diversity, demonstrating that participation significantly benefits smallholder farmers' well-being.

## 5.0 Conclusions and Recommendations

The study demonstrates that participation in the NTPSI project significantly enhanced smallholder farmers' incomes from potato sales compared to non-participants, largely driven by the adoption of improved potato seeds and the promotion of crop diversification introduced through the project. Participants also achieved higher yields and revenues, underscoring the critical role of potato production in improving household wellbeing. Moreover, the findings reveal a strong positive association between project involvement and improved household food security, as reflected by increased Household Dietary Diversity Scores (HDDS) and reduced Household Food Insecurity Access Scale (HFIAS) scores among those involved in the project.

Despite these positive impacts, the study recognises key challenges that limited equitable access to training, inputs, and market opportunities, which in turn affected overall potato output. External factors such as limited market access and inadequate infrastructure further shaped the project's outcomes, emphasising the need for integrated and comprehensive support systems to sustain and amplify these benefits over time. These results highlight significant opportunities for policymakers and stakeholders to scale similar interventions aimed at boosting smallholder productivity and income generation. However, to ensure lasting success, it is imperative to address systemic barriers by enhancing market linkages, expanding the reach and quality of extension services, and fostering an enabling policy environment that supports smallholder farmers beyond the life of the project.

To build on these gains, there is a critical need to expand access to improved agricultural technologies and training, particularly by leveraging digital platforms and mobile extension services to reach farmers in remote and underserved areas. Complementary financial incentives and subsidies should be provided to reduce the cost barriers for smallholders adopting improved seeds and innovative practices. At the same time, promoting nutrition-sensitive agriculture through integrated nutrition education and diversified cropping systems will enhance dietary outcomes and food security. Strengthening partnerships with NGOs, private sector actors, and community organisations can facilitate access to fortified foods and create market opportunities, while investments in rural infrastructure, such as storage facilities and transport networks, are essential to reducing post-harvest losses and improving profitability.

Sustainability must be reinforced through the implementation of strong monitoring and evaluation frameworks that track technology adoption and food security metrics at district and regional levels. Public-private partnerships should be cultivated to secure long-term investments in agricultural development, while improved access to affordable credit and financial services will empower smallholder farmers to make productive investments and enhance resilience. Therefore, by addressing these interconnected factors in a holistic manner, stakeholders can effectively scale the successes of the NTPSI project to foster resilient, food-secure communities and promote inclusive rural economic growth.

## Declaration of Conflict of Interest

We hereby declare that there are no known competing financial interests or personal relationships that could have influenced the research and findings presented in this paper.

## References

Amin, A., Dago, E., Kere, E., & Yogo, T. (2022). Technology Adoption and Access to Credit in Tanzania: A Spatial Econometric Analysis.

Anker Research Network. (2020). *Anker living income reference value: Rural Tanzania 2020*. Global Living Wage Coalition

Arslan, A., Floress, K., Lamanna, C., Lipper, L., & Rosenstock, T. S. (2022). A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa. *PLOS Sustainability and Transformation*, *1*(7), e0000018.

Benedetto, U., Head, S. J., Angelini, G. D., & Blackstone, E. H. (2018). Statistical primer: propensity score matching and its alternatives. *European Journal of Cardio-Thoracic Surgery*, *53*(6), 1112-1117.

Bjornlund, V., Bjornlund, H., & Van Rooyen, A. F. (2020). Why agricultural production in sub-Saharan Africa remains low compared to the rest of the world–a historical perspective. *International Journal of Water Resources Development*, *36*(sup1), S20-S53.

Booth, A., James, M. S., Clowes, M., & Sutton, A. (2021). Systematic approaches to a successful literature review.

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

Chami, A. (2020). Potentials of Commercialization of Smallholder Farming in Kigoma Region, Tanzania: Gross Profit Margin Analysis of selected Crops in Selected Districts, Kigoma Region. *World J Agri & Soil Sci*, *5*(4), 1-11.

Chegere, M. J., & Kauky, M. S. (2022). Agriculture commercialisation, household dietary diversity and nutrition in Tanzania. *Food Policy*, *113*, 102341.

East African Community. (2022, December 6). *EAC Secretary General hands over laboratory equipment to EAC Partner States to improve regional trade in seed potatoes*. https://www.eac.int/press-releases/141-agriculture-food-security/2693-eac-secretary-general-hands-over-laboratory-equipment-to-eac-partner-states-to-improve-regional-trade-in-seed-potatoes

FAO. (2023). *National gender profile of agriculture and rural livelihoods – United Republic of Tanzania*. Dodoma: FAO. https://doi.org/10.4060/cc4557en

Government of Tanzania**.** (2022). *2022 population and housing census report*. National Bureau of Statistics.

Groot, A., Duku, C., Demissie, T., Kabuka, G., & Recha, J. W. (2020). Potatoes Tanzania: Climate risk assessment.

Guo, S., Fraser, M., & Chen, Q. (2020). Propensity score analysis: recent debate and discussion. *Journal of the Society for Social Work and Research*, *11*(3), 463-482.

Harrell, Jr, F. E., & Harrell, F. E. (2015). Binary logistic regression. *Regression modeling strategies: With applications to linear models, logistic and ordinal regression, and survival analysis*, 219-274.

Hunziker, S., & Blankenagel, M. (2024). Cross-sectional research design. In *Research Design in Business and Management: A Practical Guide for Students and Researchers* (pp. 187-199). Wiesbaden: Springer Fachmedien Wiesbaden.

Integrated Food Security Phase Classification. (2023). *IPC acute food insecurity analysis of Tanzania Mainland: November 2023 - October 2024*. Published on 29 December 2023.

Jan, K., Hans, N., Yeray, S., & Theresia, M. (2022). Center for Development of Potato Industry Tanzania CD-PIT.

Jayne, T. S., & Sanchez, P. A. (2021). Agricultural productivity must improve in sub-Saharan Africa. *Science*, *372*(6546), 1045-1047.

Kane, L. T., Fang, T., Galetta, M. S., Goyal, D. K., Nicholson, K. J., Kepler, C. K. & Schroeder, G. D. (2020). Propensity score matching: a statistical method. *Clinical spine surgery*, *33*(3), 120-122.

Kinuthia, B. K., & Mabaya, E. (2017). The impact of agriculture technology adoption on farmers' welfare in Uganda and Tanzania. *Partnership for Economic Policy*, (163).

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610.

Lasway, J. A., Selejio, O., & Temba, G. R. (2021). Modeling multiple adoption decisions on agricultural technologies in Tanzania: a multinomial probit analysis. *Tanzanian Economic Review*, *10*(2).

Leavens, M. K., Gugerty, M. K., & Anderson, C. L. (2019). Gender and agriculture in Tanzania. *Gates Open Res*, *3*(1348), 1348.

Leuven, E., & Sianesi, B. (2018). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing.

Manda, J., Feleke, S., Mutungi, C., Tufa, A. H., Mateete, B., Abdoulaye, T., & Alene, A. D. (2024). Assessing the speed of improved postharvest technology adoption in Tanzania: The role of social learning and agricultural extension services. *Technological Forecasting and Social Change*, *202*, 123306.

Mbaga, S. G., Ngaga, Y. M., & Nyamoga, G. Z. (2024). Comparison of the profitability of conservation and conventional agriculture in Bahi District, Dodoma, Tanzania. *Journal of Agriculture and Environmental Sciences*, *9*(2), 111-123.

Mehmetoglu, M., & Jakobsen, T. G. (2022). Applied statistics using Stata: A guide for the social sciences.

Mugula, J. J., Kyaruzi, A. A., Msinde, J., & Kadigi, M. (2023). Adoption Intensity of Bundled Sustainable Agricultural Practices among Small-Scale Maize Growers in Morogoro Region, Tanzania. *East African Journal of Management and Business Studies*, *3*(3), 37-52.

Mutungi, C., Manda, J., Feleke, S., Abass, A., Bekunda, M., Hoschle-Zeledon, I., & Fischer, G. (2023). Adoption and impacts of improved post-harvest technologies on food security and welfare of maize-farming households in Tanzania: a comparative assessment. *Food Security*, *15*(4), 1007-1023.

Namwata, B. M., Lwelamira, J. M. O. B., & Mzirai, O. B. (2010). Adoption of improved agricultural technologies for Irish potatoes (Solanum tuberosum) among farmers in Mbeya Rural district, Tanzania: A case of Ilungu ward.

Nicholson, C. F., Stephens, E. C., Kopainsky, B., Jones, A. D., Parsons, D., & Garrett, J. (2021). Food security outcomes in agricultural systems models: Current status and recommended improvements. *Agricultural Systems*, *188*, 103028.

Olarinoye, T., Foppen, J. W., Veerbeek, W., Morienyane, T., & Komakech, H. (2023). Exploring the future impacts of urbanization and climate change on groundwater in Arusha, Tanzania. In *Groundwater* (pp. 79-93). Routledge.

Peligal, R. E. (1999). *Spatial planning and social fluidity: The shifting boundaries of ethnicity, gender, and class in Arusha, Tanzania, 1920--1967*. Columbia University.

Rahman, M. M., Tabash, M. I., Salamzadeh, A., Abduli, S., & Rahaman, M. S. (2022). Sampling techniques (probability) for quantitative social science researchers: a conceptual guidelines with examples. *Seeu Review*, *17*(1), 42-51.

RECODA (2019). Northern Tanzanian Potato System Improvement Proposal, Arusha.

Ruttan, V. W. (1977). Induced innovation and agricultural development. *Food policy*, *2*(3), 196-216.

Ruttan, V. W. (1988). Technical change and agricultural development. *World Food and Agriculture: Economic Problems and Issues*, *2*, 9-33.

Safari, J. G., Kirwa, M. K., & Mandara, C. G. (2022). Food insecurity in pastoral communities of Ngorongoro conservation area, Tanzania. *Agriculture & Food Security*, *11*(1), 36.

Turyasingura, J. B., Moses, A., Meza, O., Zombeire, J., & Kyabarongo, B. (2022). Resourcing and the sustainability of Donor funded Potatoes Projects in Kabale District, Southwestern Uganda.

Udemezue, J. C., and E. G. Osegbue. "Theories and models of agricultural development." *Annals of Reviews and Research* 1, no. 5 (2018): 555574.

United Nations. (2015**)**. *Transforming our world: The 2030 agenda for sustainable development*. United Nations General Assembly.

United Nations. *The Sustainable Development Goals Report 2023*.

Zhou, X., & Xie, Y. (2020). Heterogeneous treatment effects in the presence of self-selection: a propensity score perspective. *Sociological Methodology*, *50*(1), 350-385.