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Impacts of climate-resilient push–pull technology on farmers' income in selected counties in Kenya and Tanzania: propensity score matching approach

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Abstract

Background Agricultural research and technology adoption play a key role in improving productivity and therefore generate impact on household livelihoods. The push–pull technology developed by the International Centre of Insect Physiology and Ecology and collaborators/partners has been recognized for its multiple roles in productivity improvement and income generation. However, the subsequent impacts after its adaptation to drier agro-ecologies have not been ascertained. An *ex-post* study was conducted to evaluate the impact of the climate-resilient push–pull technology on farmers' income.

Methodology This study was conducted in eight counties in Kenya and Mara region in Tanzania, involving 486 farmers; half were climate-resilient push–pull technology adopters. The study adopted the propensity score matching (PSM) technique in order to correct the self-selection bias in adoption.

Results From the results, education of the farmer, household size, Tropical Livestock Unit and group membership positively and significantly influenced adoption. The average treatment effect on the treated was positive for all the matching methods; USD 455.8 for Nearest Neighbor Matching, USD 474.2 for the Kernel Matching and USD 439.1 for the Radius/Caliper Matching. The balancing test for self-selection bias showed that none of the observed covariates was significant after matching. The results demonstrate that adopting climate-resilient push–pull technology has a positive impact on the adopter farmers' income. Adopter farmers were able to earn much more in terms of gross margin.

Conclusion The positive change in income for adopters was attributable to the technology. With increased incomes, farmers were able to access alternative foodstuff, hence had more food security and diversity than those without. Efforts to expand dissemination and adoption of climate-resilient push–pull technology will have positive impacts on adopting families and hence to the economy.

Keywords Gross margin, Matching algorithms, Propensity score matching, Push–pull technology

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Introduction

Improving agricultural productivity and creating impacts on the livelihoods of farming households have been at the top of the research agenda for the sub-Saharan region. This is mainly through identification of the main production constraints and devising applicable cost-efficient solutions that can benefit the affected households. The International Centre of Insect Physiology and Ecology (*icipe*) has continuously embarked on studies that provide solutions for smallholder farmers particularly on constraints related to insect pests damage that negatively affect agricultural productivity. In one of such research initiatives, *icipe* and partners developed a novel technology dubbed the conventional push–pull technology (PPT) for controlling cereal stemborers, *Striga* weeds, improving soil fertility and more recently managing the Fall Armyworm (FAW) [1–3]. The technology involved intercropping a fodder legume *Desmodium spp*., including *D. uncinatum* (Jacq.), with cereals and a perimeter of Napier grass, *Pennisetum purpureum K.* (Schumach), planted around the plot [1, 4, 5]. The mechanism for operating the conventional Push–Pull in control of cereal stemborers, striga weeds and FAW has extensively been described by Khan et al. [3, 6–8], Tsanuo et al. [9], Midega et al. [2, 10], and Cook et al. [11]. In addition, its adoption and impacts have been demonstrated by Khan et al. [12, 13]; Chepchirchir et al. [14, 15]; Kassie et al. [16].

With the global changes in climate conditions which led to unpredictable weather patterns, the sustainability and expansion of this technology became difficult especially in the drier agro-ecologies. This led to follow-up adaptive research to identify companion crops that would withstand long periods of dry spells. The new initiative dubbed climate-resilient push–pull technology (CR-PPT) involved a drought-tolerant greenleaf desmodium, *Desmodium intortum* (Mill.) Urb., being intercropped with cereals and *Brachiaria* cv Mulato II used as a border crop Khan et al. [17]; Midega et al. [18, 19] producing similar results to the conventional PPT. Alternative *Brachiaria* cultivars such as *Basilisk*, *Xaraes* and *piata* were also identified in place of *Brachiaria* cv Mulato II whose productivity was being challenged by Red Spider Mite infestations [20–22].

The climate-resilient push–pull technology (CR-PPT) has been promoted for wide-scale adoption using target-specific dissemination and impact pathways, partnerships and direct private-sector involvement. However, despite the widespread dissemination, its adoption and direct economic impact on the welfare of the adopting households has not been ascertained. Most of adoption and impact studies done under by *icipe* and partners focussed on the conventional PPT [12–16] which was mainly disseminated in the higher potential sub-humid tropics. The CR-PPT extended the technology benefits to a wider range of more arid agro-ecologies. This study specifically contributed hitherto non-researched new knowledge on the impact of CR-PPT. Since the introduction of CR-PPT in 2012 in drier agro-ecologies that are also prone to striga and stemborers, no study had been undertaken to evaluate the level of its adoption and impact on the target beneficiaries. The current study was motivated by the need to provide additional data and information on CR-PPT's impacts which could be compared with the previous studies on conventional PPT. Furthermore, it was necessary to justify the additional research investment on PPT adaptation research by demonstrating its impact. Impact is the difference between the actual outcome and the outcome which would have happened if adoption did not take place. While we observe the outcome which is the adoption of CR-PPT, we do not observe the outcome without the PPT from the same individual. Providing technology impact information is undisputable as it demonstrates the causal effects of adoption and hence provides improved clarity and focus to researchers.

Technology impact is evaluated by looking at the difference between the adopters and the non-adopters. Direct comparison of the two groups however may fail to account for potential effects that are attributed to the observed differences between the adopters and non-adopters and which may contribute to the causal effects. These arise because of the self-selection bias stemming from farmers' objective functions of technology adoption. When farmers decide to adopt, it is because they have expectations and objectives which are dictated by their observed and unobserved characteristics. Failure to correct the self-selection bias leads to overstating of the outcomes. To counter this, impact evaluation requires that a good counterfactual that simulates a scenario of what would have happened if this individual did not adopt the technology be identified [23]. Assumptions to this are that individuals selected for the treatment and the controls have outcomes in both states; observed and unobserved [24]. This study was developed to evaluate the *ex-post* impacts of CR-PPT on the income of the adopting farm households.

Materials and methods

Study sites

The survey was conducted in eight counties in Kenya namely; Migori, Homabay, Kisumu, Siaya, Kakamega, Bungoma, Busia and Vihiga; and two districts in Mara region of Tanzania: Tarime and Rorya (Fig. 1). These are the areas where the climate-resilient push–pull had been

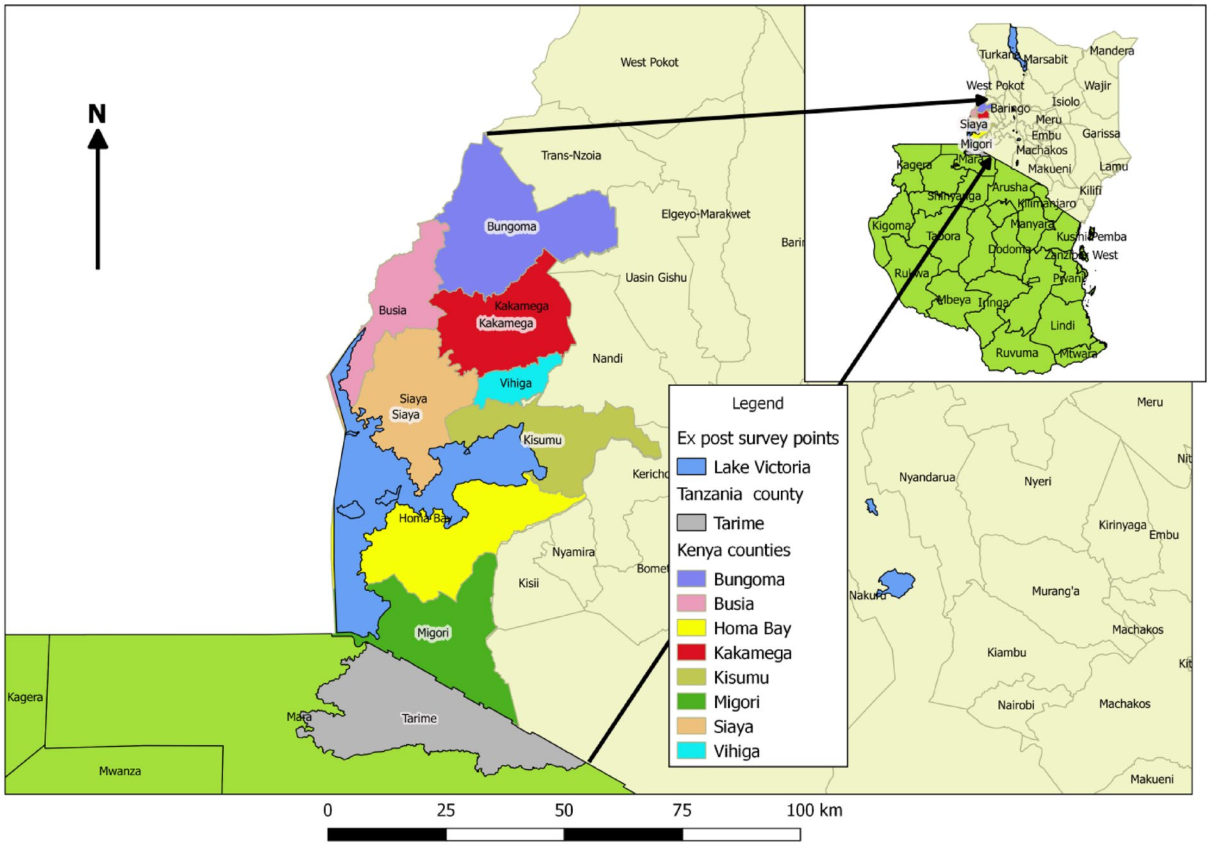

Fig. 1 Map of the study sites

disseminated and adopted since its introduction in 2012. The study was conducted between the months of September to October 2019.

Agriculture is the main economic activity in western Kenya. Maize is the main crop produced in the region, but its production is constrained by stemborers, fall armyworm and striga weeds. Other crops grown in western Kenya are sorghum, millet, cassava, sweet potato, and sugar cane. The regions receive long rains during the month of March to August and short rain on the month of October to December. With exception of Kakamega and Vihiga counties which are humid agroecological zones, the rest of the counties have varying agro-ecologies ranging from humid, sub-humid, and semi-humid to semi-arid agroecological zones. The average annual amount of rain in western region range from 500 mm in semi-arid zones to 2100 mm in humid agroecological zones [25].

Tarime and Rorya districts in Mara region of Tanzania border each other in the north-eastern part of the country. These regions receive bimodal rainfall pattern with long rainy season experienced in March to May while short rainy season in September to December. Major crops grown in the region include maize, sorghum, finger millet, cassava, banana, and rice. Agro-ecologically, the two districts are classified as highland and midland zones ranging from 1500 to 1800 m above sea level. Midland zones receive annual average rainfall ranging between 900 mm–1200 mm while the highland zones receive 1200 mm–1500 mm of rainfall highland zones, respectively [26, 27].

Both the Kenyan and Tanzanian government consider maize as the main staple food for their citizens hence the need to empower farmers for its improved productivity. The Kenyan national food and nutrition security policy of 2012 promoted the use of modern biotechnology in increasing and diversifying production of food and feed. At the same time adoption of CR-PPT resonates well with the Kenyan vision 2030 blueprint which promotes the use of sustainable agricultural practices contributing to creation of wealth and improved household livelihoods. The Tanzanian National Agricultural Policy (NAP) of 2013 was implemented in various programs aimed at maximizing crop production for the country's economic development and achievement of households' food and nutritional security. Technology dissemination is emphasized in most public and private agricultural development programs in Tanzania. This further strengthened and encouraged individual farmers to improve on their agricultural production which could be achieved through adoption of CR-PPT. Therefore, the policy environment in Kenya and Tanzania favors agricultural technology dissemination for increased maize production and productivity.

Data collection procedures

The data used in this paper are part of a wider study that was conducted to evaluate the *ex-post* impacts of CR-PPT, which was conducted between September and October 2019. Data were collected using a structured questionnaire that was developed to capture all the variables needed to answer the objectives of the study. This questionnaire was developed and pre-tested by the research team for the purpose of *ex-post* assessment of CR-PPT. Relevant to this paper, the questionnaire captured data on adoption and for gross margin analysis, production costs, yields and prices. The questionnaire was programmed in Open Data Kit (ODK) and data were captured using mobile phones. ODK is open-source software for collecting, managing, and using data in resource-constrained environments. It allows for offline data collection with mobile devices in remote areas, hence suitable for areas with limited internet connectivity. The submission of the data to a server can be performed, when Internet connectivity is available.

Sampling procedures

The study used data collected from rural household farmers in Western Kenya and North West Tanzania. These regions were purposively chosen because of high adoption rates of CR-PPT by smallholder farmers. A multistage sampling procedure was adopted to sample the farmers because it offers a more representative sample especially when resources and time are constraining [28, 29]. The first stage involved purposive selection of regions (counties and districts), and sub-counties and divisions. Eight counties in western region of Kenya (Bungoma, Busia, Homabay, Kakamega, Vihiga, Kisumu, Migori, and Siaya) and Mara region in Northwest Tanzania were purposively sampled because they were targets of the CR-PPT dissemination interventions. The regions were characterized by high prevalence of striga weed and stem borer that have had perennial devastating effects on cereal production. The emerging infestation of fall army worm (FAW) represents another threat to cereal production in the two regions.

The second stage involved random selection of 3 sub-counties in every county as well as wards and villages in Kenya and 2 districts in Tanzania (Tarime and Rorya). Since the population of CR-PPT adopter farmers were known, the study used the formula by Yamane [30] and the margin of error was taken as 5%. The population of interest at the time of study was 472 CR-PPT adopters as per the project records, 433 from Kenya side and 39 from Tanzania side.

The third stage therefore, applied probability proportional to size (PPS) sampling technique to select a fixed number of CR-PPT adopters from selected administration units because of the evenness in number of farmers at county level in Kenya and Mara region in Tanzania. CR-PPT adopters from each county were systematically randomly selected from source lists provided by ICIPE extension officers. The sample size of non-adopters was set equal to the size of adopters and was randomly selected from the neighborhood of the sampled adopters as a ratio of one to one to minimize losses of statistical power when observations are omitted in the analysis. Therefore, a total of 486 household farmers participated in the survey (243 adopters and 243 non-adopters). The sampled adopter household farmers were 208 and 35 from Kenya and Tanzania, respectively.

Modeling approach and estimation

Conceptual model

Observational studies normally treat unobserved variables and group them as residuals which might lead to inaccurate estimates [31]. In non-controlled experiments, the causal relationships of observational data can be represented graphically as directed acyclic graph (DAG). Farmers who adopted climate-resilient push–pull technology at first received the information about the technology through various dissemination pathways icipe frequently use to reach farmers. There is causal effect of CR-PPT adoption, A, on the outcome which is farmers' income is measured as gross margin, via increased productivity as a pathway. Thus, there is a causal effect between variable A and Y, as $A \rightarrow Y$ which implies A influences Y because of its implication on productivity that is gained via decreased economic losses associated with striga and pests.

Sometimes an unobserved confounder C like farmer's unobserved characteristics for instance motivation or talent may affect both adoption of CR-PPT, A or the outcome income, Y. Figure 2 illustrates effect of unobserved confounder C on A and Y. Taking unobserved confounder in the model may make it difficult to regress A (adoption) on Y (farmers income) as the causal effect of A on Y is confounded by C. this is shown by the two pathways connecting A and Y: (a) $A \rightarrow Y$ and (b) $A \leftarrow C \rightarrow Y$. Both pathways indicate statistical associations between adoption and farmers income. The first path (a) indicates that a change in A would affect Y via

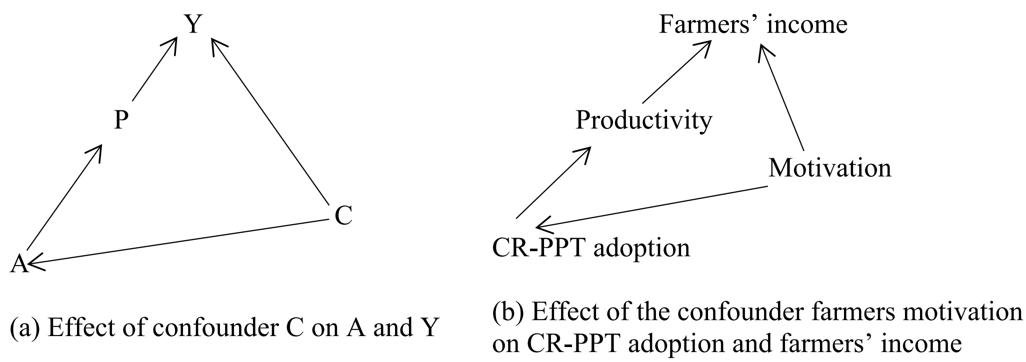

Fig. 2 Directed acyclic graphs with confounder effects

increased productivity, whereas in the second path (b) A would not affect Y. Since C is unobservable farmers' characteristics, we would statistically adjust its effect with a suitable intervening variable to help in estimating the right causal effect of A on Y. The variable access to extension services, E can be intervening variable, if it does not dependent on farmer's unobserved characteristics (C) though not independent of adoption of CR-PPT (A), and does not directly influence farmer's income (Y), but through adoption of the technology (A) [31–33]. CR-PPT being knowledge extensive gives the assumption that the more the farmer accesses the extension services offered by icipe and its partners through various dissemination pathways, the higher the probability of a farmer adopting the technology. This is clearly shown in Fig. 3 that C would not directly affect Y but only influence it through A; hence the causal chain would be established.

Empirical model

The main dependent variable for this analysis was CR-PPT adoption where farmers were allocated 1 if they had adopted and 0 if they had not. For impact variable, the study used gross margin per acre of maize as a proxy for household incomes. This was calculated by netting all the total variable costs from the total revenue generated in maize production. For the adopters, we incorporated revenue from maize and fodder (*Desmodium* spp. and *Brachiaria* spp.) which were harvested in the long rain season of 2019.

This study adopted the propensity score matching (PSM) approach to analyze the impact of adopting CR-PPT on farmers' income using Gross Margin as the proxy. PSM is a non-parametric approach which was first developed by Rosenbaum and Rubin in 1983 and has the advantage of not requiring a baseline or panel survey. It has been widely used by economists to identify the impacts of agricultural technologies [23, 34, 35].

The first step in determining the effect of CR-PPT on income is calculating the propensity score of a household, which is the likelihood of adopting CR-PPT. A probit model was used to estimate the propensity scores. Probit model is a flexible model where the dependent variable is dichotomous (adoption of CR-PPT), which takes the value of 1 if the household adopts and 0 otherwise.

Probit regression model is given by

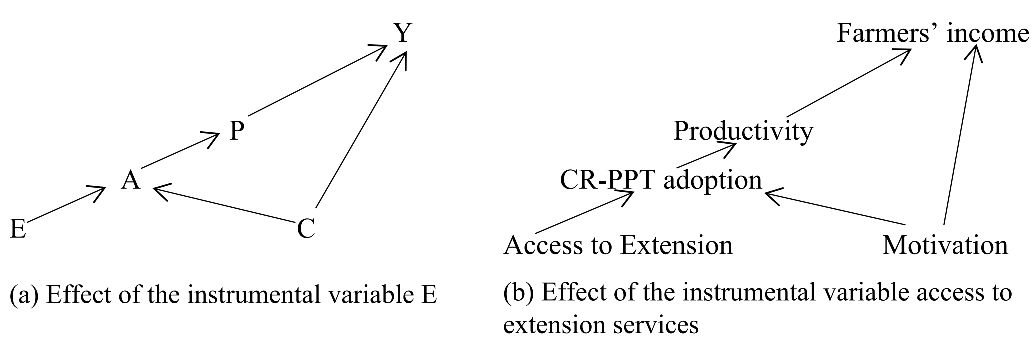

Fig. 3 Directed acyclic graph illustrating the effect of the instrumental variables

$$y_i^* = X^T\beta + \delta_i, \tag{1}$$

where y_i^* is an unobserved or latent variable, $X_i^T = [x_i1, x_i2......x_ip]$ is the ith row of the matrix $\mathbf{X}$ which is an $n \times p$ data matrix with p predictor variables. $x_i1, x_i2......x_ip$ are farmers' socio-economic, farm and institutional characteristics which are household size, group membership, tropical livestock unit (TLU) among others. $\boldsymbol{\beta}$ is a $p \times 1$ vector of regression coefficients and δi is an error term following normal distribution:

$$D_i^* = \beta X_i + \mu_{\mathrm{i}} \text{ (i = 1,....N) with } D_i = \begin{cases} 1 & \text{if } D_i^* > 1 \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

Since latent variables are unobservable, they may be examined as below dummy variable:

$$\text{with } y_i = \begin{cases} 1 & \text{if } y_i^* > 1 \\ 0 & \text{otherwise} \end{cases},$$

which is distributed as Bernoulli (μ_i), where $\mu_i = \varphi\left(X_{u_i}^T, \beta\right)$ such that φ is the cumulative distribution function of the standard normal distribution [36].

The corresponding likelihood equation of the probit regression model is given as follows.

$$\begin{aligned} L\left(y_i;\beta\right) &= \prod_{i=1}^{n} \varphi\left(X_{u_i}^T, \beta\right)^{y_i} \left[1 - \varphi\left(X_{u_i}^T, \beta\right]^{1-y_i} \right. \\ &= \prod_{i=1}^{n} \varphi_i^{y_i} (1-\varphi_i)^{1-y_i}. \end{aligned} \tag{3}$$

In general, the maximum likelihood estimation is used to acquire the parameters. To do this, the following log-likelihood function should be maximized with respect to $\boldsymbol{\beta}$:

$$\ln = \sum_{i=1}^{n} y_i \ln \varphi_i + \left(1 - y_i\right) \ln\left(1 - \varphi_i\right). \tag{4}$$

The maximum likelihood estimator of the vector of the coefficients can be calculated by solving the equation:

$$\begin{aligned} \frac{\partial \ln L}{\partial \beta} &= \sum_{i=1}^{n} X_i \left(\frac{y_i \phi}{\varphi_i} + \frac{\left(1-y_i\right)(-\phi)}{1-\varphi_i} \right) \\ &= \sum_{i=1}^{n} X_i \left(\frac{y_i - \varphi_i}{\varphi_i(1-\varphi_i)} \phi_i \right), \end{aligned} \tag{5}$$

where ϕ is the density function of the standard normal distribution. From probit regression we generate PSM.

It is defined as the conditional probability of receiving a treatment given the pre-treatment characteristics as follows:

$$P(X) = \Pr(D = 1\mathrm{I}X) = E(D\mathrm{I}X), \tag{6}$$

where $D = (0, 1)$ is an indicator of exposure to treatment, X is a multidimensional vector of pre-treatment characteristics. By using PSM, a statistical comparison group (Counterfactual) is constructed based on a model of the probability of participating in a treatment T condition on observed characteristics X also called the propensity score. The nature of treatment can be diverse as noted by Caliendo and Kopeining [37], but in agricultural research it is mostly used to compare adopters and non-adopters. Kassie et al. [38] also used PSM to evaluate the impact of improved groundnut seed variety on rural farmers' income and poverty status in Uganda and recorded a positive significant increase in crop income and poverty reduction on the technology adopters than the non-adopters. PSM compares the outcome from farmers who adopted CR-PPT (treated) with non-CR-PPT adopters (control) using similar observed covariates X. In this study, the covariates of interest were age of the farmer, sex of the farmer, education level, farming experience, main occupation, household size, Tropical Livestock Unit ownership, group membership and number of extension services received. Individuals who are not matched are dropped since they cannot be compared [39].

The aim of PSM is to develop or control group that is similar to the treatment group. The initial step is therefore to match them using the selected covariates and ensure that the two groups are as similar as possible and that the differences are insignificant. The model therefore tries to identify among the non-treated group, individuals who are similar to the treated in terms of the selected covariates. After matching the two groups, the average difference in the output variable (in our case, the gross margins) is then compared and the difference makes the technology impact. Simply stated, PSM looks at the control group and tries to identify individuals who are similar to the treated group (using selected observed covariates), then compares the output variable between the two groups and if there is a difference, it is attributed to the technology. Christopher [40] noted that the impact of a treatment on ith individual is the difference between potential outcomes with and without the treatment.

To contextualize the PSM model in the current study, let $\mathrm{A} = 1$ denote the state when the ith farmer adopts CR-PPT and $\mathrm{A} = 0$ if the farmers do not adopt; then $\mathrm{Y}_{1\mathrm{i}}$ is the outcome of farmer ith when technology is adopted and $\mathrm{Y}_{0\mathrm{i}}$ is the outcome if the farmer did not adopt the technology. These outcomes are defined as:

$$Y_1 = \gamma_i + \mu_1, \tag{7}$$

$$Y_0 = \gamma_0 + \mu_0,$$

where γ is a vector of observed individual covariates and μ_1 and μ_0 are unobserved random error terms with the assumption that $\mu_1 \neq \mu_0$. We denote the observed mean gross margin under the state of adoption as $E(Y_1|A = 1)$ and that the unobserved mean gross margin if the farmer did not adopt to be $E(Y_0|A = 1)$. For non-adopters on the other hand, we denote the mean gross margin as $E(Y_0|A = 0)$ in the non-adoption state and $E(Y_1|A = 1)$ if they had adopted. The parameter of interest is referred to as the average treatment effect on the treated (ATT) which is expressed as $E(Y_1 - Y_0|A = 1)$ and can also be expanded as $E(Y_1|A = 1) - E(Y_0\{A = 1)$. It is worth noting that for impact evaluation, the outcome of interest is $E(Y_1 - Y_0|A = 1)$ but not $E(Y_0|A = 0)$, i.e., the outcome of an adopter if he/she did not adopt; but not the outcome of the non-adopter in their non-adoption state. Therefore, it is very critical to identify a suitable counterfactual that fits that description. PSM uses balancing scores to extract the observed mean gross margin of the non-adopter who are almost similar to the adopters in their observed characteristics. It uses $E(Y_0|A = 0)$.to estimate the counterfactual outcome $E(Y_0|A = 1)$ [41]. The true parameter estimation requires that the condition $E(Y_0|A = 1) - E(Y_0|A = 0) = 0$ is maintained so as to eliminate the self-selection bias.

While estimating PSM, two assumptions must be satisfied: conditional independence which requires that the value of the outcome is independent of the treatment state given the observed individual characteristics; and the common support (CS) which ensure that persons with same X values have positive probability of being both participant and non-participant Heckman et al. [42] and that the ATT is only defined within the region of common support. Ascertaining the CS assumption is especially necessary when the covariates being matched are many, a problem that PSM solves by estimating the propensity scores $P(x) = Pr\ (A = 1 \mid X)$ [43]. The CS (overlap) implies that $0 < Pr\ (A = 1 \mid X) < 1$.

After satisfying the common support condition, the matching methods are chosen to estimate treatment effects. There are three matching methods presented in literature: nearest neighbor matching, kernel matching and radius/caliper matching. The three matching methods differ in the way they select control units that are matched with the treated and the weights given to the control when estimating the counterfactual [37]. In the nearest neighbor matching the adopter is matched with a non-adopter who has the nearest propensity score, the radius and caliper matching impose a tolerance level on the maximum propensity score (caliper) which improves the matching quality because at times the closest neighbor might be far away; and the kernel matching is known for producing quality balanced statistics as it uses weighted averages of those in comparison group and the weights are inversely proportional to the distance between the propensity score of the treated and the control. A major advantage of using kernel matching is that it has high efficiency in matching because it uses more information. This study followed the steps suggested by Caliendo and Kopeinig [37] in implementing the PSM. First, propensity scores were estimated using the probit binary model, the three matching algorithms were applied for matching the output (gross margin), the common support condition was checked and sensitivity analysis was done to ensure matching quality was tested.

The outcome variable would as well be estimated using ordinary least square (OLS) regression models such as multiple linear regression. However, CR-PPT adoption may be a case of farmers' self-selection rather than random selection and estimating Eqs. 7 would produce biased estimates [44]. Thus, PSM was more appropriate in controlling for observable confounding factors that cause self-selection process. Although the limitation of PSM is its inability to correct endogeneity problems that arise from unobservable characteristics of farmers, its alternative, the endogenous switching regression, is even more limited in cases where instrumental variables are not determined. According to Adjin et al. [44], an exclusion restriction should be satisfied to fully estimate endogenous switching regression. That is, a valid instrument—a variable that correlates significantly with CR-PPT adoption does not directly affect the outcome variable—income—is needed. In this case, all potential instruments from the data and literature, including group membership, occupation, geographic location, and access to extension and credit, were tested, and found to be invalid. Thus, ESR did not address potential empirical issues for validating the consistency of PSM estimates.

Parameter of interest and the dependent variable of the PSM model

The most frequently used parameters in PSM literature are the average treatment effect (ATE) and the average treatment effect on the treated (ATT). The average treatment effect (ATE) is the expected outcomes difference between adoption and non-adoption of CR-PPT, whereas ATT is the expected outcome difference on farmers who adopted CR-PPT and the same CR-PPT adopters had they not adopted the technology.

Gross margin

The dependent variable was farmers' income using gross margin (GM) as a proxy which is the difference between total revenues (TR) and total variable costs (TVC). That is:

$$\mathrm{GM} = \mathrm{TR} - \mathrm{TVC},$$

GM = TR − TVC, where TR = quantity of output $(Q_i) \times$ price (P_i) and TVC = quantity of input $(X_j) \times$ Price (P_j).

Two sets of GMs were calculated from farm components: GM of sole maize plots, and GM of CR-PPT plots with the intercrop of maize and desmodium surrounded by a trap fodder crop brachiaria. Total revenue (TR) comprised the value of all products produced in the plot whether sold or consumed as food, feed or seed, or given out.

Results

Sample description summary

The descriptive summaries in Table 1 show that majority of the farmers interviewed were women (57%) with the percent being higher for non-adopters (61%) than the adopters (54%). Cumulatively, the adopters had higher literacy levels with 54% registering post-secondary education compared to 33% of the non-adopters. Farming was the main occupation for over 80% of both adopters and non-adopters implying that this was main source of livelihood. In terms of social capital development, the percent of adopters registering in organized farming groups was higher (84%) compared to the non-adopters (65%).

On average the adopters were slightly older registering 52 years of age compared to 50 years for non-adopters (Table 2). The average number of years in farming was of 20 and 19 for adopters and non-adopters, respectively. The number of livestock in the farm which is represented by Tropical Livestock Unit was 4.03 and 2.80. The household size was 6 members for both adopters and non-adopters and the average extension visits were 3 for each group.

Covariate matching

The region of common support was checked using the histogram which shows the distribution of the propensity scores (x-axis) between the farmers who adopted CR-PPT (treated) and those who did not adopt (control). The results show a good match between the adopters and non-adopters. The region of common support among the treated ranged from 0.177 to 0.993 with a mean of 0.60 as shown in Fig. 4 fulfilling the condition that the observed characteristics in the treatment group were also observed in the control group. The distribution of the propensity scores and overlaps in the histogram is a clear indication

Table 1 Socio-economic characteristics of the adopter and non-adopters

Farmer characteristics	Adopters		Non-adopters		Overall		χ^2
	N	%	*N*	%	*N*	%	
Sex of the main farmer (binary)							
Female	130	53.5	148	61.1	278	57.3	2.85*
Male	113	46.5	95	38.9	208	42.7	
Education level of the main farmer (Categorical)							
No formal education	7	2.9	11	4.5	18	3.7	25.25***
Primary school level	104	42.8	150	62.1	254	52.5	
Secondary school level	98	40.3	69	28.4	167	34.4	
Certificate and diploma level	30	12.3	10	4.1	40	8.2	
University degree level	4	1.6	2	0.8	6	1.2	
Main occupation of the main farmer (Categorical)							
Farming (crop + livestock)	209	86.0	205	84.4	414	85.2	24.66***
Salaried employment	4	1.6	5	2.0	9	1.8	
Self-employed off-farm	22	9.1	23	9.4	45	9.2	
Casual laborer on other farms	0	0.0	0	0.0	0	0.0	
Casual laborer non-farm activities	4	1.6	4	1.6	8	1.6	
Others	4	1.6	6	2.5	10	2.1	
Membership to farmers' group (binary, 1 = Yes, 0 otherwise)							
Yes	205	84.4	158	64.8	363	74.5	0.55
No	38	15.6	85	35.2	123	25.5	

***Significant at 1%, *Significant at 10%

Table 2 Summaries of the continuous variables

	Adopter $N=243$		Non-adopter $N=243$		Overall $N=486$		*F*
	Mean	SD	Mean	SD	Mean	SD	
Age of the main farmer (in years)	52	12	50	14	51	13	4.66**
Farming experience of the main farmer (in years)	20	12	19	12	20	12	0.88
Current household size (number)	6	3	6	3	6	3	6.73***
Tropical Livestock Unit	4.03	3.57	2.80	2.73	3.41	3.23	18.42***
Number of extension services per year (number)	3	2	3	2	3	2	2.86*

***Significant at 1%, *Significant at 10%

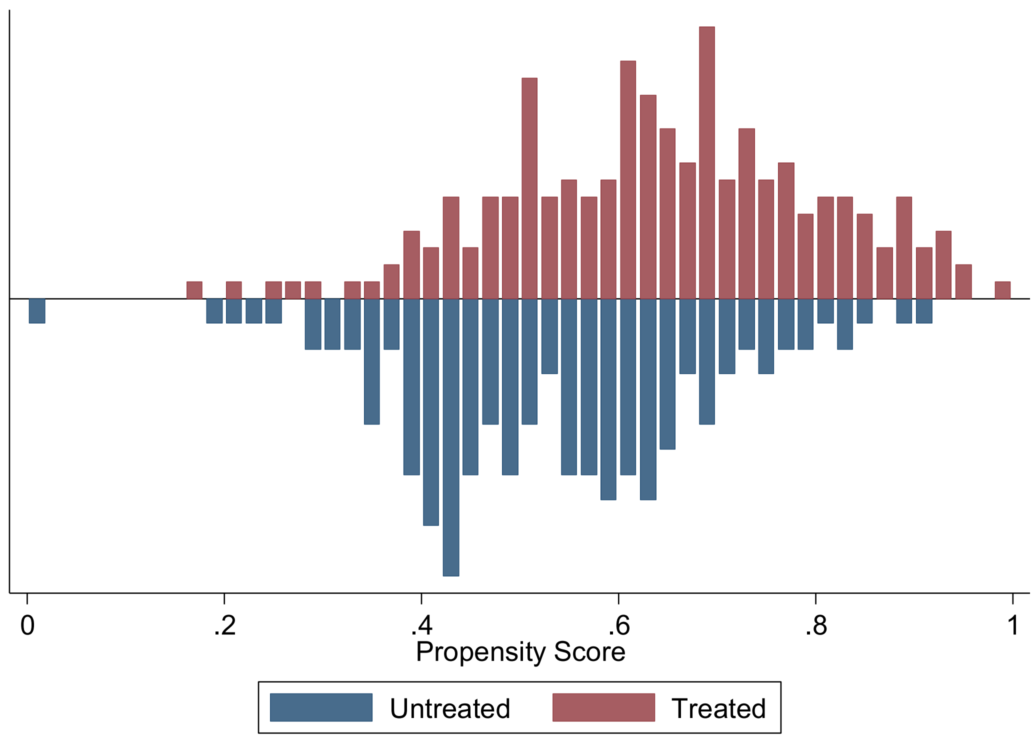

Fig. 4 Common support graph showing the distribution of propensity scores (x-axis) between farmers who adopted CR-PPT (treated) and those who did not adopt (control)

that the propensity scores between farmers with CR-PPT and those without were within the region of common support. This was indicated by more overlaps between treated and control as most of the observations were within the region of common support.

Effects of socio-economic, farm and institutional characteristics on CR-PPT adoption

A probit regression model was used to estimate propensity scores for matching the observed characteristics of the adopters and non-adopters (Table 3). Probit regression model is used to model dichotomous dependent variables. The model takes the value of '1' if the farmer adopts CR-PPT and '0' otherwise. The model is suitable in determining the probability of whether to adopt or not to adopt CR-PPT [45]. The model was significant with Prob > $Chi^2=0.000$, Pseudo-$R^2=0.088$. The variables that significantly influenced adoption of CR-PPT were education of the main farmer which was significant at 1% (coefficient = 0.3799), household size, significant at 10% (coefficient = 0.0495), TLU significant at 1% (coefficient = 0.0682) and group membership, significant at 10% (coefficient = 0.3190) all of whose influence was positive.

Table 3 Coefficient and standard errors in the probit regression of propensity score matching

Variables	Coefficients	Standard errors
Age of main farmer	0.0031	0.0071
Education level of main farmer	0.3799***	0.1079
Farming experience of main farmer	0.0036	0.0079
Household size	0.0495*	0.0284
Main occupation of the main farmer	− 0.0205	0.0636
Sex of the main farmer	0.0816	0.1587
Tropical Livestock Unit	0.0682***	0.0264
Group membership	0.3190*	0.1897
Number of extension services	0.0350	0.0426
County	− 0.0452	0.0299
Constant	− 1.2199***	0.4410
Number of observations	350	
LR chi2(10)	41.46	
Prob > Chi^2	0.000	
Pseudo-R^2	0.088	
Log-likelihood	− 215.226	

*$P < 0.05$

***$P < 0.001$

Average treatment effect on the treated (ATT) of CR-PPT on farmers' income

The results from the three matching methods indicated that adoption of CR-PPT had a positive impact on farmers' income measured by Gross margins and this was statistically significant at 1%. That is the average farm income earned by the adopters (proxied by gross margins) was greater than average farm income of matched (control) groups. The average treatment on the treated (ATT) column shows the difference in gross margin between the treated and control groups (Table 4). On average, the treated group (farmers practicing CR-PPT) performed better than their counterparts (farmers without CR-PPT). The ATT was USD 455.83 for the nearest neighbor matching, USD 474.17 for kernel matching and USD 439.09 for radius/caliper matching. All this is with reference to an acre on maize production in the main long rain season 2019.

Assessing matching procedure quality

The balancing test was used to assess the matching quality that is to determine if the differences in the

Table 4 Estimates of the ATT on farmers' income measured by gross margins

Matching algorithm	Matched treated	Matched controls	Treated (USD)	Controls (USD)	ATT (USD)	SD	*t*
Nearest neighbor	196	141	729.57	273.74	455.83	128.74	3.54***
Kernel	196	141	729.57	255.40	474.17	126.18	3.76***
Radius	181	141	706.18	267.10	439.09	131.49	3.34***

* and *** means significant at 10% and 1%, respectively

***$P < 0.001$

Table 5 Test for selection bias after matching using propensity score test (used kernel for GM)

Variable	Mean		% Bias	% reduction	*t*-test	
	Treated	Control		Bias	*t*	*p* > *t*
Age of main farmer	52.3060	51.7570	4.2	73.6	0.42	0.674
Education level of main farmer	1.6224	1.5760	6.4	87.0	0.64	0.523
Farming experience of main farmer	20.4180	20.6820	− 2.3	61.3	− 0.22	0.825
Household size	6.2296	6.2300	0.0	99.9	0.00	0.999
Main occupation of the main farmer	1.3827	1.4353	− 4.8	34.8	− 0.47	0.641
Sex of the main farmer	0.4694	0.4798	− 2.1	87.8	− 0.21	0.836
Tropical Livestock Unit	3.6037	3.8268	− 7.2	80.5	− 0.73	0.464
Group membership	0.8520	0.8478	1.1	96.0	0.12	0.907
Number of extension services	2.8878	2.9706	− 4.9	73.4	− 0.46	0.644
County	4.8878	5.0432	− 6.1	54.6	− 0.61	0.544

independent variables in the matched CR-PPT adopters and CR-PPT non-adopters were eliminated. Using the kernel matching method which gave the best results, the test for selection bias was done and the results are shown in Table 5. This test revealed that the differences in household characteristics between the treatment and control groups are jointly insignificant after matching. The result of this balancing test shown in Table 5 indicates that after the matching, the mean distribution of the selected covariates for CR-PPT adopters and non-adopters were insignificant.

The results in Table 6 show that before matching, the mean bias was 21.3 for both the matching algorithms used and after matching, the mean bias was reduced to 3.5, 3.9 and 5.2 for nearest neighbor, kernel and radius/caliper matching, respectively. The percentage reduction bias according to Rosenbaum and Rubin [46] is recommended to be above 20%, and for all the matching methods used gave a higher percentage reduction biasness of 84%, 82% and 76% with nearest neighbor, kernel and radius matching indicating a robust reduction in selection bias. The pseudo-R square also reduced after matching from original value of 0.088 to 0.006, 0.004, and 0.007, respectively, for nearest neighbor, kernel and radius matching methods. Lastly, the p-value for all the matching algorithms was rejected after the matching process, demonstrating the lack of biasness in the distribution of covariates between the CR-PPT adopters and non-CR-PPT adopters.

Discussion

Adoption and impact of technologies can be influenced by a wide range of variables related to the farmer and the farm characteristics. For example, the importance of the sex of the farmer in technology adoption and impact is seen in terms of ownership, access and use of productive resources. Men have easy access to resources such as credit, extension services and other farm inputs which makes them (men) adopt more than the women who are more constrained [47]. The age distribution may be an indication of aging farming households with less participation of youths. Age of the farmer often has mixed effects in adoption and impact studies as older farmers may have more experience and resources as compared to the younger ones and therefore adopt technologies quickly. In some cases, the younger farmers are more receptive to new ideas. In case of CR-PPT, the results shows that the technology is being practiced more by elderly farmers as compared to young farmers. This corroborates previous study by Murage et al. [48] that showed adoption of the conventional push–pull being higher among the elderly farmers than the young farmers, a fact that was attributed to resource availability. The number of extension visits which averaged three for both groups determines whether farmers have access to enough information and knowledge that can lead to adoption (see Table 2). Farmers with access to extension messages from reliable sources are likely to attain an information threshold that can trigger technology adoption as noted in previous studies [16, 48, 49].

Household size is used as a proxy for labor availability. A more significant number of adults in a household provide the family labor which supports adoption of labor-intensive technologies. Having a bigger family size had a higher propensity to adopt CR-PPT, which reflects the need for labor availability particularly during the initial stages of technology establishment (see Table 3). Previous studies have shown that adoption of Push–Pull technology was determined by labor availability in season one and season two [13, 47, 49]. However, labor requirement significantly dropped in the subsequent seasons. Farmers with higher level of education were more likely adopting CR-PPT than their counterparts with low education level as CR-PPT as it requires knowledge in establishment and management.

The positive effect of education has been described in previous Push–Pull studies, and this was attributed to the technology being knowledge intensive [49, 50]. Unlike other technologies, it requires farmers with some level of education to understand the mechanisms and operations of the CR-PPT. This is also true for other technologies that are knowledge intensive. This finding also concurs with Kassie et al. [16] that the likelihood of PPT increases with education level of the farmer. Presence of livestock in the farm can determine adoption of CR-PPT especially because of the fodder generated from the technology.

Table 6 Matching quality indicators

Matching algorithm	Mean bias		% Bias reduction	Pseudo-R^2		*P*-value	
	U	M		U	M	U	M
Nearest neighbor	21.3	3.5	83.57	0.088	0.006	0	0.981
Kernel	21.3	3.9	81.69	0.088	0.004	0	0.972
Radius	21.3	5.2	75.58	0.088	0.007	0	0.992

Probit result show that households with many livestock as evident by tropical livestock unit (TLU) were more likely to practice CR-PPT than those with less livestock stock. This finding is in line with Khan et al. [12] who argued that significance of TLU is linked to fodder availability in households adopting the technology thus allowing them to keep more livestock. Farmers in group had a higher likelihood of adopting CR-PPT than their counterparts not in group. Group membership reflects the impact of social influence on human behavior in technology adoption [51]. Furthermore, through group membership it becomes easier and cheaper to deliver extension messages hence having a larger influence on adoption.

The PSM results imply that on average farmers with CR-PPT earned more than their matched counterparts (farmers without CR-PPT). The three matching algorithms on gross margins per acre indicated that the average treatment effect on the treated was USD 439.09 for Radius/Caliper matching, USD 474.17 for Kernel matching and USD 455.83 for the nearest neighbor matching (see Table 4). This finding is in line with Chepchirchir et al. [14] that PPT adopter farmers were better off in terms of productivity and income than non-PPT adopters. These farmers matched perfectly implying that each individual had a positive probability of being either an adopter or a non-adopter of CR-PPT. The use of PSM to demonstrate income effects of technology adoption have been demonstrated in previous studies such as Acheampong and Acheampong [34] in adoption of improved cassava varieties in Ghana and Dibaba and Goshu [35] in adoption of improved wheat varieties in Ethiopia. Ogutu et al. [52] also demonstrated a positive impact of information and communication technology use by smallholder farmers in using farm input to increase productivity in Kenya.

Conclusions and recommendations

This study was conducted to assess the impact of CR-PPT on the incomes of adopting farm households. The study adopted the propensity score matching technique to compare the incomes from adopters and non-adopters and hence attribute the difference to the technology. With data collected from 486 farming households (half of them adopters), the results revealed a positive change in income for adopters which was attributable to the technology. Farmers who used CR-PPT to manage farming constraints in maize production were able to earn much more in terms of gross margin than non-adopters. This is because they were able to increase their productivity as well and generate additional products from the CR-PPT farms. With increased incomes, adopters are able to access alternative foodstuff, hence had more food security and diversity than those without. The main determinants of adoption were education of the farmer, household size, TLU, and group membership. These factors should be exploited when designing dissemination strategies for CR-PPT. For example, encouraging farmers to form organized groups would make it cheaper to train them, and through such networks, farmers are able positively to influence each other into adoption.

Our study provides evidence-based impacts of CR-PPT in terms of the positive ATT. We recommend concerted efforts on dissemination in collaboration with stakeholders. Provision of more information through extension services is key in order to improve the information resource base for the farmers to adopt. CR-PPT being knowledge intensive require farmers to be capacity build to be able to apply the technology and also share the information with the others. While income-based measures used in this study may be handy in providing indicators in the short term, we acknowledge the technical problems associated with their measurement errors including underestimation due to intermittent nature of survey data, and limited temporal comparisons and deflation. We therefore express some caveats and recommend that alternative asset-based measures be integrated in the long-term to reflect much more robust measures of adoption pathways and their benefits.

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Conceptualization: AWM, FC, ZRK, JOP. Data curation: AWM, FO, FC, JOP. Formal analysis: AWM, FO, FC. Funding acquisition: FC, ZRK, JAP. Investigation: AWM, FO, FC, JP. Methodology: AWM, FO. Project administration: ZRK, JOP. Resources: ZRK. Supervision: FC, ZRK. Validation: FC, ZRK. Visualization: AWM, FO, FC. Writing—original draft: AWM, FO, FC. Writing, review & editing: FC, JAP, JOP, ZRK. All authors read and approved the final manuscript.

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Availability of data and materials
Data are available on reasonable request.

Declarations

Ethics approval and consent to participate
All respondents who contributed to the study willingly accepted to participate as and confirmed through a signed informed consent note. Respondents were also made aware that they were free to stop participating at any point during the survey in case of discomfort or discontent.

Consent for publication
All authors read and are in support of article submission and publication.

Competing interests
The authors declare that there is no conflict of interest.

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