Adoption of climate-resilient potato varieties under partial population exposure and its determinants: Case of smallholder farmers in Meru County, Kenya

Sally Mukami Kimathi1,*, Oscar Ingasia Ayuya1 and Benjamin Mutai1

Abstract: Production of Potato (Solanum tuberosum. L) has been declining over the years in Sub-Saharan Africa due to climate change resulting into low food supply and low income among smallholder farmers. Despite Climate-Resilient Potato Varieties (CRPVs) having the potential of increasing farmers’ resilience to climate change, previous studies show that uptake of these varieties is still significantly low. More so, standard techniques such as Tobit and Probit models yield biased adoption rate estimates despite existence of vast literature on technology adoption. This study sought to determine true population adoption rates under partial exposure and their determinants using the modern Average Treatment Effect (ATE) framework. Multistage sampling technique was used to sample 384 farmers from Meru County. Focus group discussions and structured questionnaires through household survey were used to collect primary data. Results revealed that the main factors affecting adoption were access to information, quality seeds, training, group membership and variations in agro-ecological zones. The actual population adoption rate was 6.3% whereas the potential adoption rate was 30.7% revealing an
adoption gap of 24.4% due to partial exposure. To improve adoption rates, this study recommends increased efforts in exposing farmers to CRPVs through training and increased extensions services.

**Subjects:** Agriculture & Environmental Sciences; Statistics for Social Sciences; Economics; Environmental Economics

**Keywords:** climate-resilient-varieties; adoption; ATE; potatoes; Kenya

1. Introduction

Potato (Solanum tuberosum. L) is an important food crop in Kenya. It doubles up as a major source of income and a staple food. Despite being a key crop, farm produce is usually below the potential level at 8–15 T/ha against a potential production of 40–50 T/ha (CIP, 2019; Kyamanywa et al., 2011; Ogeto et al., 2019). This low productivity has been majorly attributed to adverse effects of climate change and variability such as increased severity of pests and diseases, lack of quality seeds and other inputs such as fertilizers, and poor extension services (Gildemacher et al., 2009). Reduced precipitation due to prolonged drought has resulted in reduced yields in the previous cropping seasons. Further, increased temperatures due to global warming has led to emergence of new pests and diseases, heat stress on plants and increased cases of late blight and bacterial wilt (Patrick et al., 2020).

Heat stress due to increased humidity and high temperatures results into drying of seed materials and causes potato plants to produce small, poor quality tubers that fetch very low market prices (Chakraborty & Newton, 2011). Singh et al. (2020) further argues that heat stress on potatoes reduce crop yield especially at the tuber formation stage which is highly sensitive to increasing temperatures. Heavy rains also increase the incidence of bacterial wilt and late blight hence resulting into reduced yields. Floods cause seeds to rot when planted and make land preparation and planting difficult (Mwongera et al., 2019). To counter these effects, some farmers either abandon that variety or increase input use in terms of chemicals sprayed, which are quite costly for the smallholder farmer (Sinelle, 2018).

Potato production is highly susceptible to variations in rainfall. To yield an approximate of 20 T/ha in one farming season, a minimum of 575 mm of rainfall is required. During the 2016–2017 drought in Kenya, a tremendous reduction in potato yields of 56% was reported due to reduced rainfall which reduced from seasonal mean of 737 mm to 126 mm (International Potato Center, 2017). Furthermore, predictions show that due to global warming, equatorial East Africa is likely to further experience 5–20% increased rainfall during the short rain season and 5–10% decreased rainfall during the long rain season by 2050 (Dai, 2011). This is bound to greatly reduce potato production if farmers do not embrace adaptation practices to increase their resilience against climate change and variability.

To counteract the effect of climate change, various actors in agricultural sector are promoting farming practices and technologies termed as Climate Smart Agriculture (CSA) among other coping strategies (Chandra et al., 2018). These practices and technologies include crop rotation, agro-forestry, intercropping, maintenance of soil cover, minimum tillage, residue retention, conservation of water, improved livestock management, climate-resilient crop varieties and animal breeding to adapt to future hostile conditions. Compared to convention methods of production in agriculture, CSA has been documented to register stable and higher yields and thus stable income from farming leading to high resilience in some regions (Wekesa et al., 2018).

Previous studies show that farmers have adopted different climate smart innovations to adapt to climate change and variability. A study by Senyolo et al. (2018) reveals that climate smart agricultural innovations such as Conservation Agriculture, rainwater harvesting, and seed varieties
that are adapted to climate change have the potential to address climate-related challenges. However, Conservation Agriculture requires intensified management whereas rainwater harvesting is normally associated with high initial investment costs, intensified labour and management hence making it difficult for smallholder farmers to adopt them. On the other hand, seed varieties adapted to climate change in terms of maturation period and resistance to pests and diseases are said to be less costly when accompanied by appropriate agronomic practices, less management intensive and hence have a better chance for adoption by farmers (Atlin et al., 2017). According to Fadina and Barjolle (2018), farmers prefer improved crop varieties as the mainstream strategy to cope with climate change.

Previous studies also show that in addition to increasing farmers’ resilience to climate change effects, crop production levels can double up without expanding the area under production by developing, disseminating, and adoption of climate resilient varieties (Parker et al., 2019). This has prompted research organization such as KALRO and CIP into developing potato varieties that are climate smart in the last 15 years in Kenya. These varieties are usually characterized by heat tolerance, resistance to drought, and resistant to pests and diseases, for instance, Unica which was released in 2005. In 2016 and 2017, 5 climate-resilient potato varieties were released by CIP which have the properties of tolerance to water stress and increased resistance to late blight and bacterial wilt (International Potato Center, 2017). The varieties include Unica, Wanjiku, Lenana, Chulu and Nyota. Improvement of potato varieties can be a pathway to climate change resilience, increased production, and food security in Kenya (Kyamanywa et al., 2011).

However, adoption of these climate resilient potato varieties is said to be low in Kenya. A study by Kagwungo et al. (2008) shows that adoptions rates for improved potato varieties in Uganda are higher than those of Kenya by 24.8%, a difference that is quite significant. According to Bondiera and Rasul (2006), uptake of agricultural technologies is usually poorly understood by farmers hence resulting to slow adoption. Awareness of climate-resilient potato varieties by farmers is said to be one of the most constraining factor to the uptake. More so, standard techniques such as Probit and Tobit used by previous studies that do not control for exposure tend to yield biased adoption rates estimates. Therefore, this paper explores various agronomic adaptation practices by potato farmers in Meru county, estimates true population adoption rates while controlling for exposure/awareness using the Average Treatment Effect Framework and determines factors influencing adoption rates of climate-resilient potato varieties.

Smallholder farming is critical for the economic development of Kenya (IFAD, 2008). Smallholder potato farming is mainly concentrated in the central and Rift valley, and Mount Kenya regions. Meru County, which is located in the Mt. Kenya region, is among the leading potato producing counties in the country. Potato is grown for both commercial and household consumption purposes and takes up 3.3% of the county’s total agricultural land (Republic of Kenya, 2013). However, smallholder farmers are believed to be the most hit by the negative events of climate change and variability and are assumed to have inadequate knowledge and resources regarding response mechanism (IPCC, 2014). Instead of adopting adaptation strategies, most smallholder farmers respond by abandoning the varieties or reducing their investments in farming which further results into low crop production, threatening food security in the country.

2. Methodology

2.1. Study area
The study was carried out in Meru County, Kenya. Meru county is an agricultural county whereby 23% of its overall land is under food crop including potato. It is located on the eastern side of Mt. Kenya. According to Republic of Kenya (2013), Meru County occupies an overall land area of 693,620 hectares (Ha). It has an altitude that lies between 2230 and 2900 m above the sea level. The estimated potato-producing area is 17,534 Ha with production being 196,434 T (CIP, 2019). The county lies between longitudes 38° East and 37° West and also along the equator at
latitudes 0°6’ North and 0°1’ South. It is made up of 45 Wards and 9 Sub-Counties, namely; Tigania West, Tigania East, Igembe Central, Igembe North, Igembe South, Imenti North, Imenti South, Central Imenti, and Buuri (Republic of Kenya, 2013).

Meru County is characterized by four main agro-ecological zones; the upper highlands where potatoes are mainly grown, the lower highlands, the upper midlands and the lower midlands which is a semi-arid area. The upper highlands have an average precipitation of 700 mm to 1000 mm per year and average temperatures ranging from 14.90 to 10.50°C. The altitude levels ranges from 2230–2900 mm above sea level. The lower midlands have an average rainfall of 580–1600 mm and 24.0°C-20.90°C temperatures. The altitudes range from 750 to 1300 m above sea level (Jaetzold et al., 2007). This zone falls in arid and semi-arid areas.

The data used for the study was cross-sectional and was obtained from household survey at farm level conducted by well-trained enumerators and administered through structured questionnaires. Cross-sectional survey method was used because it allows researchers to collect data on different variables at a given point in time and determine possible relationships with the critical variables of interest which were adoption and exposure. It also provides information about what is happening in the current population which was vital in estimation of true population adoption rates for climate-resilient potato varieties while controlling for exposure. Furthermore, cross-sectional analysis does not need an assumption that the nature of relationship between variables is stable overtime (Ntshangase et al., 2018). The sample was drawn from smallholder potato farmers in various agro-ecological zones of Meru County using multistage sampling technique. In the first stage, Meru County was selected purposively because it is among the highest potato-producing counties in Kenya. In the second stage, three out of the nine sub-counties were selected based on potato production and climatic conditions. Imenti South, Imenti Central, and Buuri Sub-counties were purposively selected. In the third stage, four wards (Abothuguchi West, Abogeta West, Kiuru/Naari, Kibirichia) were randomly selected from the three sub-counties and finally, in the final stage, a random sample of 384 farmers was selected from the four wards using simple random sampling technique. Data collected at farm-level included farmer knowledge of climate-resilient potato varieties and varieties cultivated in the 2018/2019 cropping seasons. Prior to the survey a list of known climate-resilient and traditional potato varieties in the wards was constructed and respondents selected for the survey were asked whether they knew each of the varieties. For a “yes” answer the farmer was asked whether they ever cultivated the variety in the 2018/2019 cropping seasons. In this study awareness or exposure was defined as knowledge to a climate-resilient potato variety while adoption was cultivation of the variety in the 2018/2019 cropping seasons. Multi-stage sampling and simple random sampling were used to ensure that the sample was representative, complete, unbiased, and reliable for this study. Table 1 shows the distribution of the sample size in the county.

### 2.2 Analytical framework

Recent literature on uptake of agricultural technologies has acknowledged that awareness is a necessary condition for uptake, (Diagne & Demont, 2007; Simtowe et al., 2016) hence shifting

| Wards          | Population | Percentage | Sample Size Proportion |
|----------------|------------|------------|------------------------|
| Abothuguchi West | 35,901     | 30.51%     | 117                    |
| Abogeta West    | 30,338     | 25.78%     | 99                     |
| Kiuru/Naari     | 27,031     | 22.97%     | 88                     |
| Kibirichia      | 24,409     | 20.74%     | 80                     |
| Total           | 117,679    | 100%       | 384                    |

Source: (Ngugi et al., 2013)
from the use of classical models such as logit and probit. This is because, classical models are associated with inconsistent results due to non-exposure and selection biases. Non-exposure bias results from the fact that farmers who are not exposed to the new technology will not adopt it even if they had the capacity to had they been exposed (Simtowe et al., 2011). This leads to underestimation of true population adoption rates. Exposure is usually non-random and may also suffer from selection bias.

Therefore, a modern evaluation technique, the Average Treatment Effect (ATE) Framework was used so as to control for both non-exposure and selection biases leading to estimation of true population adoption rates and determinants of uptake as recommended by (Diagne & Demont, 2007) and modified by (Muthini, 2018; Simtowe et al., 2016).

The treatment variable was exposure or awareness to at least one climate-resilient potato variety. The “treated” were those exposed whereas the unaware were the “untreated”. According to Wooldrige (2002), the ATE parameter is a measure of the population mean potential adoption outcome. The difference between the population mean potential adoption outcome and observed adoption outcome is the non-exposure bias which is basically the adoption gap (Diagne & Demont, 2007).

The treatment effect estimation is usually grounded on a counterfactual outcome framework. Following Rosenbaum and Rubin (1983), let $Y_1$ = Potential adoption outcome of a farmer when exposed to climate-resilient potato varieties and $Y_0$ = Potential adoption outcome when not exposed. Since exposure is a necessary condition for uptake, $Y_0 = 0$ thus;

$$E(Y_1 - Y_0) = E(Y_1) = ATE$$

(1)

That is the adoption impact of farmer $i$.

Since $Y_1$ is only observed for the exposed population, $E(Y_1)$ underestimates the true population impact of adoption. Thus;

Let $w = 1$ denote exposure and $w = 0$ otherwise. The impact of exposed sub-population (ATE1) can be derived as a conditional-expected value which applies also for the non-exposed sub-population (Asuming-Brempong et al., 2011).

$$ATE_1 = E(Y_1/w = 1)$$

$$ATE_0 = E(Y_1/w = 0)$$

(2)

The two equations in 2 show consistent estimates of the average impact of adoption on the two sub-populations. If $\pi(w = 1)$is the probability of exposure, then the expected adoption impact on total population ATE can be obtained by taking the difference of the two equations in (2) to get;

$$ATE = E(Y_1) = \pi(w = 1) \times ATE_1 + 1 - \pi(w = 1) \times ATE_0$$

(3)

$$ATE_0 = \frac{ATE - \pi(w = 1) \times ATE_1}{\pi(w = 0)}$$

(4)

From here, we can obtain the non-exposure bias (NEB) which is also a measure of the adoption gap, and the population selection bias (PSB):

$$NEB = \pi(w = 1) \times ATE_1 - ATE$$

(5)

$$PSB = ATE_1 - ATE$$

(6)

Adoption can be obtained as an observed outcome $Y$: 

\[ Y = wY_1 + (1 - w)Y_0 = wY_1 \]  

Identification of ATE is based on the assumption of conditional independence which states that status of treatment is independent of potential outcomes conditioned on an observed set of covariates \( x \). The ATE adoption model can be estimated using two models according to Diagne and Demont (2007): Pure Parametric Approach and the two stage approach. This study used the parametric regression-based method where covariates were interacted with treatment variables to account for any heterogeneous impact. Parametric approach was used because parametric tests are said to have a higher statistical power than non-parametric tests. The pure parametric method was also used because there is no much difference between the pure and semi-parametric method (Dibba et al., 2012). The equation that identified ATE \( (x) \) was given as:

\[ \text{ATE}(x) = E(Y_1 / x) = E(Y / x, w = 1) \]  

A parametric model for the conditional expectation was then specified as:

\[ E(Y / x, w = 1) = g(x, \beta) \quad (9) \]

Where \( g \) was a parametric probabilistic model since \( Y \) was a binary variable, of covariates \( x \) and unknown parameter vector \( \beta \), which was estimated using maximum likelihood estimation procedures using observations \( (Y, x) \) from the exposed sub-population only. After estimating \( \hat{\beta} \), predicted values of \( g(x_i, \hat{\beta}) \) were computed for all the observations in the sample, both exposed and non-exposed sub-populations (Simtowe et al., 2016). Therefore, the estimated average treatment effects were given by:

\[ \hat{\text{ATE}}_E = \frac{1}{n} \sum_{i=1}^{n} g(x_i, \hat{\beta}) \quad (10) \]

\[ \hat{\text{ATE}}_1 = \frac{1}{n_e} \sum_{i=1}^{n_e} w_i g(x_i, \hat{\beta}) \quad (11) \]

\[ \hat{\text{ATE}}_0 = \frac{1}{n - n_e} \sum_{i=1}^{n_e} (1 - w_i) g(x_i, \hat{\beta}) \quad (12) \]

\[ \hat{\text{JE}}_A = \frac{1}{n} \sum_{i=1}^{n} Y_i \quad (13) \]

The effects of determinants of uptake were estimated as measures of marginal effects of the vector of covariates \( x \) at a given point \( \bar{x} \):

\[ \frac{\partial E(Y_i / \bar{x})}{\partial x_m} = \frac{\partial g(x, \hat{\beta})}{\partial x_m} \quad m = 1 \ldots m \quad (14) \]

For the factors influencing exposure, parametric estimation of ATE reduced to a standard probit estimation restricted to the exposed sub-sample. The estimation was done in STATA using STATA routine developed by Diagne and Demont (2007).

3. Results and discussion

3.1. Adaptation practices among potato farmers in Meru County

Besides estimating adoption rates of CRPVs, this study also sought for other agronomic adaptation practices embraced by potato farmers in Meru County. This section presents descriptive results of a comparison of different agronomic adaptation practices against climate change by adopters and non-adopters of climate-resilient potato varieties as shown in Table 2. The average land size under potato production per farmer in the study area was about 1.55 acres as per each cropping season.
From the above results in Table 2, most adopters of climate-resilient potato varieties had also adopted appropriate agronomic practices to maximize on yield and increase resilience against adverse effects of climate change. Of all the adopters, 91.67% practiced seasonal crop rotation. Crop rotation reduces the rate at which pests and diseases spread in the agricultural land hence reducing the negative effects of climate variability (Fadina & Barjolle, 2018). There were significant differences between adopters and non-adopters using irrigation and organic fertilizers at 1% and 10%, respectively, with adopters having higher percentages that is 70.83% and 95.83% respectively. Issahaku et al. (2019) argued that irrigation could play a positive role in minimizing the adverse effects of rainfall variability. On the other hand, use of organic fertilizers could help with adapting to climate change since fertilizers tend to replenish soils of nutrients that have been depleted over time due to continuous cropping. This finding is consistent with Issahaku et al. (2019) who argued that fertilizers used in recommended proportions increased crop productivity.

Intercropping was practiced by 75% of the adopters whereas soil conservation measures such as minimum tillage, mulching and terracing were practiced by 33.33% of the adopters of climate resilient potato varieties. Intercropping is said to reduce soil erosion which is as a result of adverse weather conditions. It also acts as a form of preserving food and nutrition security of the household since farmers argue that if one crop fails another one will at least produce significant yield (Fadina & Barjolle, 2018). Soil conservation is an important adaptation measure as it helps preserve fertile soils that are crucial for crop growth and productivity. Asrat et al. (2018) reported that farmers were more likely to adopt soil conservation measures in areas that were more susceptible to the risks of climate change.

To reap maximum benefits from adoption of CRPVs in increasing farmers’ resilience against climate change and variability, it is important for potato farmers to combine climate resilient varieties with appropriate agronomic practices.

### 3.2. Determinants of exposure to CRPVs

This section presents results for the parametric (probit) estimation of the exposure model which was estimated using the ATE framework. Exposure/awareness was considered as a binary variable with an exposed farmer being one aware of one or more of climate-resilient potato varieties. The fitness results of the model are presented in the lower panel of Table 3. The number of observations was 384. The log likelihood for the fitted model was −124.902 whereas the log likelihood chi-squared was 68.92 and significant at 1% level of significance indicating that the model had a strong explanatory power. Pseudo R² of 21.6% was above the statistical threshold of 15% confirming that effects on exposure to CRPVs was attributed to covariates considered in the model. From the entire sample, 14.6% were exposed to either one or more CRPVs. The empirical results in Table 3 showed that education, land size owned, group leadership, number of trainings attended, number of groups, credit access and Kiirua/Naari location were statistically significant in determining exposure to CRPVs.

| Agronomic Practices       | Adopters (n = 24) | Non-adopters (n = 360) | Chi2 |
|---------------------------|-------------------|------------------------|------|
| Crap Rotation (%Yes)      | 91.67             | 91.11                  | 0.009|
| Irrigation (%Yes)         | 70.83             | 43.89                  | 6.586***|
| Organic Fertilizer (%Yes) | 95.83             | 79.72                  | 3.754*|
| Intercropping (%Yes)      | 75.00             | 78.05                  | 0.122|
| Soil Conservation (%Yes)  | 33.33             | 23.06                  | 1.314|

***, **, * = level of significance at 1%, 5% and 10% respectively.
Table 3. ATE Parametric (Probit) Estimation of Exposure Model

| CRPV Aware                  | Coefficients | Robust Std. Errors | P>|z| | dy/dx |
|-----------------------------|--------------|--------------------|--------|--------|
| Socio-economic factors      |              |                    |        |        |
| Household Head Age          | 0.073        | 0.051              | 0.155  | 0.012  |
| HHAge²                     | −0.001       | 0.000              | 0.204  | −0.000 |
| HH Gender                   | 0.297        | 0.205              | 0.147  | 0.048  |
| HH Education                | 0.163***     | 0.061              | 0.007  | 0.028  |
| Institutional factors       |              |                    |        |        |
| Farm size                   | −0.208***    | 0.081              | 0.010  | −0.035 |
| Group leadership            | 0.585**      | 0.282              | 0.038  | 0.126  |
| No. of groups               | −0.243**     | 0.121              | 0.044  | −0.041 |
| No. of trainings attended   | 0.286***     | 0.067              | 0.000  | 0.048  |
| Soil fertility level        | −0.356*      | 0.183              | 0.052  | −0.060 |
| No. of Extension visits     | 0.161        | 0.129              | 0.212  | 0.027  |
| Credit used for Farming     | 0.491**      | 0.219              | 0.025  | 0.098  |
| Locations                   |              |                    |        |        |
| Kibiricha                   | 0.262        | 0.267              | 0.326  | 0.045  |
| Kiuru/Naari                 | −0.591*      | 0.336              | 0.078  | −0.085 |
| Abogeta West                | 0.167        | 0.347              | 0.630  | 0.031  |
| Goodness of fit             |              |                    |        |        |
| No. of observations         | 384          |                    |        |        |
| Log likelihood              | −124.902     |                    |        |        |
| Likelihood Ratio (Chi²)     | 68.92***     |                    |        |        |
| Pseudo R²                   | 0.216        |                    |        |        |

***, **, * = level of significance at 1%, 5% and 10% respectively.

The effects of the household head’s level of education was positive and statistically significant at 1%. This means that an increase in household head’s education level by 1% increases the propensity of being exposed to CRPVs by 2.8%. Education influences exposure in that, household heads who are more learned have a higher propensity of being exposed because they can seek more information and knowledge about CRPVs. Education enhances the ability of farmers to acquire, synthesize, and respond quickly to disequilibria hence increasing their probability of being exposed. This is in line with literature as shown by (Simtowe et al., 2011). Further, education enhances reasoning capability and awareness of a farmer placing them in a better position to recognize risks associated with climate change and therefore in search for coping strategies, the propensity of being exposed to CRPVs becomes higher. The finding is also similar to Chandio and Yuansheng (2018) and Kumar et al. (2016) where level of farmer’s education is reported to have a positive and significant influence on exposure to farm technology.

Farm size had a negative and significant effect on propensity of exposure. An increase in farm size by 1% reduced the probability of being exposed to CRPVs by 3.5%. This could be attributed to the fact that a farmer who owned less land was more likely to be exposed to CRPVs because land pressure on small plots obligates farmers to find solutions to increase farm productivity. Thus, in search of high yielding varieties, these farmers are more likely to get exposed to CRPVs.
On the contrary, Kabunga et al. (2012) and Baiyegunhi et al. (2019) reported a positive and significant influence of land size on awareness and argued that land size can be used as a proxy for wealth whereby farmers with larger land plots were considered to be wealthier and hence were more likely to afford the cost of knowledge acquisition. Amengor et al. (2018) also reported that farmers with more plots had a higher propensity of being exposed to climate-resilient varieties because with more plots, farmers were likely to search for more crop varieties increasing their chances of being exposed to improved varieties.

A farmer being a leader in a farmers’ group increased the chances of being exposed to CRPVs. The results show that the effect was positive and significant at 5% level of significance. Being a leader increased the propensity of exposure by 12.6%. Group leaders tend to have more contacts with extension officers, agricultural experts and access more training forums than the members. They also act as entry points for various farm innovations as in most cases, their farms are used as demonstration plots. From the focus group discussion report, most group leaders were referred to as Decentralized Seed Multipliers (DSMs) as they were responsible for multiplying seeds for other group members. This was an arrangement between farmers and non-governmental organizations such as CIP and FIPS Africa who are key disseminators of improved seed varieties to farmers. Wossen et al. (2015) reported similar findings and argued that holding a leadership position can be used as a measure of social capital since it provides the household with formal and informal support and information dissemination.

There was a negative and significant effect of number of groups a farmer was in, on exposure. The higher the number of groups, the lower the propensity of being exposed to CRPVs. This could possibly be explained by the fact that not all farmer groups are based on potato farming whereas CRPVs are mainly discussed only in potato-based farmer groups. The results were contrary to Hunecke et al. (2017) and Kabunga et al. (2012) who found a positive effect of group membership emphasizing on the role of social networks and social capital in dissemination of information.

The effect of number of trainings attended by a farmer was positive and significant at 1% significance level whereby, an increase in the number of trainings attended by 1% increased the probability of being exposed by 4.8%. Farmers who attend more trainings on potato farming are more likely to get exposed to CRPVs because they acquire knowledge and information on climate change adaptation using improved varieties. More so, trainings are offered by different stakeholders who comprise climate change adaptation experts, seed providers among others. Trainings also come with field demonstrations hence increasing the propensity of exposure to CRPVs for farmers who attend such trainings. These results are in line with literature for instance, Mwololo et al. (2019) who argued that improved varieties are usually introduced and promoted through training of farmers in organized groups. Similar results were also reported by (Aryol et al., 2018).

Soil fertility level had a negative and significant effect on exposure. Farmers whose farms were acidic or less fertile were less likely to seek information on CRPVs. A 1% change in soil fertility level to the negative side resulted reduced propensity of a farmer being exposed by 6%. Farmers whose farms were revealed to be fertile through the test had a higher propensity for exposure. These results are consistent with previous assertions from farmers in the study area where farmers who had conducted soil tests and found their farm soil fertile showed more interest in learning about adapting to climate change through use of improved varieties (Abdulai, 2016; Chandio & Yuansheng, 2018; Tadesse et al., 2017).

Access to credit for farming had a positive effect on propensity of being exposed that was significant at 5% level of significance. Farmers who had access to credit had a higher probability of being exposed to CRPVs. An increase in credit used for farming by 1% results in an increase in the propensity of exposure by 9.8%. Access to credit is usually accompanied by extension services including risk management which involves climate change adaptation practices such as the use of CRPVs. This increases the propensity of farmers with access to credit of being exposed to CRPVs.
This was in line with Mwololo et al. (2019) who argued that access to credit acted as an incentive for farmers to seek more information about CRPVs to maximize on returns. Further, Aryal et al. (2018) reported similar results and argued that farmers with access to credit are more likely to adopt resource-saving agricultural practices such as drought-resistant varieties hence are more likely to be exposed to CRPVs.

The effect of a farmer being located in Kiirua/Naari on exposure to CRPVs was negative and significant at 10% level of significance. The probability of a farmer in Kiirua/Naari being exposed to CRPVs decreases by 8.5%. This could be explained by various reasons such as the climatic conditions of Kiirua/Naari in relation to climatic conditions of Abothuguchi West. According to literature, potato is said to be a cool season crop which grows in areas with temperatures between 15ºC and 18ºC (Muthoni et al., 2017). However, Kiirua/Naari is characterized by higher temperatures falling in between 24.0ºC-20.90ºC. This negatively affects the growth of potato varieties discouraging farmers from growing potatoes. This lowers farmers’ propensity of being exposed to CRPVs which have the ability of doing well in such harsh climatic conditions due preferred attributes of resistance to heat stress. These findings were similar to (Amengor et al., 2018; De Groote et al., 2016) who argued that awareness of CRPVs is location-specific.

### 3.3. Adoption rates for CRPVs

Table 4 presents results of Average Treatment Effect (ATE) corrected adoption rates including the actual Joint Exposure and Adoption (JEA) and potential ATE adoption rates and the adoption gap which is given by the difference between JEA and ATE, that is, (GAP = JEA-ATE). Adoption gap originates from incomplete exposure to climate-resilient potato varieties among the sampled farmers. ATE is the effect of a treatment on a randomly selected person from the population. In this study, “treatment” is the exposure to one or more CRPVs whereas the average treatment effect (ATE) on adoption outcomes is the potential adoption rate which is the rate of adoption when all farmers are exposed the CRPVs.

The results indicate that 14.6% of all the farmers sampled were aware of at least one CRPV. This incomplete exposure to CRPVs restricted the Joint Exposure and Adoption rate (JEA) to 6.3% which was the actual adoption rate whereas the potential adoption rate (ATE) was at 30.7%. The

| CRPV Adopt                        | Parameter | Std. Err. | P > z |
|-----------------------------------|-----------|-----------|-------|
| ATE (Potential adoption rate)     | 0.307***  | 0.033     | 0.000 |
| ATE1 (Adoption rate among exposed sub-sample) | 0.433***  | 0.038     | 0.000 |
| ATE0 (Adoption rate among non-exposed sub-sample) | 0.285***  | 0.035     | 0.000 |
| JEA (Joint exposure and adoption rate) | 0.063***  | 0.006     | 0.000 |
| GAP (Adoption gap)                | −0.244*** | 0.029     | 0.000 |
| PSB (Population selection bias)   | 0.126***  | 0.025     | 0.000 |
| Observed                          | Ne/N      | 0.146***  | 0.018 |
|                                  | Na/N      | 0.063***  | 0.012 |
|                                  | Na/Ne     | 0.429***  | 0.085 |

***, **, * = level of significance at 1%, 5% and 10% respectively.
adoption rate of CRPVs could have been 30.7% in Meru County if the whole population was exposed instead of the Joint and Exposure rate of 6.3%.

The difference yields an adoption gap of 24.4% which is attributed to the incomplete exposure. The estimated adoption gap was negative and statistically significant at 1% level of significance. This means that there is a potential of increasing the actual adoption rate by 24.4% if all farmers are made aware of one or more climate-resilient potato varieties (Simtowe et al., 2016). Furthermore, the joint exposure and observed adoption rates are considered to be inaccurate indicators of adoption due to non-exposure bias. The true population adoption rate corresponds to ATE which is the potential adoption rate after correcting for heterogeneous exposure (Muthini, 2018).

ATE1 which can be defined as the adoption rate among the exposed sub-sample or the treated sample, shows that 43.3% of the farmers exposed to CRPVs grew at least one of them in the reference period. The mean potential adoption rate among the non-exposed sub-population (ATE0) was estimated at 28.5%. The population selection bias (PSB) which was estimated at 12.6% is a measure of the difference between the potential adoption rate in the exposed sub-population and the actual population adoption rate.

The population selection bias is highly significant at 1% implying that the probability of adoption for a farmer from the exposed sub-population is different from the probability of adoption of CRPVs for a farmer randomly selected from the entire population. According to literature, positive PSB could occur due to either self-selection of farmers into exposure or progressive farmers being targeted by extension workers or both (Diagne & Demont, 2007).

### 3.4. Determinants of adoption of CRPVs

Table 5 presents results on the determinants of climate-resilient potato varieties uptake for the classical “adoption” model and the ATE parametric (probit) adoption model. The results of model fitness are presented in the lower panel of Table 5. The number of observations was for the ATE corrected parametric model was 57. The log pseudo likelihood for the fitted model was −16.549 whereas the Wald chi-squared was 32.60 indicating that all parameters were jointly significant at 1% and the model had a strong explanatory power. Pseudo R² of 56.7% was above the statistical threshold of 15% confirming that effects on exposure to CRPVs was attributed to covariates considered in the model.

Consistent with theoretical expectation, there was a notable difference in the magnitude of the coefficients between the two models. The magnitude of the marginal effect of a factor determining adoption without controlling for exposure computed from the classical adoption model is always between 0 and 1 and is very small in most cases when few farmers are aware of the improved technology. This is because the magnitude of the marginal effect is calculated from multiplying the marginal effect of the true adoption model by the conditional probability of awareness (Diagne & Demont, 2007). It is also important to note that some coefficients may be significant in either one model or both.

Results show that gender of the household head had a negative and significant effect on the uptake of climate-resilient potato varieties at 5% level of significance. Female-headed households had a higher propensity to adopt CRPVs than males. The probability of adopting at least one variety of climate-resilient potatoes decreases by 21.1% with being a male farmer. Women farmers are responsible for half of world’s food production and usually produce around 60–80% of food in developing countries (Doss, 2014). Therefore, they are more concerned with varieties (climate-resilient varieties) that ensure consistent production despite the prevailing climatic shocks. Potato is also referred to as a female crop where most females are engaged in potato growing whereas males mostly grow perennial crops such as coffee and tea in the study area. This is consistent with...
| CRPV Adopt | ATE Corrected Adoption | Classical Adoption |
|------------|------------------------|---------------------|
|            | Coefficient (RSE)      | dy/dx               | Coefficient (RSE) | dy/dx |
| Gender (male) | -1.981 (0.996)       | -0.211**            | -0.303 (0.332)   | -0.007 |
| Age of Household head | 0.465 (0.233)       | 0.021**             | 0.244 (0.101)    | 0.005** |
| HHAge² | -0.004 (0.002)       | -0.000**            | -0.002 (0.001)   | -0.000** |
| Size of Household | -1.009 (0.654)      | -0.047              | -0.196 (0.109)   | -0.004* |
| Decision Maker | 1.871 (0.794)      | 0.086**             | 0.538 (0.192)    | 0.011*** |
| Farm Size | 1.008 (0.996)        | 0.022               | 0.009 (0.019)    | -0.000 |
| Distance to Agricultural office | 0.044 (0.079)    | 0.002               | 0.482 (0.521)    | 0.008 |
| Credit Access |                      |                     | 0.002            | 0.000 |
| Total Land under Potatoes | -0.053 (0.304)   | -0.002              | -0.002           | 0.003 |
| Information on Climate Change | 1.489 (0.650)   | 0.019**             | 0.904 (0.578)    | -0.027 |
| Soil Fertility Level | -0.129 (0.157)        |                     | 0.006***        | 0.008 |
| No. of trainings attended | 0.234 (0.084)      | 0.011***            | 0.426 (0.319)    | 0.002 |
| No. of Extension visits | 0.922 (0.460)       | 0.043**             | 0.085 (0.146)    | 0.002 |
| No. of farmer groups | -0.610 (0.590)       |                     | -0.610 (0.590)   | 0.008 |
| Extension Services |                      |                     | 0.022            | 0.002 |
| Lack of seeds | -1.069 (0.612)       | -0.041**            | -0.119 (0.303)   | -0.002 |
| Household Education |                      |                     | 0.081 (0.092)    | 0.002 |

(Continued)
| CRPV Adopt       | ATE Corrected Adoption | Classical Adoption |
|------------------|------------------------|--------------------|
|                  | Coefficient (RSE) | dy/dx  | Coefficient (RSE) | dy/dx |
| Credit used for farming | 2.492 (0.883) | 0.119*** | 0.306 (0.517) | 0.007 |
| Other farmers    | 2.415 (1.200) | 0.230** | -0.490 (0.338) | -0.010 |
| Kibirichia       | 5.408 (1.975) | 0.992*** | -1.708 (0.618) | -0.023*** |
| Kilua/Naari      | 3.537 (1.641) | 0.833** | -0.303 (0.378) | -0.005 |
| _cons            | -19.290 (6.909)*** | 384 |
| Number of Observations | 57 | 384 |
| Wald chi²        | 32.60*** | 82.90*** |
| Log pseudo likelihood | -16.549 | -54.360 |
| Pseudo R²        | 0.567 | 0.394 |

***, **, * = level of significance at 1%, 5% and 10% respectively.
previous literature as shown by Simtowe et al. (2016) who found out that women farmers preferred cultivation improved pigeon pea due to its high protein content.

Age of the farmer had a positive and significant influence on adoption indicating that the older the farmer, the higher the propensity to adopt. An increase in age by 1% increases the probability of adoption by 2.1% which was significant at 5% level of significance. This could be attributed to the fact that the older a farmer gets, the more experience they gather with the potato crop, acknowledging the benefits associated with growing an improved variety of such a crop. Similar results were reported by Fadina and Barjolle (2018) who argued that experience with a technology is a critical factor for affecting its adoption and age can be used as a proxy for experience where such information on how long a farmer has been using the technology cannot be accessed. Simtowe et al. (2016) also found a positive relationship between age and adoption and argued that older farmers are less constrained in terms of financial capacity to adopt improved technologies such as CRPVs as compared to younger farmers. However, age had a quadratic pattern in uptake of CRPVs whereby as age increased, propensity to adopt increases up to a certain level and then starts to decline in line with the life cycle hypothesis. This is indicated by the square of age (Age²) which had a negative effect on adoption of CRPVs at 5% level of significance. This could be due to reduced commitments of the farmers hence low incentive to adopt innovations. This is consistent with Kapalasa et al. (2019) who found a decreasing effect of age on adoption of improved potato varieties.

The effect of decision making unit (decision maker) on adoption of CRPVs was positive and significant at 5% level of significance. Households whose decisions were made jointly had a higher propensity of adopting CRPVs by 8.6% than households with individual decision-making. This could be because household with joint decision-making units were able to share ideas and convince each other of adoption of certain innovations that enhance adaptation to climate change such as CRPVs. Similar results emphasizing the role of joint or participatory decision making on adoption of improved varieties were reported by Shiferaw et al. (2008), Acosta et al. (2020), and Bjornlund et al. (2019) because joint decision making allows for consensus forming on merits of CRPVs.

The results show that access to information on climate change and its impacts had a positive and significant effect on uptake of CRPVs. An increase in access to information on climate change and its impact by 1% increased the propensity to adopt by 1.9% at 5% level of significance. A farmer with access to information on climate change and its impact was more likely to adopt CRPVs as a climate adaptation practice because of awareness of the adverse effects of climate change on potato crop. Awareness of the impact of climate change is a necessary condition for climate change adaptation among smallholder farmers. Knowledge of impact prompts farmers to seek for measures to cope with the situation. This explains why farmers with such knowledge have a higher propensity to adopt CRPVs. Other farmers used as a proxy for source of information from fellow farmers was also positive and significant emphasizing on the importance of access to climate information on adoption of CRPVs (Simtowe et al., 2019). These results are in line with previous literature as shown by Nzeadibe et al. (2011) and Aryal et al. (2018) who reported that farmers aware of the impact of climate change was more likely to uptake adaptation innovations such as CRPVs because they understood the risks associated with climate change. Other sources of information revealed by farmers in Meru county include television, radio, mobile phones, print media, non-governmental institutions and government extension officers

The number of trainings attended by a farmer in the 2017/2018 cropping season had an effect on adoption of CRPVs that was positive and significant at 1% level of significance. This shows that farmers who had attended more trainings on potato farming had a higher propensity to adopt CRPVs than farmers who had attended lesser training sessions. A 1% increase in number of trainings attended increased farmers’ propensity to adopt by 1.1%. Through training, farmers acquire knowledge, skills and better understanding of CRPVs and their role in adapting to climate change. The knowledge gained could also capacitate farmers with the technical know-how required for adoption of CRPVs. Number of training sessions attended highlights the importance
of human capital development. These results are similar to (Ahmed et al., 2016; Feleke et al., 2019; Kapolasa et al., 2019).

There was a positive and significant effect of number of farmer groups a farmer was engaged in on adoption of CRPVs. Membership in many groups increased the propensity of adopting CRPVs by 4.3%. Farmers who were in more farmer groups had a greater chance of adopting CRPVs. This could be because farmer groups offer platforms for trainings, information access and even credit access through pooling of resources. Similarly, Wabwile et al. (2016) found a positive and significant relationship between adoption and farmer groups and argued that, groups presented an opportunity for farmers to ascertain their decision on the relevance of new technologies being introduced to them. Further, Muthini (2018) argued that groups as proxies for social networks increased channels for access to information. Other farmers as a source of climate information had a strong positive effect on adoption emphasizing on the importance of social capital on adoption (Hunecke et al., 2017).

Lack of seeds had a negative and significant effect on adoption of CRPVs. Farmers whose access to seeds was constrained or difficult had a lower propensity to adopt. This was as expected since farmers cannot adopt a variety they had no access to its seeds in terms of availability, affordability and timely delivery. Similar results were reported by Asante et al. (2017) who argued that availability and affordability of seeds was a necessary condition for adoption. Awotide et al. (2016) also argued that some farmers were seed dealers and not only sold potato as ware but also as seed and therefore lack of access encouraged them to deal in traditional varieties that were readily available.

Out of the four locations considered in the study, Kibirichia, Abogeta West and Abothuguchi West had positive and significant influence on adoption of CRPVs. Farmers from these locations were more likely to adopt CRPVs than farmers from Kiirua/Naari. This could possibly be explained by variations in climate conditions. Kiirua/Naari is relatively drier compared to the other three locations hence comprising potato growth which is a cool season crop. The probability of adoption in Abogeta West (0.992) and Abothuguchi West (0.833) was higher than Kibirichia (0.23) probably because Kibirichia has poor infrastructure as compared to the two locations hence make flow of information and extension services difficult. The results were similar to (Mansaray et al., 2019) who argued that areas with high propensity of adoption had higher targeted extension effort and development of local seed systems. Similarly, De Groote et al. (2016) and Kaliba et al. (2018) argued that farming systems with favorable soils and climatic conditions were more likely to have farmers with high propensity to adopt improved varieties.

4. Conclusion and recommendations
Results revealed that the actual population adoption rate for climate-resilient varieties was still low at 6.3% compared to the potential adoption rate of 30.7%. The adoption gap of 24.4% was due to incomplete exposure of farmers to CRPVs. Ensuring that the entire population is exposed to CRPVs could increase adoption rate from 6.3% to 30.7%. The key factors influencing exposure to CRPVs positively were education, training, and access to credit. Adoption of CRPVs was positively affected by access to information, access to quality seeds, training, group membership and variations in agro-ecological zones. To increase the adoption rate of CRPVs as an adaptation practice against climate change, this paper recommends that farmer exposure to and knowledge of climate resilient potatoes should be increased. This can be achieved through organizing more trainings on climate change adaptation and encouraging farmers to attend. Stakeholders should also organize participatory variety selection events for potato farmers to increasing their understanding of CRPV traits. Farmers should also be encouraged to acquire membership in farmer groups that address issues in potato farming. This will boost farmers’ exposure to CRPVs which is a necessary condition for adoption. Differences in agro-ecological zones should be put into consideration when promoting adoption of CRPVs. The government should improve infrastructural facilities in potato growing areas to enable free flow of extension services for CRPVs and potato farming in general. The government should also establish more training centers and deploy more trained extension officers to avail information on climate
change adaptation practices such as use of CRPVs. Information can also be made available to farmers through electronic and print media. Finally, to reap maximum benefits from adoption of CRPVs, it is important for farmers to combine climate-resilient varieties with appropriate agronomic practices such as crop rotation, minimum tillage and soil conservation measures.

Acknowledgements
This paper is part of Master’s degree research work for the corresponding author. The authors wish to acknowledge African Economic Research Consortium (AERC) for funding this research through a research grant. Special thanks to smallholder farmers of Meru County who took their time to enrich us with the knowledge on climate change issues and adaptation practices in the study area.

Funding
This work was supported by the African Economic Research Consortium (AERC) [AERC Thesis Grant].

Author details
Sally Mukami Kimathi1
E-mail: sallymukami93@gmail.com
ORCID ID: http://orcid.org/0000-0002-1071-9495
Oscar Ingasia Ayuva1
E-mail: ingasiaoo@gmail.com
Benjamin Mutia1
E-mail: bmutmial@yahoo.com
1 Department of Agricultural Economics and Agribusiness Management, Egerton University, Nakuru, Kenya.

Citation information
Cite this article as: Adoption of climate-resilient potato varieties under partial population exposure and its determinants: Case of smallholder farmers in Meru County, Sally Mukami Kimathi, Oscar Ingasia Ayuva & Benjamin Mutia, Cogent Food & Agriculture (2020), 7: 1860185.

References
Abdulai, A. N. (2016). Impact of conservation agriculture technology on household welfare in Zambia. Agricultural Economics, 47(6), 729–741. https://doi.org/10.1111/agec.12269
Acosta, M., van Wessels, M., Van Bommel, S., Am沛rea, E. L., Twyman, J., Jossogne, L., & Feindt, P. H. (2020). What does it mean to make a ‘joint’ decision? Unpacking intra-household decision making in agriculture: Implications for policy and practice. The Journal of Development Studies, 56(6), 1210–1229. https://doi.org/10.1080/00220388.2019.1650169
Ahmed, M. H., Mesfin, H. M., Abody, S., Mesfin, W., & Kebede, A. (2016). Adoption of improved groundnut seed and its impact on rural households’ welfare in Eastern Ethiopia.Cogent Economics & Finance, 4(1), 682–747. https://doi.org/10.1080/23320399.2016.1268747
Amengor, N. E., Owusu-Asante, B., Adof, K., Acheampong, P. P., Nishai-Frimpong, B., Nimoo-Wiredu, A., & Sagoe, R. (2018). Adoption of Improved Sweetpotato Varieties in Ghana. Asian Journal of Agricultural Extension, Economics & Sociology, 23(3), 1–13. https://doi.org/10.9734/AJAEES/2018/39874
Aryal, J. P., Rahut, D. B., Maharanj, S., & Erentstein, O. (2018). Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. Natural Resources Forum, 42(3), 141–158. https://doi.org/10.1111/nrf.12152
Asante, B. O., Villano, R. A., Patrick, I. W., & Battesse, G. E. (2017). Impacts of exposure and access to seed on the adoption of dual-purpose Cowpea and Groundnut varieties in Ghana. The Journal of Developing Areas, 51(3), 173–194. https://doi.org/10.1353/jda.2017.0067
Asrat, P., & Simone, B. (2018). Farmers’ perception of climate change and adoption strategies in the Dabus watershed, North-West Ethiopia. Ecological Processes, 7(1), 7. https://doi.org/10.1186/s11701-018-0118-8
Assuming-Brempong, S., Gyasi, K. O., Marfo, K. A., Diagne, A., Wiredu, A. N., Boakye, A. A., & Frimpong, B. N. (2011). The exposure and adoption of New Rice for Africa (NERICAs) among Ghanaian rice farmers: What is the evidence? African Journal of Agricultural Research, 6(27), 5911–5917. https://doi.org/10.5897/AJAR11.882
Atlin, G. N., Cairns, J. E., & Das, B. (2017). Rapid breeding and varietal replacement are critical to adaptation of cropping systems in the developing world to climate change. Global Food Security, 12, 31–37. https://doi.org/10.1016/j.gfs.2017.01.008
Awotide, B. A., Karimov, A. A., & Diagne, A. (2016). Agricultural technology adoption, commercialization and smallholder rice farmers’ welfare in rural Nigeria. Agricultural and Food Economics, 4(1), 3. https://doi.org/10.1186/s40100-016-0047-8
Baiyegunhi, L. J. S., Hassan, M. B., Danso-Abbeam, G., & Ortmann, G. F. (2019). Diffusion and adoption of Integrated Striga Management (ISM) technologies among smallholder maize farmers in rural northern Nigeria. Technology in Society, 56, 109–115. https://doi.org/10.1016/j.techsoc.2018.09.009
Bandiera, O. and Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. The Economic Journal, 116, 869–902 514. doi:10.1111/j.1468-0297.2006.01115.x
Bjornlund, H., Zuo, A., Wheeler, S. A., Parry, K., Pittack, J., Mdumu, M., & Moyo, M. (2019). The dynamics of the relationship between household decision-making and farm household income in small-scale irrigation schemes in southern Africa. Agricultural Water Management, 213, 135–145. https://doi.org/10.1016/j.agwat.2018.10.002
Chakraborty, S., & Newton, A. C. (2011). Climate change, plant diseases and food security: An overview. Plant Pathology, 60(1), 2–14. https://doi.org/10.1111/j.1365-3059.2010.02411.x
Chandio, A. A., & Yauansheng, J. I. A. N. G. (2018). Determinants of adoption of improved rice varieties in northern Sindh, Pakistan. Rice Science, 25(2), 103–110. https://doi.org/10.1108/rjsc.2017.10037
Chandra, A., McNamara, K. E., & Dargusch, P. (2018). Climate-smart agriculture: Perspectives and framings. Climate Policy, 18(4), 526–541. https://doi.org/10.1080/14693062.2017.1316988
CIP. (2019). CIP Annual Report 2018. Towards food system transformation. International Potato Center. https://doi.org/10.1601/25636112018
Dai, A. (2011). Drought under global warming: A review. Wiley Interdisciplinary Reviews: Climate Change, 2(1), 45–65. https://doi.org/10.1002/wcc.81
De Groote, H., Gunaratna, N. S., Fisher, M., Kebebe, E. G., Mmbando, F., & Friesen, D. (2016). The effectiveness of extension strategies for increasing the adoption of biofortified crops: The case of quality protein maize in East Africa. Food Security, 8(6), 1101–1121. https://doi.org/10.1007/s12237-016-0621-7
Diagne, A., & Demont, M. (2007). Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rates and their
determinants. Agricultural Economics, 37(2), 201–210. https://doi.org/10.1111/j.1574-0862.2007.00266.x

Dibbo, L., Diagne, A., Fialor, S. C., & Nimoh, F. (2012). Diffusion and adoption of new rice varieties for Africa (NERICA) in the Gambia. African Crop Science Journal, 20(1), 141–153.

Doss, C. (2014). If women hold up half the sky, how much of the world’s food do they produce? Gender in Agriculture, 69–88. https://doi.org/10.1076/978-94-017-8616-4_4

Fosha, A., & Borjille, D. (2018). Farmers’ adoption strategies to climate change and their implications in the Zou department of South Benin. Environments, 5(1), 15. https://doi.org/10.3390/environments5010015

Felleke, A., Muche, M., & Regassa, G. (2019). Factors influencing adoption of improved potato (Belete) variety: Evidence from Ethiopia. Journal of Agricultural Science, 30(2), 85–92. https://doi.org/10.15159/jas.19.17

Gildemacher, P. R., Koguowo, W., Ortiz, O., Tesfaye, A., Woldegiorgis, G., Wagoire, W. W., & Leeuwis, C. (2008). Improving potato production in Kenya, Uganda and Ethiopia: A system diagnosis. Potato Research, 52(2), 173–205. https://doi.org/10.1007/s11540-009-9127-4

Hunecke, C., Engler, A., Jara-Rojas, R., & Poortvliet, P. M. (2017). Understanding the role of social capital in adoption decisions: An application to irrigation technology. Agricultural Systems, 153, 221–231. https://doi.org/10.1016/j.agsy.2017.02.002

International Potato Center. (2017). Accelerated value chain development program. Root crops quarter 3 of year 2 report

IPCC. (2014). Climate change 2014: Impacts Adaptation and Vulnerability, Part B Regional Aspects, Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Issahaku, G., & Abdulai, A. (2019). Can farm households improve food and nutrition security through adoption of climate-smart practices? Empirical evidence from Northern Ghana. Applied Economic Perspectives and Policy 4 3 159-579. doi:10.1003/oeep/jppz002

Jaetzold, R., Schmidt, H., Horset, Z. B., & Shinoyama, C. A. (2007). Farm Management Handbook of Kenya. Natural Conditions and Farm Information (Vol. 11/C, 2nd ed.). Ministry of Agriculture/ITZ.

Kabunga, N. S., Dubois, T., & Qaim, M. (2012). Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya. Agricultural Economics, 43(5), 673–486. https://doi.org/10.1111/j.1574-0862.2012.00597.x

Koguowo, W. P., Gildemacher, P., Demo, P., Wagoire, W., Kinyae, P., Andrade, J., & Thiele, G. (2008). Farmer practices and adoption of improved potato varieties in Kenya and Uganda. Social Sciences Working Paper, 5(85), 67–68.

Kalibo, A. R., Mzvimavi, K., Gregory, T. L., Mgonja, F. M., & Mgonja, M. (2018). Factors affecting adoption of improved sorghum varieties in Tanzania under information and capital constraints. Agricultural and Food Economics, 6(3), 18. https://doi.org/10.1186/s40100-018-0114-4

Kapalaso, E., Demo, P., Nyekonyeya, T., & Okero, J. (2019). Assessing Factors Influencing Farmers Adoption of Improved Potato Varieties in Malawi. International Journal of Modern Economy, Energy and Environment, 4(1), 1–10. https://doi.org/10.11616/j.ijmeme.20190401.11

Kyamanywa, S., Kashaigye, I. N., Getu, E., Amata, R., Senkeshia, N., & Kullaya, A. (2011). Enhancing food security through improved seed systems of appropriate varieties of cassava, potato and sweet potato resilient to climate change in Eastern Africa. ILRI.

Mansaray, B., Jin, S., & Horlu, G. S. A. (2019). Do land ownership and agro-ecological location of Farmland influence adoption of improved rice varieties? Evidence from Sierra Leone. Agriculture, 9(12), 256. https://doi.org/10.3390/agriculture9120256

Muthini, D. (2018, July 28–August 2). Variety Awareness, Nutrition Knowledge and Adoption of Nutritionaly Enhanced Crop Varieties: Evidence from Kenya (Paper Presentation). The International Association of Agricultural Economists Conference, Vancouver, British Columbia.

Muthoni, J., Nyamongo, D. O., & Mbuyu, M. (2017). Climatic change, its likely impact on potato production in Kenya and plausible coping measures. International Journal of Horticulture, 7(14), 115–123. http://dx.doi.org/10.11648/j.ijih.2017.7.14.004

Mwololo, H. M., Nzuma, J. M., Ritho, C. N., Ogutu, S. O., & Kabungo, N. (2019). Determinants of actual and potential adoption of improved indigenous chicken under asymmetrical exposure conditions in rural Kenya. African Journal of Agricultural Research, Evidence and Innovation Development, 12(4), 505–515. https://doi.org/10.1080/20421338.2019.1636489

Mwongera, C., Nowak, A., Notenboert, A. M., Grey, S., Osimo, J., Kinyua, I., & Girvetz, E. (2019). Climate-smart agricultural value chains: Risks and perspectives. In The climate-smart agriculture papers (pp. 235–245). Springer. https://doi.org/10.1007/978-3-319-92798-5

Ngugi, E., Kiprutu, S., & Samoei, P. (2013). Exploring Kenya’s Inequities: Pulling apart or pulling together? Kenya National Bureau of Statistics.

Nishangase, N. L., Muroyiwa, B., & Shibanda, M. (2018). Farmers’ perceptions and factors influencing the adoption of no-till conservation agriculture by small-scale farmers in Zawshe, KwaZulu-Natal Province. Sustainability, 10(2), 555.

Nzlidebe, T. C., Egbule, C. L., Chukuwuone, N. A., & Agu, V. C. (2011). Climate change awareness and adaptation in the Niger Delta Region of Nigeria. African Technology Policy Studies Network. Working paper series, (57).

Ogeto, M. A., Mohammed, J. H., & Bedada, D. G. (2019). Adoption of improved potato varieties in Jeldu district, Oromia region, Ethiopia: A double-hurdle model. International Journal of Agricultural Research, Innovation and Technology, 9(2), 15–22. https://doi.org/10.3329/jariat.v9i2.r20145405

Parker, M. L., Low, J. W., Andrade, M., Schulte-Geldermann, E., & Andrade-Piedra, J. (2019). Climate change and seed systems of roots, tubers and bananas: The cases of potato in Kenya and sweet potato in Mozambique. In The climate-smart agriculture papers (pp. 99–111). Springer.

Patrick, E. M., Koge, J., Zwarts, E., Wesongo, J. M., Atela, J. O., Tonui, C., & Koomen, I. (2020). Climate-resilient horticulture for sustainable county development in Kenya (No. WCDI-20-107).

Republic of Kenya. (2013). Meru County Integrated Development Plan 2013-2017. Government Printers.

Rosenbaum, P. R., & Rubin, D. B. (1983). Constructing a control group using multivariate matched sampling method that incorporate the propensity score. The American statistician, 39, 33–38.

Senyolo, M. P., Long, T. B., Blok, V., & Omata, D. (2019). How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. Journal of Cleaner
Production, 172, 3825–3840. https://doi.org/10.1016/j.jclepro.2017.06.019
Shiferaw, B. A., Kebede, T. A., & You, L. (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeon pea varieties in Tanzania. Agricultural Economics, 39(3), 309–323. https://doi.org/10.1111/j.1574-0862.2008.00335.x
Simtowe, F., Asfaw, S., & Abate, T. (2016). Determinants of agricultural technology adoption under partial population awareness: The case of pigeon pea in Malawi. Agricultural and Food Economics, 4(1), 7. https://doi.org/10.1186/s40100-016-0051-z
Simtowe, F., Kassie, M., Diagne, A., Asfaw, S., Shiferaw, B., Silim, S., & Muange, E. (2011). Determinants of agricultural technology adoption: The case of improved pigeon pea varieties in Tanzania. Quarterly Journal of International Agriculture, 50(4), 325–345. http://dx.doi.org/10.22004/ag.econ.155537
Simtowe, F., Moreno, P., Amondo, E., Worku, M., & Erenstein, O. (2019). Heterogeneous seed access and information exposure: Implications for the adoption of drought-tolerant maize varieties in Uganda. Agricultural and Food Economics, 7(1), 15. https://doi.org/10.1186/s40100-019-0135-7
Sinelle, S. (2018). Potato variety adoption and dis-adoption in Kenya. https://www.syngentafoundation.org/file/12806/download
Singh, B., Kukreja, S., & Goutam, U. (2020). Impact of heat stress on potato (Solanum tuberosum L.): Present scenario and future opportunities. The Journal of Horticultural Science and Biotechnology, 95(4), 407–424. https://doi.org/10.1080/14620316.2019.1700173
Todesse, Y., Almekinders, C. J., Schulte, R. P., & Struik, P. C. (2017). Understanding farmers’ potato production practices and use of improved varieties in Chencha, Ethiopia. Journal of Crop Improvement, 31(5), 673–688. https://doi.org/10.1080/15427528.2017.1345817
Wabwile, V. K., Ingasia, O. A., & Longet, J. K. (2016, September 23–26). Effect of the improved sweet potato varieties on household food security: Empirical evidence from Kenya [Paper Presentation]. The 5th International Conference of the African Association of Agricultural Economists, Addis Ababa, Ethiopia.
Wekesa, B. M., Ayuya, O. I., & Logat, J. K. (2018). Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. Agriculture & Food Security, 7(1), 80. doi:10.1186/s40066-018-0230-0
Wooldridge, J. (2002). Econometric analysis of cross section and panel data. The MIT Press.
Wossen, T., Berger, T., & Di Falco, S. (2015). Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. Agricultural Economics, 46(1), 81–97. https://doi.org/10.1111/agec.12142

© 2020 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.
You are free to:
Share — copy and redistribute the material in any medium or format.
Adapt — remix, transform, and build upon the material for any purpose, even commercially.
The licensor cannot revoke these freedoms as long as you follow the license terms.
Under the following terms:
Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made.
No additional restrictions
You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

Cogent Food & Agriculture (ISSN: 2331-1932) is published by Cogent OA, part of Taylor & Francis Group.
Publishing with Cogent OA ensures:
• Immediate, universal access to your article on publication
• High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
• Download and citation statistics for your article
• Rapid online publication
• Input from, and dialog with, expert editors and editorial boards
• Retention of full copyright of your article
• Guaranteed legacy preservation of your article
• Discounts and waivers for authors in developing regions
Submit your manuscript to a Cogent OA journal at www.CogentOA.com