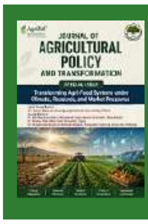

Journal of Agricultural Policy and Transformation *(AgriPaT)*
ISSN: 3134-819X
Journal Homepage: http://www.ageconfrontiers.com/agripat
Vol. 2(SI) Open Access
Special Issue: Transforming Agri-Food Systems under Climate, Resource, and Market Pressures

Effects of Adoption of Agricultural Technologies on the Income of the Irish Potato Farmers: Application of Propensity Score Matching

David Mwangi Kihoro[1*], Geofrey Kingori Gathungu[2], & Vicky Nyambura Wairimu[3]
[1]Department of Agricultural Economics, Agribusiness Management and Agricultural Education and Extension, Faculty of Agriculture, Chuka University, P.O Box 109-60400, Chuka
[2]Department of Plant Sciences, Chuka University, P.O Box 109-60400, Chuka
[3]Department of Environmental Studies and Resources Development, Chuka University, P.O Box 109
* *Corresponding author*: davidkihoro.12@gmail.com

ARTICLE INFO

Keywords

- *Adoption*
- *Agricultural Technologies*
- *Income*
- *Irish Potato*
- *Propensity Score Matching*

Article History
Received: 27 June 2026
Revised: 25 July 2026
Accepted: 02 August 2026
Available online: 12 August 2026

License
CC BY 4.0 – Open Access

DOI
10.66529/agripat.2026.2.SI.100

ABSTRACT

Farm-level uptake of improved agricultural technologies is a key lever for raising Irish potato incomes worldwide. As global population growth continues to strain the food system, there is a pressing need for strategies that lift productivity and, with it, farmer earnings. Yet despite the crop's economic weight, many smallholders still record modest returns because they have not fully embraced modern production technologies. This study therefore investigated how technology adoption shapes the income of Irish potato growers in Ol Kalou Sub-County, Kenya. Using a descriptive cross-sectional design, 385 respondents were drawn from a population of 21,942 smallholder Irish potato farmers. Descriptive statistics and Propensity Score Matching (PSM) were used, via SPSS version 28 and STATA version 17, to compare farmers who had and had not adopted technologies such as certified seed, fertilizer use, mechanization, irrigation, and integrated pest management. Adopters earned a significantly higher average income of KES 45,546.25 per acre against KES 30,230.10 per acre for non-adopters, with an estimated Average Treatment Effect on the Treated (ATT) of KES 15,316.15 per acre, a 50.67% income gain attributable to adoption. The results show that adopting agricultural technologies meaningfully lifts farm profitability by raising productivity, cutting production risk, and strengthening market participation. The study therefore recommends wider adoption of these technologies as a route to more efficient, lower-cost production.

Citation: *Kihoro, D.M., Gathungu, G.K. & Wairimu, V.N. (2026). Effects of Adoption of Agricultural Technologies on the Income of the Irish Potato Farmers: Application of Propensity Score Matching.* J. Agric. Pol. & Transf. 2(SI): 9-16.
https://doi.org/10.66529/agripat.2026.2.SI.100

1. INTRODUCTION

Technology adoption has emerged as one of the principal pathways through which agriculture can become more productive, more profitable, and better able to secure food supplies worldwide. Continued growth in the world's population is placing mounting demands on farming systems to deliver more output from a fixed natural-resource base (Hoque & Mondal, 2026). Innovations in production methods have accordingly been championed as key instruments for lifting efficiency, cutting costs, raising output quality, and sharpening the competitive position of agricultural enterprises (Rambe & Khaola, 2022). Within Irish potato farming specifically, uptake of improved seed, fertilizer, irrigation, mechanization, integrated pest and disease control, better storage, and information and communication technologies (ICTs) have reshaped production systems across numerous countries (Evelyne et al., 2021; Kansiime et al., 2025). Such innovations allow farmers to harvest more potatoes from each unit of land while lowering production risk and raising household earnings.

Irish potato (Solanum tuberosum) ranks among the world's most valuable food crops, prized for its nutrient density, short growing cycle, and adaptability to a wide range of climates (Khurshid et al., 2026 and Mairiga et al., 2026). It underpins food security, generates employment, and provides income for millions of households, especially across the developing world (Djaman et al., 2021 and Naseeb et al., 2026). Global output has risen quickly on the back of population growth, urban expansion, shifting diets, and growing demand for affordable, nutritious staples (Richards & Rickard, 2020). Even so, yields in many developing countries continue to fall short of their potential because farmers have yet to fully take up the modern technologies that would raise production efficiency.

Applying scientifically developed farming practices, innovations, and inputs boosts both agricultural output and farmers' earnings (Ashraf & Riaz, 2026). Such technologies range from certified, disease-free seed potatoes and balanced fertilizer use to irrigation, mechanization, integrated pest and disease management, precision agriculture, improved post-harvest handling, and digital advisory services (Tehreem & Ashfaq (2025)). Taking these up lets farmers raise productivity while making more efficient use of the resources they already have (Akoto et al., 2020 and Mairiga et al., 2026). How readily farmers adopt them depends on several factors, including education, access to extension services, farm size, access to credit, market access, institutional support, and household income.

Technology adoption benefits Irish potato farmers' incomes in several ways (Atieno et al., 2026, Ngalaga et al., 2026). Chief among these is higher productivity: improved seed varieties carry greater genetic potential, stronger disease resistance, and better germination than traditional stock. Paired with proper fertilizer use and sound crop management, they lift yields per hectare markedly (Setiawan & Inayati, 2020 and Kangogo et al., 2024). Larger harvests mean bigger marketable surpluses, more revenue, and higher household incomes, while also helping farmers meet market demand consistently and deepen their participation in commercial markets.

Modern technologies also cut production costs and sharpen efficiency. Mechanization, for instance, reduces the labor needed for land preparation, planting, spraying, and harvesting (Mahmood et al., 2025), lowering costs while keeping farm operations on schedule, a key factor in maximizing yields. Irrigation, similarly, loosens the grip of unreliable rainfall and lets farmers grow potatoes year-round, lifting cropping intensity and annual income (Evelyne et al., 2021). Irrigating farmers are also better placed to supply the market when supply elsewhere is thin, capturing higher prices in the process.

Integrated pest and disease management also carries real weight for farm income. Irish potato crops are vulnerable to pests and diseases such as late blight, bacterial wilt, aphids, and potato cyst nematodes, which can cause heavy yield losses when left unmanaged. By combining resistant varieties, biological control, cultural practices, and careful pesticide use, integrated pest management curbs these losses while limiting environmental harm (Sharifi et al., 2018), leaving farmers with more and better-quality potatoes to sell and, in turn, higher profitability.

Across the globe, countries that have transformed their potato sectors have generally done so through widespread technology adoption (Chiarini et al., 2026). China and India, the world's leading producers, have poured investment into improved seed systems, irrigation infrastructure, mechanization, and agricultural research (Badea et al., 2025), investments that have lifted productivity, farm incomes, and national food security alike (Wang et al., 2020; Siamalube et al., 2025). Comparable gains have been recorded in Europe and North America, where precision agriculture, mechanized farming, and efficient supply chains underpin high yields and profitable commercial production (Abdelhamid et al., 2024).

In Africa, by contrast, potato productivity still trails the global average despite the crop's rising economic importance. Yields lag those in Europe, North America, and Asia largely because many smallholders still rely on traditional methods and have limited access to modern production technologies (Djaman et al., 2021). Low uptake of improved seed, fertilizer, irrigation, mechanization, and post-harvest technologies keeps both productivity and incomes down, while weak extension services, limited credit access, poor rural infrastructure, costly inputs, and thin market linkages continue to hold back adoption among smallholders (Unekwu et al., 2020).

Evidence suggests that closing the technology-adoption gap could substantially lift potato productivity and income across the continent. Richards and Rickard (2020) estimated production could rise by as much as 140 percent under full adoption of available technologies, while Fitz-Koch et al. (2018) found that technological innovation opens real opportunities for smallholders in sub-Saharan Africa to raise productivity, engage more with markets, and reduce rural poverty. Higher productivity, in turn, lifts household income and strengthens national food security by making affordable food more available.

Despite these benefits, adoption rates vary widely among farmers in Kenya and specifically in Ol Kalou Sub-County. Socioeconomic factors (education, farming experience, household income, farm size, age, and gender) shape both willingness and ability to adopt new technologies, while institutional factors such as access to extension services, farmer organizations, credit, government support, and input supply systems also matter a great deal (Qin et al., 2022; Ishak & Mazlan, 2025; Ashfaq & Tehreem, 2025). Farmers in areas with well-developed markets and infrastructure tend to adopt improved technologies more readily than those in remote rural areas.

While a large body of research links technology adoption to higher farm income, the size of that effect differs across countries, farming systems, and socioeconomic settings. Differences in the technology packages used, market conditions, institutional support, environmental factors, and policy frameworks all shape how far adoption translates into higher incomes (Wang et al., 2020; Ngalaga et al., 2026). This points to a continuing need for context-specific studies of how particular agricultural technologies affect Irish potato farmers' income under different production conditions, evidence that policymakers, extension providers, development partners, and researchers can use to design interventions that promote adoption, raise productivity, lift household incomes, and strengthen food security.

Taken together, the evidence points to agricultural technology adoption as a critical driver of productivity, profitability, and income among Irish potato farmers. Technologies that improve seed quality, soil fertility, water management, pest and disease control, mechanization, and market access can turn potato farming from a subsistence activity into a profitable commercial enterprise. Widening farmers' access to these technologies through better extension services, affordable credit, quality inputs, and supportive policy will therefore remain central to improving Irish potato farmers' livelihoods and advancing sustainable agricultural development. Therefore, there is need to investigated how technology adoption shapes the income of Irish potato farmers in Ol Kalou Sub-County, Kenya.

2. MATERIALS AND METHODS

Study Area and Research Design

The study was conducted across the five words of Ol Kalou Sub-County (Kanjuire Ridge, Kaimbaga, Ruria, Karau, and Mirangine) which together cover an area of 384.9 km^2 and are home to a population of 75,262 (County Government of Nyandarua, 2018). The sub-county was chosen for its strong potential for Irish potato production, output that has nonetheless been declining in recent years (Mumia et al., 2018). Most of the land is arable thanks to fertile soils, and Ol Kalou sits on the western slopes of the Aberdare Ranges, one of Nyandarua County's five sub-counties. It lies at roughly 1^o South latitude, and 27^o East. Ol Kalou Sub County is characterized by Potato, maize and horticulture are the main crops grown by farmers in the area while dairy, sheep and goats form the major livestock enterprise in Ol Kalou Sub County. The annual Irish potato production in Ol Kalou Sub County is approximately 27,519 tonnes with a value of about KES 900,000,000 (County Government of Nyandarua, 2018). Ol Kalou Sub County is at an altitude of 2361 m hence enjoys a Mediterranean climate with rainfall of between 700 mm and 1500 mm per year and temperatures ranging from 12 ^{o}C in cold months and 25 ^{o}C in hold months (Kamau et al. 2015).

This study used a descriptive cross-sectional research design, which describes the farmers' circumstances in the study area as they currently stand. Descriptive cross-sectional designs are well suited to building an accurate picture of situations or events as they exist on the ground (Blazy et al., 2009). It also allowed for the collection of both qualitative and quantitative data from smallholder potato farmers and was well suited to gauging the potential effect of technology adoption on yield and income, since descriptive surveys are built to capture a population's current status on one or more variables.

The study's target population was smallholder Irish potato farmers. Li and Song (2019) define a target population as the group of individuals a study seeks to draw conclusions about. Here, that population totaled 21,942 smallholder Irish potato farmers in Ol Kalou Sub County (County Government of Nyandarua, 2018). To qualify as a respondent, a farmer had to be a smallholder potato producer who had grown the crop continuously for at least the past five years. This criterion excluded recent entrants, who would not yet have had the chance to build adequate knowledge of the available agricultural technologies.

Sample Size Determination and Sampling Procedures

Sample size was computed using the Cochran (2007) formula for the smallholder Irish potato producers in Ol Kalou.

$$n = \frac{Z^2 pq}{e^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots (1)$$

$$n = \frac{(1.96)(1.96)(0.5)(0.5)/0.5}{(0.05)(0.05)} = 385$$

At a 95% confidence level, this yielded a sample of 385 smallholder Irish potato farmers (Table 1). Respondents were selected through multi-stage sampling: proportionate sampling first allocated the sample across Ol Kalou's five wards, then simple random selection drew respondents from lists obtained from the Ministry of Agriculture, Nyandarua County, and local administrative leaders. Finally, purposive sampling identified three key informants from the Ministry of Agriculture Nyandarua County, KALRO Tigoni, and ADC Molo.

Data Collection

Primary data on farmers' income were collected using a structured questionnaire administered through Open Data Kit (ODK) and later exported into SPSS. Enumerators fluent in the local language administered the questionnaires. Data on how technology adoption affected income were additionally gathered across two Irish potato seasons i.e. June-August and August-October 2022 using a production schedule that recorded total output and production costs for both adopters and non-adopters. Enumerators were trained beforehand to familiarize them with the data to be collected. Additional data were gathered from three key stakeholders: KALRO Tigoni, ADC Molo, and the Ministry of Agriculture, Nyandarua County.

Propensity Score Matching

Propensity Score Matching (PSM) was used to estimate the effect of technology adoption on income. Adopters and non-adopters were first coded 1 and 0 respectively, then matched on the propensity scores generated for the adoption (treatment) and non-adoption (control) groups using the Nearest Neighbor Matching (NNM) procedure. As Austin (2011) explains, NNM matches units on the nearest propensity value, giving equal weight to each unit compared. This made it a suitable choice here. The study also enforced common support by matching adopters and non-adopters on observable characteristics, excluding from the covariate set any respondents whose propensity values fell outside the matched range.

PSM was essential because it confined the impact estimate to adopting and non-adopting households matched on observable characteristics. Its implementation rested on two assumptions: the Conditional Independence Assumption (CIA), under which treatment is exogenous so any systematic difference between the comparison and treatment groups can be attributed to treatment itself; and common support, which requires that individuals with the same covariate values have a positive probability of being either a participant or non-participant in treatment. If the potential outcomes of the control and treated groups are independent of treatment allocation once conditioned on covariates X, they are likewise independent of treatment conditional on the propensity score, as shown in Eq 2.

$$\mathrm{P} = (\,D = 1|X) = P(X)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (2)$$

If the un-confoundedness assumption holds and a study establishes sufficient overlap between the control and treatment groups, the propensity score matching estimator for the Average Treatment Effect on the Treated conditional can be written as;

$$\mathrm{ATT} = \{\mathrm{E}[\,|D = 1, P(X)] - \mathrm{E}[\,|D = 0, P(X)]\}\ldots\ldots\ldots\ldots\ldots\ldots.\ (3)$$

where;

ATT is the Average Treatment Effect of the Treated
E[|D=1 is the average value of the income of the interest for treated households
P(X) is the probability of the variable X
E[|D=0 is the average value of the income for the control group

The propensity score, the conditional probability of adopting a given technology, was used to identify the counterfactual group of farmers who did not benefit, based on a set of observable variables. PSM allowed the score for treated and control units to be calculated from these observable characteristics, addressing the dimensionality problem. Once the appropriate control group had been identified, the impact of adoption was determined as follows:

$$\mathrm{Impact} = \{\mathrm{E}[\,|D = 1, P(X)] - \mathrm{E}[\,|D = 0, P(X)]\}\ldots\ldots\ldots\ldots\ldots\ldots\ (4)$$

This equation gives propensity score matching as the mean outcome difference over the common support region, weighted by the distribution of treated participants. The treatment effect was obtained by averaging this difference between adopters and the control group. To check balance, the study compared the Pseudo-R2 before and after matching. The Pseudo-R2 shows how well the covariates X explain the probability of treatment participation. Variable minima and maxima were compared to check overlap and common support. As Austin (2011) notes, observations whose propensity scores fall outside the range of the opposite group are dropped from the sample under this approach which can discard a large number of observations where overlap between adopters' and non-adopters' scores is poor. A trimming procedure can be applied to keep the common support region well defined.

3. RESULTS AND DISCUSSION

Type of Adopters of Agricultural Technologies

The study classified the Irish potato farmers of Ol Kalou Sub County by adopter type, based on how many years after a technology's introduction they were expected to take it up: innovators within one-year, early adopters within two, the early majority within three, the late majority within four, and laggards taking more than five. The largest share of respondents, 36.88%, fell into the early majority category (Figure 1), followed by 22.34%, 21.04%, 12.73%, and 7.01% who were early adopters, late majority, innovators, and laggards respectively (Figure 1).

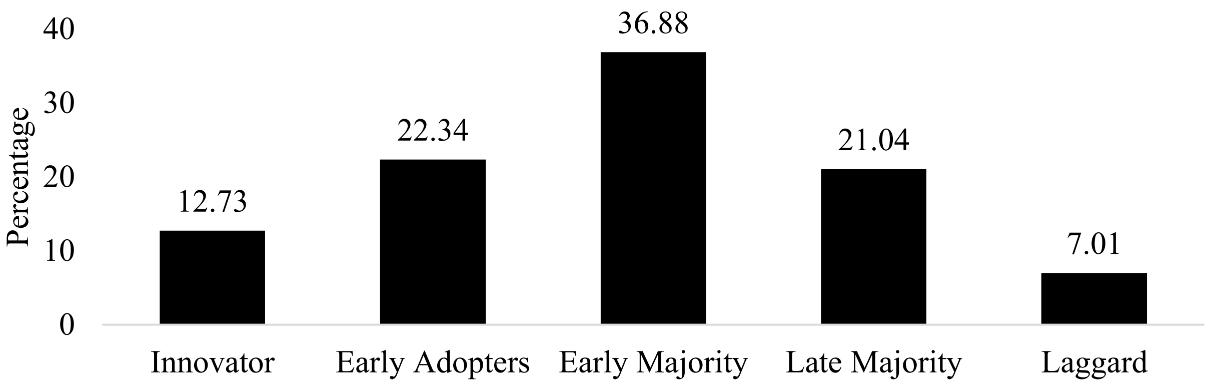

Figure 1: Type of Adopters among the Irish Potato Farmers in Percentage

This suggests that most Irish potato farmers are fairly open to new information and tend to adopt a technology within about three years of learning it exists. 12.73% classified as innovators were, notably, ready to take up technology as soon as it became available. This contrasts with Siamalube et al. (2025), who found that most agricultural adopters in India were late adopters who took longer to learn about a new technology's benefits and usability.

Effects of Adoption of Agricultural Technologies on the Income of the Irish Potato Farmers

Difference in Income Between the Adopters and Non-Adopters

This part of the study tested whether income differed significantly between high and low adopters of agricultural technology among the Irish potato farmers, using an independent-samples t-test. The equality-of-variances test returned an F value of 39.48 and a significant p-value of 0.00 (Table 1), pointing to significant variability in income between adopters and non-adopters. The t-test itself confirmed a significant income difference between the two groups, with a t-value of 5.27 and a p-value of 0.00<0.05 (Table 1).

Table 1: Independent Samples Test of Income Variation

Variable	Category	F	Sig	t	df	Sig (2-tailed)
Income	Equal Variances Assumed	39.48	0.00	5.16	383	0.00
	Equal Variances not Assumed	383		5.27	329.91	0.00

Note: *** significant at 1% level, ** significant at 5% level, *significant at 10% level

This gap is unlikely to be due to chance; it more plausibly reflects differences in technology uptake. The results point to a measurable income effect from adopting different agricultural technologies among Irish potato farmers and suggest that technology use in the sub-sector contributes meaningfully to changes in income per acre, consistent with Tufa et al. (2019), who likewise found an income gap between farmers who had and had not adopted agricultural technologies.

Propensity Score Matching Analysis of the Effects of Adoption of Agricultural Technologies on Income

The PSM analysis estimated the effect of technology adoption on farmers' income. The Average Treatment Effect on the Treated was computed using Nearest Neighbor Matching on the propensity scores of the 385 respondents, 184 non-adopters and 201 adopters, which ranged from 0.07 to 0.98 (Figure 2).

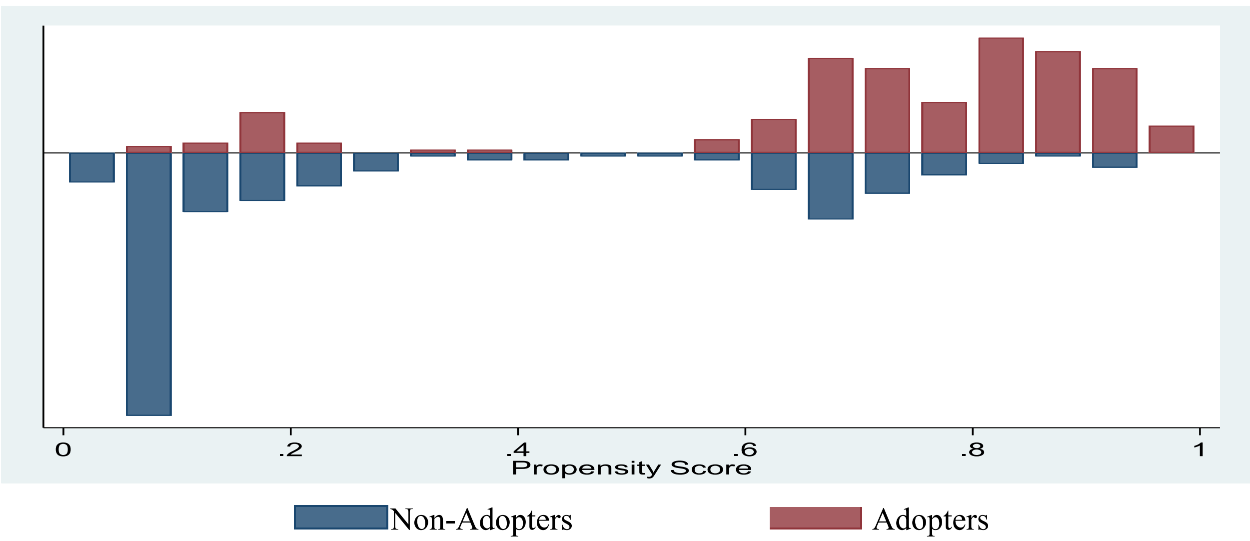

Figure 2: Propensity Score Distribution and Area of Common Support for Estimation

The upper part of the PSM graph plots propensity scores for treated (adopter) farmers, and the lower part plots scores for untreated (non-adopter) farmers. Adoptability ranged from as low as 0.07 to as high as 0.98. The overlap between adopter and non-adopter scores defines a common support region, making comparison between the two groups possible. Covariate balancing was then carried out to test whether adopters' and non-adopters' covariates followed similar distributions after matching.

Table 2: Covariate Balancing Before and After Matching

Variable	Sample	Mean		Difference
		Adopters	Non-Adopters	
Contact with Extension Services	Unmatched	3.25	2.35	0.90
	Matched	3.25	3.34	-0.09
Size of Land	Unmatched	3.88	3.90	-0.02
	Matched	3.88	3.69	0.19
Farmers Experience	Unmatched	15.67	17.53	-1.86
	Matched	16.89	17.44	-0.545
Availability of Off-Farm Income	Unmatched	29670.6	25620.0	4,050.60
	Matched	44,870.0	29,630.98	15,239.98
Availability of Credit	Unmatched	0.19	0.11	0.09
	Matched	0.24	0.14	0.10
Production Risk	Unmatched	0.39	0.26	0.13
	Matched	0.49	0.27	0.22
Production Cost	Unmatched	0.19	0.11	0.08
	Matched	0.18	0.27	0.09
Availability of Farm Income	Unmatched	0.198	0.107	0.09
	Matched	0.20	0.10	0.10
Distance to Market	Unmatched	7.36	8.76	-1.40
	Matched	7.30	8.10	-0.80
Market Stability	Unmatched	0.19	0.09	-0.10
	Matched	0.21	0.11	0.10
Availability of Market Information	Unmatched	0.20	0.108	0.09
	Matched	0.20	0.11	0.09

Before matching, extension-service access, land size, farming experience, off-farm income, credit access, production risk, production cost, farm income, distance to market, market stability, and access to market information all differed significantly between the two groups. Once matching was carried out, however, none of these differences remained significant (Table 2), indicating that the matching covariates had converged to a similar distribution between adopters and non-adopters. This suggests the impact estimate was not driven by selection bias, and that the income difference observed between the two groups can reasonably be attributed to technology adoption rather than to pre-existing differences between them.

Propensity Score Estimates for Effects of Adoption of Agricultural Technologies on the Income of Irish Potato Farmers

This section reports on the propensity score estimates for technology adoption. The following hypothesis was tested to determine the effect:

H01: *There is not statistically significance effect of adoption of agricultural technology on income of smallholder Irish potato farmer in Ol Kalou Sub County.*

The ATT estimates confirmed that technology adoption significantly raised farmers' income, with a t-value of 3.64 significant at $p=0.02<0.05$ (Table 3) evidence that adoption affected income. Farmers who adopted more agricultural technologies earned an estimated KES 45,546.25 per acre, against roughly KES 30,230.10 per acre for those who had not (Table 3).

Table 3: Propensity Score for Effects of Adoption of Agricultural Technologies on the Income of Irish Potato Farmers

	Mean Income				
	Adopters	Non-adopters	ATT	% Increase	t-Value
Income (KES/acre	45,546.25	30,230.10	15,316.15	50.67	3.64**

Note: ** significant at 5% level

The estimated causal effect of adoption on Irish potato farmers' income was KES 15,316.15 per acre, a 50.67% change (Table 3), which rejects the null hypothesis of no statistically significant effect. This higher income among adopters likely reflects complementary innovations and greater yields, and possibly a reduced exposure to environmental stress that would otherwise have depressed productivity.

The lower income among non-adopters, in turn, may stem from delayed or out-of-season planting that pushed back maturity and reduced tuber yield, as well as from continued reliance on traditional production methods that limit productivity at farm level. Even among some adopters, income may have been dampened by the time it takes to resolve production challenges, which can erode productivity in the interim. These findings echo Kimbi et al. (2020) and Hailu et al. (2014), both of whom found that investment in agricultural technologies is central to raising farmer income. A similar pattern emerges in Tufa et al. (2019), who linked technology use to higher income through greater productivity per unit area. These results diverge, however, from Nnahiwe et al. (2023), who found that income and production gains from technology adoption tend to materialize only after a longer stretch of time, since farmers need time to learn how to optimize a technology and adjust its application to their circumstances.

4. CONCLUSIONS

This study concludes that adopting agricultural technologies significantly raises the income of Irish potato farmers. Those who adopted technologies such as certified seed, fertilizer application, mechanization, and integrated pest management earned KES 45,546.25 per acre, against KES 30,230.10 per acre for their counterparts, a statistically significant difference. Technology adoption therefore has the potential to turn Irish potato farming into a viable commercial enterprise, strengthening food security and improving farmers' livelihoods.

References

Abdelhamid, A. A., Alhussan, A. A., Qenawy, A. S. T., Osman, A. M., Elshewey, A. M., & Eed, M. (2024). Potato harvesting prediction using an Improved ResNet-59 model. Potato Research, 1-20. https://doi.org/10.1007/s11540-024-09773-6

Akoto, E., Othieno, C., & Ochuodho, J. (2020). Influence of Phosphorus Fertilizer on Potato Seed Production in Acid Soils in Kenya. Sustainable Agriculture Research, 9(2), 101. https://doi.org/10.5539/sar.v9n2p101

Ashfaq, M. A., & Tehreem. (2025). Determinants of Solar-Powered Irrigation System Adoption Among Rice Farmers in Hafizabad, Pakistan. Journal of Agricultural Policy and Transformation (AgriPaT), 1(1). https://doi.org/10.66529/agripat.2025.1.1.13

Ashraf, I., & Riaz, A. (2026). Improving Agricultural Productivity and Sustainability through Modern Extension Services: A Case Study in Rural Pakistan. Inverge Journal of Social Sciences, 5(1), 415-431. https://doi.org/10.63544/ijss.v5i1.257

Atieno, E. O., Almekinders, C. J., & Struik, P. C. (2026). Developments and Challenges of the Kenyan Potato Sector: Implications for Smallholder Farmers. Potato Research, 69(3), 98. https://doi.org/10.1007/s11540-026-10038-7

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate behavioral research, 46(3), 399-424. https://doi.org/10.1080/00273171.2011.568786

Badea, C. A., Iorga, A. M., Soare, E., & Stoicea, P. (2025). The global dilemma of potato yield: between expansion and efficiency. Scientific Papers Series Management, Economic Engineering in Agriculture & Rural Development, 25(4), 69.

Blazy, J. M., Ozier-Lafontaine, H., Doré, T., Thomas, A., & Wery, J. (2009). A methodological framework that accounts for farm diversity in the prototyping of crop management systems. Application to banana-based systems in Guadeloupe. Agricultural systems, 101(1-2), 30-41. https://doi.org/10.1016/j.agsy.2009.02.004

Chiarini, M., Furlan, L., Hiltpold, I., Barbanti, L., & la Forgia, D. (2026). Integrated Management of Potato Pests and Diseases with a Focus on Europe: A Review. Potato Research, 69(2), 44. https://doi.org/10.1007/s11540-025-09951-0

Cochran, P. L. (2007). The evolution of corporate social responsibility. Business horizons, 50(6), 449-454. https://doi.org/10.1016/J.BUSHOR.2007.06.004

County Government of Nyandarua (2018). Transforming Nyandarua: Unlocking the Great Potential. Development Plan CIDP 2018-2022

Djaman, K., Irmak, S., Koudahe, K., & Allen, S. (2021). Irrigation Management in Potato (Solanum tuberosum L.) Production: A Review. Sustainability, 13(3), 1504. https://doi.org/10.3390/su13031504

Evelyne, N., Daniel, N., Irene, N., & Ariel, K. (2021). Physico-chemical properties of selected Irish potato varieties grown in Kenya. African Journal Of Food Science, 15(1), 10-19. https://doi.org/10.5897/ajfs2020.2025

Fitz-Koch, S., Nordqvist, M., Carter, S., & Hunter, E. (2018). Entrepreneurship in the agricultural sector: A literature review and future research opportunities. Entrepreneurship theory and practice, 42(1), 129-166. https://doi.org/10.1177/1042258717732958

Hailu, B. K., Abrha, B. K., & Weldegiorgis, K. A. (2014). Adoption and impact of agricultural technologies on farm income: Evidence from Southern Tigray, Northern Ethiopia. International Journal of Food and Agricultural Economics (IJFAEC), 2(1128-2016-92058), 91-106. http://doi.org/10.22004/ag.econ.190816

Hoque, M., & Mondal, S. (2026). The way forward for sustainable food production. In Genetic and Reproductive Approaches for Sustainable Livestock Production (pp. 335-346). Academic Press.

Ishak, N. F., & Mazlan, Z. (2025). Key Challenges and Potentials of Potato (Solanum tuberosum L.) Farming in Malaysia: A Mini Review. Potato Research, 1-16. https://doi.org/10.1007/s11540-024-09845-7

Kamau, S. W., Kuria, D. N., & Gachari, M. K. (2015). Crop-land suitability analysis using GIS and remote sensing in Nyandarua. Journal of Environment and Earth Science, 5(6): 121-132. https://www.iiste.org/Journals/index.php/JEES/article/view/20999/21248

Kangogo, E., Otieno, D. J., Okello, J., Mwenye, O., & Kapalasa, E. (2024). Impact of farmer training on potato yield: a case of smallholder potato farmers in Malawi. Frontiers in Sustainable Food Systems, 8, 1496064. https://doi.org/10.3389/fsufs.2024.1496064

Kansiime, M. K., Aliamo, C., Alokit, C., Rware, H., Murungi, D., Kamulegeya, P., ... & Kusasira Mulema, J. M. (2025). Pathways and business models for sustainable youth employment in agriculture: A review of research and practice in Africa. CABI Agriculture and Bioscience, 6(1), 0045. https://doi.org/10.1079/ab.2025.0045

Kimbi, T. G., Akpo, E., Kongola, E., Ojiewo, C. O., Vernooy, R., Muricho, G., ... & Tabo, R. (2020). A probit Analysis of Determinants of Adoption of Improved Sorghum Technologies Among Farmers in Tanzania. Journal of Agricultural Science (TSI), 13(1), 73-87. https://doi.org/10.5539/jas.v13n1p73

Khurshid, M., Khurshid, I., Wattoo, F. M., & Rahman, M. (2026). Agro-Climatic Adaptability and Performance Evaluation of Potato (Solanum tuberosum L.) Varieties in the Hazara Region of Pakistan: Performance Evaluation of Potato (Solanum tuberosum L.). Journal of Agricultural Policy and Transformation, 2(2): 87-93. https://doi.org/10.66529/agripat.2026.2.2.78

Li, X., & Song, Y. (2019). Target Population Statistical Inference with Data Integration Across Multiple Sources-An Approach to Mitigate Information Shortage in Rare Disease Clinical Trials. Statistics In Biopharmaceutical Research, 12(3), 322-333. https://doi.org/10.1080/19466315.2019.1654913

Mahmood, G. G., Liberatori, S., & Mazzetto, F. (2025). Agricultural mechanization perspective in Pakistan: present challenges and digital future. Journal of Agricultural Engineering, 56(2), 1636. https://doi.org/10.4081/jae.2025.1636

Mairiga, B., Omomoh, E., Gujahar, R. R. D., Nannim, S., Emmanuel, G. P., & Omirinde, M. O. (2026). Geospatial Techniques for Spatial Variability of Soil Physicochemical Properties and Their Impact on Irish Potato Production on the Jos Plateau: A Case Study of Jos South and Riyom Local Government Areas. International Journal of Research and Innovation in Social Science (IJRISS), 10(3). https://dx.doi.org/10.47772/IJRISS.2026.100300262

Mumia, B., W. Muthomi, J., D. Narla, R., W. Nyongesa, M., & M. Olubayo, F. (2018). Seed Potato Production Practices and Quality of Farm Saved Seed Potato in Kiambu and Nyandarua Counties in Kenya. World Journal of Agricultural Research, 6(1), 20-30. https://doi.org/10.12691/wjar-6-1-5

Naseeb, A., Al-Khayat, A., Al-Shamali, S., Abdulmalik, N., Al-Asfour, M., Al-Jaber, A. F., & Behbehani, M. S. (2026). Economic Impacts Attributable to Climate Change on Arid Lands Agriculture and Food Security-Policy Development. In Fostering Arid Lands Agriculture in the Face of Climate Change: Mitigation and Adaptation Synergy (pp. 251-269). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-98490-7_12

Ngalaga, T. B., Wolfram Mlengule, D., & Sawe, J. R. (2026). Resilience among Smallholder Irish Potato Farmers to the Impacts of Climate Variability in Wanging'ombe District, Tanzania. Journal of Humanities and Social Sciences, 14(4), 21-41 https://commons.udsm.ac.tz/cgi/viewcontent.cgi?article=1323&context=jhss

Nnahiwe, P., Hejkrlík, J., & Bavorová, M. (2023). Adopting modern agricultural technologies and impact on economic performance: evidence from cashew farmers in Kenya. International Food and Agribusiness Management Review, 1-26. https://doi.org/10.22434/ifamr2021.0100

Qin, R., Zhang, F., Yu, C., Zhang, Q., Qi, J., & Li, F. M. (2022). Contributions made by rain-fed potato with mulching to food security in China. European Journal of Agronomy, 133, 126435. https://doi.org/10.1016/j.eja.2021.126435

Rambe, P., & Khaola, P. (2022). The impact of innovation on agribusiness competitiveness: the mediating role of technology transfer and productivity. European Journal of Innovation Management, 25(3), 741-773. https://doi.org/10.1108/EJIM-05-2020-0180

Richards, T. J., & Rickard, B. (2020). COVID-19 impact on fruit and vegetable markets. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 68(2), 189-194. https://doi.org/10.1111/cjag.12231

Setiawan, A., & Inayati, C. (2020). The Analysis of Production Factors and Income of Potato Farming. JEJAK, 13(1), 17-29. https://doi.org/10.15294/jejak.v13i1.21965

Sharifi, P., Astereki, H., & Pouresmael, M. (2018). Evaluation of variations in chickpea (Cicer arietinum L.) yield and yield components by multivariate technique. Annals Of Agrarian Science, 16(2), 136-142. https://doi.org/10.1016/j.aasci.2018.02.003

Siamalube, B., Lambert, E., Anyaji, C., & Ehinmitan, E. (2025). Advancements in Potato Science: Agronomy, Genetics, And Biotechnology for Sustainable Food Security. Potato Journal of India, 51(2): 244-258. http://doi.org/10.56093/potatoj.v51i2.159011

Tehreem, & Ashfaq, M. A. (2025). Harnessing artificial intelligence for agricultural marketing: Evidence from farmers in Faisalabad, Pakistan. Journal of Agricultural Policy and Transformation (AgriPaT), 1(1), pp. 34–40. https://doi.org/10.66529/agripat.2025.1.1.11

Tufa, A. H., Alene, A. D., Manda, J., Akinwale, M. G., Chikoye, D., Feleke, S., ... & Manyong, V. (2019). The productivity and income effects of adoption of improved soybean varieties and agronomic practices in Malawi. World development, 124, 104631. http://doi.org/10.1016/j.worlddev.2019.104631

Unekwu, O., Mojisola, A., Tina, E., & Ogala, D. (2020). Perception and uptake of aquaculture technologies in Kogi state, central Nigeria: imperative for Improved Management practices for sustainable aquaculture development. African Journal of Agricultural Research, 16(6), 819-828. https://doi.org/10.5897/ajar2019.14558

Wang, N., Reidsma, P., & Ittersum, M. (2020). Scope and strategies for sustainable intensification of potato production in Northern China. Agronomy Journal, 112(5), 3591-3604. https://doi.org/10.1002/agj2.20269

Declarations

Acknowledgement: Special acknowledgements to the Agricultural Development Corporation (ADC) Molo, small-scale farmers in Ol Kalou Sub County and Kenya Agricultural and Livestock Research Organization Tigoni for providing valuable data. The study also acknowledges Chuka University, specifically the department of Agricultural Economics, Agribusiness Management and Agricultural Education and Extension for administrative support.

Conflict of Interest: The authors declare no conflict of interest.

Data Availability: Available on request.

Author Contributions: *Kihoro, D.M.* - conceptualization, data collection, writing (original draft), *Gathungu, G.K. & Wairimu, V.N. - Data collection, analysis and* writing (review & editing).