

EFFECT OF SELECTED CLIMATE SMART AGRICULTURAL TECHNOLOGIES ON POVERTY AMONG SMALL SCALE POTATO FARMERS IN UASIN-GISHU COUNTY, KENYA

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DOI: <https://doi.org/10.5281/zenodo.14202921>

Published Date: 22-November-2024

Abstract: Climate change is negatively impacting agricultural activities and welfare of those depends on them in Kenya. Currently Potato farmers in Uasin-Gishu County are embracing the climate-smart agricultural technologies in order to alleviate household poverty. Previous studies show that these technologies enhance farming efficiency, productivity, household incomes and consequently alleviate poverty. However, despite efforts to implement these technologies among the potato farmers, scanty information exists on whether these technologies positively alleviate poverty or not. This study therefore aimed at filling this knowledge gap by examining the impact of climate-smart agricultural technologies on poverty levels among the small-scale potato farmers. The study utilized the innovation and diffusion theory and employed a descriptive research design. A sample of 155 respondents were selected using a multi-stage sampling technique from a population of 17,115 small-scale potato farmers. Data was collected through interviews and analyzed using the Foster Greer and Thorbecke measure of poverty. The mean income level of CSA non-adopters is 30,755.98, while the mean income level of CSA adopters is 48,588.09. This suggests that there is a positive association between CSA adoption and income level. Among the farmers who adopt climate-smart agricultural technologies, the poverty incidence, depth, and severity are significantly lower at 20.63%, 1.181%, and 0.28% respectively, compared to non-adopters at 55.43%, 15.19%, and 5.96%. These results suggest that the adoption of climate-smart agricultural technologies can effectively reduce poverty. The lower poverty incidence among adopters indicates a decrease in the number of individuals living below the poverty threshold, while the reduced poverty depth and severity indicate an improvement in the quality of life for those still experiencing poverty. Overall, these findings underscore the potential of climate-smart agriculture as a poverty reduction strategy, emphasizing the importance of promoting its adoption among small-scale farmers through reliable extension services and affordable credit facilities.

Keywords: Adoption, Climate-smart Agriculture, Income, Poverty, Small scale farmer.

1. INTRODUCTION

Potato production is an important agricultural activity in Kenya, contributing to food security, poverty alleviation, and economic development (Keya *et al.*, 2019). The International Potato Center (CIP) states that potatoes are the second most important food crop in Kenya, with over 800,000 smallholder farmers involved in their cultivation (CIP, 2015). However, potato production in Kenya is constrained by various factors, such as climate change, low soil fertility, pests and diseases,

lack of access to quality seed, and limited market opportunities (Mwema *et al.*, 2015). Regardless of these challenges, potato farming can generate high returns for smallholder farmers under favorable conditions and it can also contribute to food security and poverty reduction, particularly in areas where other crops struggle due to climate and soil conditions. (Ochieng *et al.*, 2016). Recognizing the importance of potato farming, the Kenyan government has implemented policies and programs to promote its growth, including the establishment of the National Potato Council of Kenya in 2016 (Ministry of Agriculture, Livestock, Fisheries and Cooperatives, 2020).

The impact of climate change is particularly pronounced in Africa due to its reliance on non-irrigated farming, high temperatures, low precipitation, and limited adoption of agricultural technologies (Partey *et al.*, 2018). Over the past century, Africa's temperature has risen by approximately 0.5 degrees Celsius, and it is projected to increase by an average of 1.4-3.9 degrees Celsius per year by 2099 (IPCC, 2014). Research conducted by the Intergovernmental Panel on Climate Change (IPCC) suggests that Sub-Saharan Africa may experience a reduction in agricultural output of 2.5 to 6% of GDP by 2100 (IPCC, 2007a). Additionally, the rural population is expected to reach 2 billion by 2050, exacerbating the challenges faced by regions such as the Arid and Semi-Arid Lands (ASALs), which are already vulnerable to food scarcity, hunger, and disease (Clark *et al.*, 2020; Kotir, 2011).

In Kenya, poverty levels are estimated to be 36.1%, with rural areas experiencing poverty rates above 70% (Diwakar and Shepherd, 2018). Climate change directly and indirectly affects agricultural production, leading to increased poverty among individuals and households. As a result, agrarian households are forced to adapt their agricultural practices in response to changing climatic and environmental conditions worldwide. According to available data, the poverty level in Uasin Gishu, Kenya is a significant concern among its population. According to a study conducted by the Kenya National Bureau of Statistics (KNBS) in 2019, it was found that around 32.5% of the population in Uasin Gishu is living below the poverty threshold (KNBS, 2019). This indicates that a significant portion of the region's population is facing economic difficulties and struggling to meet their basic needs. The high poverty level in Uasin Gishu has consequences for various sectors, including agriculture. Small-scale potato farmers, who make up a notable proportion of the population, are particularly susceptible to the impacts of poverty. Their productivity and overall economic well-being can be hindered by limited access to resources such as capital, quality inputs, and under-utilization of CSA technologies (Oluoko, 2011).

2. LITERATURE REVIEW

Rural areas are home to about 75% of the world's impoverished population, with agriculture being their primary source of income (Castaeda *et al.*, 2016). Agricultural growth has proven to be effective in reducing poverty and enhancing food security, particularly in countries where a significant portion of the population is engaged in agriculture (Castaeda *et al.*, 2016). Improving resource efficiency and increasing productivity are key approaches to achieving agricultural growth. Smallholder farmers in developing nations often face significant "yield gaps," which refer to the difference between their actual yields and the maximum potential yields (FAO, 2014). Closing these gaps by enhancing agro-ecosystem productivity and optimizing the efficiency of agricultural inputs such as soil, water, fertilizer, and livestock feed can lead to higher returns for farmers, poverty reduction, and improved food availability (FAO, 2014). Furthermore, these efforts tend to result in reduced greenhouse gas emissions compared to previous practices.

Empirical evidence from both developed and developing nations, including India, demonstrates that simple adaptation strategies within the context of Climate-Smart Agriculture (CSA) can boost agricultural output and farm revenue. Changes in cropping patterns, planting dates, and the adoption of new agricultural technologies that promote water efficiency have a positive impact on agricultural productivity and profitability, ultimately reducing poverty levels (Challinor *et al.*, 2014; Khatri *et al.*, 2016; Zulfigar *et al.*, 2017). Various studies have also shown that CSA techniques and technologies have increased crop output, resource efficiency, net farm revenue, and contributed to the reduction of greenhouse gas emissions (Xionget *et al.*, 2014).

Additionally, studies conducted in Pakistan have revealed that the adoption of new agricultural methods, technologies, and climate change adaptation measures significantly influence agricultural output, farm revenue, and resource efficiency. It has been found that increased farm revenue leads to a reduction in household poverty (Ali and Erenstein, 2017). Researchers have also highlighted the substantial impact of groundwater quality variations on agricultural production, farm revenue, and rural livelihoods in different regions of Pakistan (Hussain *et al.*, 2004; Ashfaq *et al.*, 2009; Shakooret *et al.*, 2015; Punthakay *et al.*, 2016). To address these challenges, farmers in Pakistan are increasingly utilizing CSA techniques and technologies that are water-smart, energy-smart, carbon-smart, and knowledge-smart (World Bank, 2017).

3. RESEARCH METHODOLOGY

The research project utilized a descriptive survey design to analyze the effect of climate smart agricultural technology on poverty level among small scale potato farmers in Ainabkoi and Kesses Sub-Counties. This study design was chosen as it allowed for data collection from a large population. The target population consisted of 17115 small scale potato farmers in the Ainabkoi and Kesses Sub-Counties of Uasin Gishu County. The sample size of 155 respondents for data analysis was determined using Yamane's (1967) formula for sample size determination. The study utilized a multi-stage sampling technique to collect primary data through interviews with small scale potato farmers. Descriptive statistics, such as frequencies and percentages, were employed to present the analyzed data. The impact of climate smart agricultural technologies on observed poverty among small scale potato farmers was analyzed using the Foster Greer and Thorbecke (2010) measure of poverty.

The FGT formula for poverty severity is given as follows;

$$FGT_a = \frac{1}{N} \sum_{i=1}^H \left(\frac{z - y_i}{z} \right)^a$$

Where;

H is the total number of low-income families with incomes below the poverty level.

y_i is the i^{th} individual household's revenue.

N is the number of households in total

Z is the poverty line

$\left(\frac{z - y_i}{z} \right)$ - Proportion shortfall in income below the poverty line.

When $\alpha=0$, The formula calculates the headcount index as well as the relative poverty and intensity with $\alpha=1$ and 2 respectively.

The formula for calculating head count is expressed as follows;

$$\text{Head count} = \frac{\text{Number of people living below the poverty line}}{\text{Total population}}$$

The P1 poverty gap index quantifies the degree to which individuals are below the poverty line (the poverty gaps) relative to the poverty line itself. The total of these poverty gaps represents the minimum expense required to eradicate poverty, assuming transfers were precisely directed. However, this measure does not account for any shifts in inequality within the impoverished population.

$$\text{Poverty Gap Index} = \frac{1}{N} \sum_{j=1}^q \left(\frac{z - y_j}{z} \right)$$

In this equation, N represents the overall population, q represents the total number of individuals living with incomes that fall at or below the poverty threshold, z represents the poverty line, and y_j represents the income of each impoverished individual, denoted as j. It should be noted that when calculating the poverty gap, individuals whose income exceeds the poverty line are assigned a gap value of zero.

4. RESEARCH FINDINGS AND DISCUSSION

The hypothesis of this study was that the adoption of CSA technologies has no significant effect on the level of poverty among the small scale potato farmers in Ainabkoi and Kesses Sub Counties. Table 4.1 shows the t-test for adopter and non-adopter category. Table 4.2 presents effect of adoption of CSA technologies on observed poverty among small-scale potato farmers.

Table 4.1: t-test for Poverty Measures among CSA Adopters and CSA non- adopters

Indicators	CSA adopters	CSA non-adopters
Mean	0.075733333	0.255266667
Variance	0.009633198	0.051896643
Observations	3	3
Pooled Variance	0.03076492	
Hypothesized Mean Difference	0	
df	16	
t Stat	-2.171318118	
P(T<=t) one-tail	0.022645912	
t Critical one-tail	1.745883676	
P(T<=t) two-tail	0.045291825	
t Critical two-tail	2.119905299	

CSA: climate smart agriculture

$\alpha=0.05$

$p=0.0453 < \alpha$.

According to Table 4.1, the t-test conducted to compare poverty measures between CSA adopters and CSA non-adopters resulted in a p-value of 0.0453, which is lower than the predetermined significance level of 0.05. This suggests that there is a significant difference in poverty levels between individuals who adopted CSA and those who did not.

Table 4.2: t-Test: CSA adopters and CSA non-adopters level of income

	CSA non-adopters	CSA adopters
Mean	30755.97826	48588.09524
Variance	249667683.6	738246186.6
Observations	92	63
Hypothesized Mean Difference	0	
df	91	
t Stat	-4.693967264	
P(T<=t) one-tail	0.000004712	
t Critical one-tail	1.661771155	
P(T<=t) two-tail	0.00000942401	
t Critical two-tail	1.986377154	

$\alpha=0.005$

Based on the results of the t-test in table 4.2, it was found that the mean income level of CSA adopters is significantly higher than that of CSA non-adopters. The mean income level of CSA non-adopters is 30,755.98, whereas the mean income level of CSA adopters is 48,588.09. This indicates a positive relationship between CSA adoption and income level. Additionally, the variance of income levels is greater among CSA adopters compared to non-adopters, indicating more variability in income levels among adopters. The t-statistic value of -4.69 further confirms that the difference in mean income levels between CSA adopters and non-adopters is statistically significant. The p-value for a one-tailed test is 0.000004712, which is below the significance level of 0.05, allowing us to reject the null hypothesis of no difference in mean income levels. The two-tailed p-value of 0.00000942401 also falls below the significance level of 0.05, signifying the statistical significance of the difference in mean income levels, regardless of the direction. Overall, these statistics indicate that CSA adopters have a higher mean income level than CSA non-adopters, and this difference is statistically significant.

Table 4.3: Effect of adoption of CSA technologies on observed poverty among small-scale potato farmers.

Indicators	Adopters N=63	CSANon N=92	AdoptersTotal
Incidence of poverty	0.2063	0.5543	0.7606
Poverty depth	0.0181	0.1519	0.17
Poverty severity	0.0028	0.0596	0.0624
Poverty line income	27360	27360	27360

Source: Author's Research Survey, 2022

Table 4.3 showcases the results obtained from the Foster-Greer and Thorbecke (2010) model regarding poverty incidence, poverty depth, and poverty severity index. These findings suggest a significant disparity between individuals who have adopted certain practices and those who have not, as indicated by the poverty indicators at a 5% level of significance. Specifically, among small-scale potato farmers who have adopted Climate-Smart Agriculture (CSA) and those who have not, the incidence of poverty was observed to be 20.63% and 55.43% respectively. This reveals an unconditional headcount ratio of poverty that is approximately 34.8% lower for CSA adopters compared to non-adopters. Consequently, it can be concluded that CSA non-adopters in Uasin Gishu County are more vulnerable to poverty than CSA adopters.

These findings are consistent with recent studies conducted by Belay and Mengiste (2021) on the impact of agricultural technology adoption on poverty in the north Shewa zone of the Amhara region, Ethiopia, as well as Habtewold (2021) who investigated the effects of climate-smart agricultural technology on multidimensional poverty in rural Ethiopia. Both studies found that adopting agricultural technology led to increased yields, improved household food security, and a reduction in poverty. These findings also support the study by Ofa *et al.*, (2021) regarding the positive influence of adopting improved agricultural technology on household poverty in eastern Ethiopia. Collectively, these studies highlight the potential of adopting improved agricultural technologies as a promising approach to achieving food security and reducing poverty in developing nations.

The findings also showed that the study area's poverty depth were 0.0181 for CSA adopters and 0.1519 for CSA non-adopters. The outcome suggests that, in order to raise poor CSA adopters' and CSA non-adopters' incomes from below poverty line to the poverty line income, respectively, 1.81% and 15.19% of per capita income are required. This indicates that, in the study area, CSA non-adopters experience poverty at a higher rate than CSA adopters. The overall poverty depth index for the sampled farmers was 0.17, indicating that approximately 17% of per capita income is needed to raise poor farmers in the study area from below the poverty line to the threshold level of poverty line income. The results is in support of Ogwumikeet *al.*, (2013), who found that the major cause of poverty in Nigeria was the reluctance of the farmers to adopt new farming techniques that will enhance their productivity.

In Uasin Gishu County, the poverty severity index was 0.0028 for CSA adopters and 0.0596 for CSA non-adopters. According to this finding, CSA adopters need per capita income increase of 0.28% or more to lift them out of severe poverty. The CSA non-adopters similarly require a 5.96% increase in per capita income to get themselves out of severe poverty. For the sampled farmers, an average severe poverty index of 0.0624 was found. Accordingly, it takes around 6.24% of per capita income to lift the small scale farmers who are trapped in extreme poverty above the poverty line. The findings are consistent with the research conducted by Edoumiekumoet *al.*, (2014), which revealed that rural farmers who rely on outdated farming methods are more susceptible to poverty. The study emphasized the need for government intervention to help these farmers overcome the challenges associated with poverty.

5. SUMMARY, CONCLUSION AND RECOMMENDATION

The findings of the study revealed notable discrepancies in poverty indicators between CSA adopters and non-adopters in Uasin Gishu County. Among CSA adopters, the incidence of poverty was 20.63%, the poverty depth was 1.81%, and the poverty severity was 0.28%. In contrast, CSA non-adopters had higher rates of poverty, with an incidence of 55.43%, a poverty depth of 15.19%, and a poverty severity of 5.96. These results highlight the significant impact of CSA adoption on reducing poverty among small-scale farmers.

This study supports the findings and recommendations of Ofa *et al.*, (2021) regarding the positive impact of improved agricultural technologies on food security and poverty reduction in developing countries. To promote the adoption of

climate-smart agricultural technologies among small-scale farmers, it is suggested to provide training and education programs, facilitate access to credit, and ensure the availability of high-quality inputs. Furthermore, the government should improve small-scale farmers' access to markets, storage facilities, and other essential infrastructure to enhance their profitability.

In conclusion, this study emphasizes the significance of adopting agricultural technologies in reducing poverty and achieving food security. Encouraging the adoption of climate-smart agricultural practices among small-scale farmers is crucial for improving their livelihoods and reducing poverty levels in rural areas.

ACKNOWLEDGEMENT

First I convey my sincere gratitude to the almighty God for blessing me with good health and wisdom throughout the study period. My special thanks goes to my able supervisors, Dr. Noah Kibet and Dr. Millicent Otiende for their tireless efforts, assistance and guidance during the process of my research work.

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