The Impact of Sludge Manure Adoption on Crop Yields: Evidence from a Propensity Score Matching Approach.

Jordan Paul Semwanga,[‡] John Sseruyange[†] & Aggrey Niringiye[§]

Abstract
This study examines the impact of sludge manure adoption on household farm production, focusing on matooke (bananas), maize, beans, sweet potatoes, coffee and cassava. We employ a propensity score matching methodology and estimate the average treatment effect on the treated (ATT), and we report the results from the nearest neighbor algorithm and test for robustness using the kernel algorithm. The study uses household survey data collected from the central districts of Uganda between January and February 2023. Our key findings indicate increased and significant yields of bananas, maize, coffee and cassava. These results are similar to those of different estimation algorithms. From a policy perspective, our results suggest that the design of agricultural productivity enhancing programmes, especially for farm households, requires leveraging organic technologies to promote agricultural production.

Keywords: Sludge manure; Adoption; Farm production; Households; Propensity scores

JEL Classification Codes: Q11, Q15

[‡] Corresponding author; School of Economics, Makerere University. Plot 51, Pool Road, semwangajordan@gmail.com

[†] School of Economics, Makerere University. Plot 51, Pool Road, johnsseruyange@gmail.com

[§] School of Economics, Makerere University. Plot 51, Pool Road, aggrey1970@yahoo.com

1. Introduction

Over the years, the use of agricultural supplements in agro-based countries has increased considerably. This has been caused by the persistent increase in the world population, which has translated into increased demand for food and raw materials for agro-processing firms. However, soils have continuously degraded, failing to support increased farm production. In Africa, for example, Dimkpa et al. (2023) reported that over 40% of African soils are degraded, which causes both immediate and long-term adverse effects on agricultural production and the well-being of rural agricultural households (Amare et al., 2017). Soil fertility affects food security (Mwaniki, 2006; Zakari et al., 2014), household crop income (Hörner & Wollni, 2021; Yamano & Kijima, 2011) and school enrolment (Hörner & Wollni, 2021). Hörner and Wollni (2021) argued that enhanced soil fertility improves farm production and household incomes, which positively impacts education attainment and overall human capital development.

In sub-Saharan Africa (SSA), food insecurity is still a major challenge, with FOASTAT data showing that 26.6% of the total population in the region is experiencing severe food insecurity (FAO, 2023). This food insecurity is attributed to a number of factors, e.g., insufficient nutrient application and poor soil management practices, as well as harsh climatic conditions (Hörner & Wollni, 2021; Onyeneke et al., 2018; Sanginga & Woomer, 2009). Sanginga and Woomer (2009) attributed food insecurity in SSA to high fertilizer costs and adverse policy environments.

Several agricultural interventions have been implemented across the globe to counteract food insecurity and enhance farm household welfare. Such interventions include input subsidy programs, agricultural technological training and the provision of improved quality inputs, especially inorganic fertilizers. Such interventions have also been implemented in many African countries, though to varying degrees. Sheehan and Barret (2017) document varying consumption of inorganic fertilizers in some African countries. More specifically, Sheehan and Barret (2017) reported that the consumption of inorganic fertilizers across all households in Malawi stands at 146 kg/ha, followed by Nigeria (128 kg/ha), Ethiopia (45 kg/ha), Tanzania (16 kg/ha), Niger (2.5 kg/ha), and Uganda (1.2 kg/ha). Although Uganda uses 1.2 kg/ha of fertilizer nutrients, the country still has a high rate of annual nitrogen, phosphorous, and potassium depletion per hectare (MAAIF, 2016), which suggests limited soil nutrients and supports the argument that future growth in Uganda’s farm production will depend on improved soil management (Bekunda et al., 2002; Nkonya et al., 2008), e.g., through the application of more agricultural supplements.

Agricultural supplements can be broadly categorized into two groups, i.e., organic and inorganic supplements. Organic supplements are mainly made of plant and animal wastes, while inorganic supplements are synthetics mainly composed of minerals and chemicals mined from the earth. Even though inorganic supplements support high farm yields (because they are manufactured to fit a specific crop), they tend to affect the environment (Rahman & Zhang, 2018; Walsh et al., 2012) and, over time, can affect crop yields (Rahman & Zhang, 2018). With such effects, the use of organic supplements can be thought of as “a game changer” for sustainable farming (Oyetunde-Usman et al., 2021). The adoption of organic fertilizers increases soil bulk density, organic matter, and critical soil elements such as nitrogen, phosphorus, potassium, calcium, and magnesium (Agbede et al., 2019; Sarka & Siegh, 2003). They also improve the physical structure and biochemical elements of soils and have long-term impacts on farm production (Ball et al., 2005; Li et al., 2017) and the environment (Li et al., 2017).

Organic supplements are mainly decompositions of plant and animal wastes, but recently, human wastes (hereafter, sludge manure) have been adopted by farmers to enhance farm production or fight pests (with pests, farmers mainly use urine collected in containers). Although the use of sludge manure improves farm yields (see Akdeniz et al., 2006; Grau et al., 2017; Guzha, 2005; Zuo et al., 2018), the literature on this effect is still limited. Moreover, most of the existing studies are crop specific (e.g., Akdeniz et al., 2006 for sorghum; Andersson, 2011 and Guzha, 2005 for maize; Zuo et al., 2018 for rice). Only Grau et al. (2017) focused on two crops, Rapharus sativus and Capsicum Anuum. Additionally, most of the aforementioned literature is based on sludge manure collected from human waste at the household level. By implication, most of these materials are unprocessed with the possibility of no technical guidance on their application. In this paper, we examined the impact of sludge manure processed at the Lubigi Sewarage Treatment Plant (LSTP) (a detailed process is described in subsection 1.1 below) a government-managed facility on a number of crops.

1.1 Processing of sludge manure at the LSTP

Sludge manure is an agricultural input made from faecal sludge, and by itself, faecal sludge is the material or primarily faecal solids and urine that accumulate at the bottom of a pit, septic tank or vault (Tayler, 2018). The process of making sludge manure starts with the deposition of faecal sludge at the LSTP[1].

Faecal sludge reaches the LSTP through two inlets. The first inlet consists of cesspool trucks that deliver faecal sludge from household pits and septic tanks to the LSTP. Cesspool trucks are emptied directly into screening/sedimentation tanks to remove grit, e.g., bottles, wood, clothes, etc. During the sedimentation process, liquids/effluents are separated from solids, and some solid particles can be pumped directly to the drying ponds. However, the remaining liquids with some solid particles are pumped to anaerobic ponds where they mix with faecal sludge from inlet 2. The second inlet (Inlet 2) is through national water and sewerage cooperation sewerage pipes, which are directly deposited into screening ponds to remove grit; thereafter, the effluent is pumped into anaerobic ponds. The primary function of anaerobic ponds is stabilization and to allow for the breakdown of the high concentrations of organic pollutants contained in sludge. This is done by removing oxygen from the affluent to encourage the growth of bacteria, which helps in the decomposition process. Another important function of anaerobic ponds is to reduce pathogens that are harmful to human life. After decomposition in anaerobic ponds, the sludge is pumped into facultative ponds to remove ammonia through a biological process. The use of facultative ponds is to increase the efficiency of bacterial removal from sludge manure. From the facultative ponds, the sludge manure is pumped out to drying ponds (beds), where it is allowed to dry and foster further decomposition for approximately five to six months. During this period, sludge manure reaches a moisture content of 60%, and at this moisture content, pathogens (disease-causing organisms) are believed to be lifeless and fit for human handling. When the sludge manure is dry enough, it is ready for use by farmers. The graphical description of the same process is given in appendix 3.

[1] LSTP is a government owned sewerage processing plant affiliated to National Water and Sewerage Corporation (NWSC). A government institution mandated to provide viable water and sewerage services in the country at affordable costs. LSTP provides sludge manure to farmers without any restrictions except, farmers incur a cost of transporting the manure to their farms. LSTP is located in Lubigi water stream along Northern Express highway in Kampala district.

The remainder of this paper is organised as follows. Section 2 reviews the literature on sludge manure and farm production. Section 3 describes the methodology. Section 4 presents and discusses the estimated results. Section 5 concludes.

2.0 Literature Review

2.1 Sludge manure and farm production

The potential of human excreta to enhance farm production has been documented (see Andersson et al. 2011; Akdeniz et al., 2006; Grau et al., 2017; Zuo et al., 2018). For instance, Zuo et al. (2018) reported an increase in the yield of rice on newly reclaimed mudflat lands in China. Specifically, the study reported 125.1%, 124.7% and 127.9% increases in rice production in 2016, 2017 and 2018, respectively, in sludge-treated mudflats. Zuo et al. (2018) also reported a significant reduction in soil salinity in sludge-treated areas.

Zou et al. (2021) reported increased biomass and gross energy content in sweet sorghum resulting from sewerage sludge amendment in China. Specifically, sweet sorghum exhibited maximum biomasses of 4.73 and 6.62 t ha^{-1} at a 250 t ha^{-1} sewerage sludge amendment rate in 2016 and 2017, respectively, while the maximum gross energy contents were 79.62 and 104.47 GJ ha^{-1} at a sewerage sludge amendment rate of 250 t ha^{-1} in the same period. Similarly, Akdeniz et al. (2006) reported increased grain yield of sorghum in the Van areas of Turkey when sewerage sludge and nitrogen supplements were applied to sorghum. Grau et al. (2017) reported improved yields of Rapharus sativus and Capsicum Anuum in Sri Lanka when cocomposited manure (a mixture of dewatered faecal sludge and organic fractions of municipal solid waste) was applied by farmers. Furthermore, during 1997–1999, Jonsson et al. (2004) tested human urine, chicken manure and meat +bone meal on spring grain and winter wheat. The study reported an average increase in winter wheat yield of 18 kg of grain per N for human urine, 14 kg for dry chicken manure and 10 kg for meat +bone meal.

On the African continent, the application of sludge supplements by farmers is still limited, and the majority of sludge users apply it on a small scale; however, such supplements are among the least expensive and most environmentally friendly agricultural supplements that African farmers can adopt. Existing studies on the African continent show positive effects of sludge supplements. For example, Guzha (2005) reported a positive effect on maize production in Zimbabwe when exhausted soils were restored by sanitized human excreta. Similarly, Andersson (2011) reported improved maize yields among smallholder farmers in South Africa's Thurela River basin resulting from fertilization with stored human urine, while Andersson (2015) reported increased maize yields of up to 120% among smallholder farmers in Tororo district in eastern Uganda after the application of urine collected from their households.[2]

Furthermore, Cofie et al. (2005) reported that composting faecal sludge with organic waste is a good approach for recovering locked nutrients and organic matter for food production. The study documented that the users of excreta in Ghana earned three times greater net income than nonusers. Moya Diaz-Aguado et al. (2017) compared the impact of faecal sludge manure to that of chemical fertilizers in Madagascar and reported that human excreta had significant effects on farm yields. Yanggen et al. (1998) documented an average increase in cereal production of approximately 50 kg of cereals per person per year when human excreta was used as a farm supplement. Andersson & Rosemarin (2016) predicted that the safe reuse of

[2] Smallholder farmers use urine because it is considered pathogen free and safe to use in the gardens after a one-week storage for cooling purposes.

nutrients contained in urine and faecal sludge from on-site systems is sufficient to sustain 50,000 hectares of cultivated rice in Dakar, Senegal.

This paper makes three contributions to the literature. First, it contributes to the literature that relates organic manure to farm production in the context of developing countries. Most of the existing studies on sludge manure and farm production are based more advanced countries (see Akdeniz et al., 2006 on Turkey, Annandale et al (2020) on Bangladesh Grau et al. (2017) on Sri Lanka and Zou et al. 2021 on China) with a few studies on developing contries (see Cofie et al. (2005) on Ghana, Guzha, (2005) on Zimbabwe, and Moya Diaz-Aguado et al. (2017) on Madgascar). moreover, most of the literature is crop specific. The studies on African continent has focused on cereals. This paper provides more insights on the impact of sludge manure on the number of crops including perenial crops (bananas and coffee). Second, the paper presents evidence from sludge manure collected from a formally instituted government institution where faecal sludge is processed into sludge manure. Other literature is based on unprocessed human excreta, which is likely to elicit resentment owing to diseases and stigma. This can cause limited use of sludge manure, thereby, leading to a lower measured impact than its potential.

3. 0 Methodology

3.1 Data and sampling strategy

To test whether sludge manure has an effect on farm production, we use household survey data collected from central Uganda between January and February 2023. The data were collected from the districts of Mpigi, Masaka, Mityana, Mukono, Luweero, and Wakiso. Our respondents were users of sludge manure processed at the Lubigi Sewerage Treatment Plant (LSTP). The use of sludge manure processed at the LSTP is still limited in a few districts, possibly because (1) the existence of plants is still unpopular among farmers countrywide and (2) the plant is located at the border of Kampala city and Wakiso district, and the cost of transporting manure to distant districts could be relatively high. We collected data from 522 farm households (199 sludge manure adopters and 323 nonadopters).

During sample selection, we employed a mix of sampling procedures. First, the selection of adopters was guided by lists of farmers who had collected sludge manure from the LSTP. The lists contain information about the farmer, e.g., name and contact, district, subcounty and village. From the lists, we purposively selected six districts based on the number of farmers who collected sludge manure[3]. From each district, two subcounties were randomly sampled, and from each subcounty, two parishes were selected (still randomly) as study areas. At the parish level, all adopters participated in the study except those who chose not to participate or who were absent at the time of the field visit.

The nonadopters were selected from the same study area. Prior to the fieldwork, we previsited the local/village leaders and obtained village census books. We dropped the adopters using the lists obtained from the LSTP and dropped immediate neighbours (defined by distance and relationship) to adopters using guidance from village leaders. From the remaining residents in each village, we randomly selected and constructed a list of nonadopters. In Table 1, we summarize the basic demographic information combining adopters and nonadopters of sludge manure, and in Table 2, we present a summary of demographic information separating the adopters of sludge manure from nonadopters.

[3] At the time of the survey, some districts had very few adopters, to a total of approximately 5 which would be unviable in logistical terms. We also remained silent about Kampala because evidence obtained from LSTP showed that many adopters in the city take very small quantities of manure for their house-bound flowers or for planting paspalum grass in their courtyards.

Table 1: Summary statistics (adopters and nonadopters combined, N = 522)[4]

Variables	Mean	SD	Min	Max
Dependent variables				
Banana (bunches)	85.618	120.635	0	960
Maize (sacks)	12.226	19.265	0	180
Beans (sacks)	1.848	5.428	0	100
Swt potato (sacks)	2.807	7.891	0	55
Coffee(kgs)	406.408	965.498	0	6800
Cassava (sacks)	2.018	4.462	0	50
Independent variables				
Age_household head	45.927	12.280	20	86
household_size	6.295	3.008	1	23
Distance market	3.782	6.575	0	46
Income_household	378243.3	546851.6	0	6000000
Hired_labor	0.492	0.500	0	1
Synthetic_fertilizer	0.417	0.493	0	1
Compost_manure	0.281	0.450	0	1
Hybrid_seeds	0.567	0.495	0	1
Government_support	0.151	0.358	0	1
Credit_access	0.461	0.499	0	1
Education_household head	0.906	0.291	0	1
Leadership	0.243	0.429	0	1
Group member	0.229	0.421	0	1
Irrigation	0.201	0.401	0	1
Landsize	4.623	6.301	0	100

Results in table 1 shows that on average, the respondents were approximately 46 years old, with an average family size of 6 people. The average distance to the market is 3.4 to 4 kilometers, and each household earns an average income of 378243 shillings per month (≈100.27 USD). On average, households hire 5 people on their farms, and close to 42 percent of the households use synthetic fertilizers, 28 percent use composite manure, and 57 percent have planted hybrid seeds at least in the last 2 seasons. Furthermore, 46 percent of the surveyed households accessed loans in the year preceding the survey, while only 15 percent had accessed government support. The majority of the respondents (90 percent) attended formal education, and more than 24 percent of the household heads held at least a leadership position. Twenty-three percent of the household heads are members of at least one farmer group, 20 percent of the households irrigate their crops, and the average land size owned by households is 4.6 acres.

[4] The variables used in the logistic estimation are described in section 3.2

Table 2: T test for adopters and nonadopters of sludge manure (n=522)[5]

Variables	Adopters (N=199)	Nonadopters (N=323)	Mean Difference	P Value
Age_household head	44.412	46.860	2.448	0.013
household_size	6.432	6.210	-0.221	0.793
Distance market	3.378	4.031	0.653	0.135
Income_household	319598	414374.6	94776.6	0.027
Hired_labor	0.623	0.411	-0.211	1.000
Synthetic_fertilizer	0.100	0.613	0.512	0.000
Compost manure	0.155	0.359	0.203	0.000
Hybrid_seeds	0.492	0.613	0 .120	0.003
Government_support	0.155	0.148	-0.007	0.588
Credit_access	0.402	0.498	0.096	0.016
Education_household head	0.889	0.916	0.026	0.153
Leadership	0.201	0.269	0.068	0.039
Group member	0.201	0.247	0.046	0.120
Irrigation	0.125	0.247	0.122	0.001
Landsize	5.015	4.381	-0.633	0.868

Source: *Author's computation using survey data*

Turning to Table 2, in which we split the sample between sludge adopters and nonadopters, several two-sample t test statistics indicate that some variables are differently distributed between the two groups, for example age of the household head, synthetic fertilizer, compost manure, hybrid seeds use, whether a household head hold a leadership position in the community, and whether a household irrigates its crops regularly. This suggests a need to control for them in our regression estimations.

3.2 Variable definitions and their influence on sludge manure adoption

This section describes the variables that influence the adoption of sludge manure. It also shows the hypothesised direction of influence. The variables are based on the literature that relates organic manure to farm production (Ajewole, 2010; Kateme & Bauer, 2011; Orinda, 2013; Uaiene et al., 2009; Uwagboe et al., 2012). These variables are presented in table 3.

[5] We also try to balance the sample size between adopters and nonadopters to check whether the groups remain statistically homogeneous when the two groups are relatively equal. We use Stata command sample 62 if nonadopters and randomly dropped 38% of the respondents in the control group. We remained with 200 observations and compare them with 199 adopters. We observe that even with relatively balanced samples, the groups remain robustly similar (see appendix 2) which supports the accuracy of our randomization.

Table 3: Variable names, variable descriptions and expected signs

Variable	Variable description	Expected influence
Age_household head	Age of household head in complete years.	-
household_size	Average number of people in a household	+/-
Distance market	Distance to the market from a household in kilometers	-/+
Income_household	Average monthly income of the household measured in Uganda shillings	+
Landsize	Number of acres under crop production.	+
Hired_labor	1 = household uses hired labour on crop production, 0 otherwise	+
Synthetic_fertilizer	1= household uses synthetic fertilizers, 0 otherwise	-
Compost_manure	1= household uses homemade compost manure, 0 otherwise	-
Hybrid_seeds	1= household uses hybrid seeds in the last 12 months, 0 otherwise	+
Government_support	1= household received government support in the last 12 months, 0 otherwise	+
Credit_access	1= household accessed a loan in the last 12 months, 0 otherwise	+
Education_household head	1= household head attended at least a level of formal education, 0 otherwise	+
Leadership	1= household head has at least a leadership role in the community, 0 otherwise	+
Group member	1= household head is a member of at least a farmers' group/cooperative	+
Irrigation	1= household irrigates crops regularly, 0 otherwise	+

3.3 Estimation Strategy

Before estimating the effect of sludge manure on farm production, we need to be thoughtful about the potential problems that can affect our results. Our study uses data collected from adopters of sludge manure for which the choice to adopt is not exogenous. The adoption of sludge manure can be influenced by a number of factors, e.g., access to information about the manure, the cost of collecting the manure from the LSTP to the farm, and farm size. By implication, the choice to adopt sludge manure is nonrandom and thus causes a threat of endogeneity arising from selection bias.

To address this threat, we use the propensity score matching (PSM) method to generate counterfactual estimates. This method has been used in a number of studies to control for endogeneity even when only one data wave is available (see Ntakyo & van den Berg, 2019; Melesse & Bulte, 2015; Melesse et al., 2018). Ravallion (2007) emphasized that propensity score matching does not necessitate a parametric model relating the result to the treatment and enables the calculation of mean impacts without making arbitrary assumptions about functional forms and error distribution. This increases the precision of causal estimations (DiPrete & Gang, 2004).

The propensity score *(p)* is the conditional probability *(p(X))* of households adopting sludge manure given observable characteristics *(X),* and the propensity of observations is assigned to the treated group using a logit model. In the model, only variables that simultaneously influence adoption and outcomes are included (Heckman et al., 1997). Therefore, in the logit estimation, we include a dummy variable (D_i) that takes the value of 1 if a household adopted sludge manure and 0 otherwise, as well as a vector of controls defined from the socio demographics of the respondents and geographical characteristics.

Suppose that the impact of sludge manure on farm production is given by $Y_i(D_i)$ for farm household i, where i = *1, 2….. N*[6]*;* then, we estimate the average treatment effect on the treated as:

$$ATT = E(ATT|D = 1) = E[(Y(1)|D = 1)] - [E(Y(0)|D = 1)] \quad (1)$$

where ATT is the average treatment effect on the treated, $E[(Y(1)|D = 1)]$ is the expected level of farm production for sludge manure adopters, and $E[(Y(0)|D = 1)]$ is the expected level of farm production if sludge manure had not been adopted. Since $E[(Y(0)|D = 1)]$ is not observed, PSM uses data from nonadopters with similar characteristics to estimate the counterfactuals. Matching helps in the construction of the counterfactual group from nonadopters while controlling for selection bias caused by observable covariates (Heckman et al., 1997). The comparison group needs to be statistically equal to the treated group, and all observable factors must be matched.

Using PSM involves the imposition of two critical identifying assumptions (Heckman et al., 1997)[7] The first is the conditional independence assumption (CIA), which asserts that treatment selection should be based entirely on a set of observable characteristics that determine both the chance of adoption and the outcome of interest. Rosenbaum and Rubin (1983) propose matching on the propensity score, p(X), which is the chance of receiving treatment conditional on all relevant factors, X, to avoid dimensionality issues. The second condition is the common

[6] N is the total number of farm households.

[7] Also see Caliendo and Kopeinig, 2008; Melesse & Bulte, 2015.

support condition, which ensures that households with identical observable characteristics have a good chance of being in both the treatment and comparison groups. If the CIA and common support assumptions are met, the PSM estimator for the ATT follows:

$$ATT = E(p(X)|D = 1)\langle E[(Y(1)|D = 1), p(X)] - [E(Y(0)|D = 0), p(X)]\rangle \quad (2)$$

To estimate ATT with PSM, many matching techniques have been developed. Nearest-neighbor matching and kernel-based matching are the most widely used algorithms. Using the nearest-neighbor matching method, each adopter is paired with a nonadopter who has the attributes closest to those of the adopters. It can be used in control units with or without replacement. In the kernel-based method, a weighted average of all nonadopters is matched with each adopter. In this paper, we report the results from the nearest neighbor estimation and the results from the kernel matching algorithm as a robustness check[8].

The selection of covariates was based on the literature on agricultural technology adoption and crop yield (Kassie et al., 2015; Kassie et al., 2020; Manda et al., 2019). The covariates include age of the household head, education level attained by the household head, household size, and social networks via membership in farmers' groups, access to credit, wealth indicators (such as land size) and production input costs (e.g., manure and fertilizers, labour, irrigation, and hybrid seeds) to control for the observed heterogeneity between adopters and nonadopters. We hypothesize that household characteristics and input costs affect farmers' crop production levels.

[8] Also results from radius calliper matching algorithms are presented in appendices 1, 1.2 and 1.3

4.0 Results and discussion

4.1 Propensity Score Matching Results

Table 4: Adoption selection model (logit) for specific crops

Variables	**odds ratios**						**Summary of findings**	
	Bananas (bunches)	Maize (sacks)	Beans (sacks)	Swt potato (sacks)	Coffee (kgs)	Cassava (sacks)	***Positive, Significant***	***Negative, Significant***
Age_household head	0.006	-0.004	0.023**	0.026**	0.039***	0.017*	Beans, Swt potatoes, coffee, cassava	N/A
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)		
household_size	0.104**	0.017	-0.013	0.078*	0.094**	0.088*	Bananas, Swt potatoes, coffee, cassava	N/A
	(0.039)	(0.038)	(0.033)	(0.035)	(0.036)	(0.034)		
Distance market	-0.036*	-0.050**	0.036*	0.084***	-0.019	0.006	Beans, Swt potatoes	Bananas, maize
	(0.016)	(0.018)	(0.017)	(0.021)	(0.015)	(0.016)		
Income_household	-0.000*	-0.000	-0.000**	-0.00***	-0.000	-0.000	N/A	Bananas, beans, Swt potatoes
	(0.000)	(0.000)	(0.000)	(0,000)	(0.000)	(0.000)		
Landsize	0.198***	0.079*	0.009	0.006	0.0381	0.017	Bananas, maize	N/A
	(0.039)	(0.032)	(0.016)	(0.017)	(0.024)	(0.016)		
Hired_labor	-0.132	-0.239	0.022	-0.001	-0.174	-0.245	N/A	N/A
	(0.224)	(0.234)	(0.202)	(0.218)	(0.209)	(0.215)		
Synthetic_fertilizer	-0.094	0.421*	0.462*	0.328	1.04***	0.154	Maize, beans, coffee	N/A
	(0.223)	(0.235)	(0.202)	(0.217)	(0.210)	(0.213)		
Compost_manure	0.783**	0.287	0.608**	0.586*	0.385	1.08***	Bananas, beans, Swt potatoes, cassava	N/A
	(0.275)	(0.277)	(0.228)	(0.240)	(0.236)	(0.231)		
Hybrid_seeds	0.222	1.83***	0.69***	0.560*	-0.255	0.483*	Maize, beans, Swt potatoes, cassava	N/A
	(0.227)	(0.248)	(0.209)	(0.227)	(0.214)	(0.222)		
Government_support	0.522	0.396	0.126	0.071	0.301	0.250	N/A	N/A
	(0.360)	(0.371)	(0.297)	(0.315)	(0.313)	(0.305)		
Credit_access	0.345	0.258	0.531*	0.670**	0.734***	0.635**	Beans Swt potatoes, coffee, cassava	N/A
	(0.229)	(0.238)	(0.208)	(0.229)	(0.214)	(0.221)		
Education_household head	-0.333	-0.633	0.271	0.311	0.450	0.212	N/A	N/A
	(0.384)	(0.403)	(0.340)	(0.372)	(0.346)	(0.366)		
								N/A

Leadership	-0.151 (0.281)	0.045 (0.293)	-0.044 (0.255)	0.048 (0.273)	0.264 (0.258)	-0.166 (0.267)	N/A	
Group member	-0.622* (0.294)	-0.581* (0.312)	-0.206 (0.265)	-0.693* (0.296)	0.108 (0.270)	-0.541* (0.287)	N/A	Bananas, maize, Swt potatoes, cassava
Irrigation	-0.711* (0.281)	-1.09*** (0.283)	-0.88*** (0.274)	-0.080 (0.281)	0.031 (0.267)	-0.247 (0.276)	N/A	Bananas, maize, beans
Constant	-0.278 (0.623)	0.739 (0.637)	-2.202 (0.580)	-3.345 (0.655)	-3.60 (0.617)	-2.988 (0.625)	N/A	N/A
Pseudo-R^2	0.1507	0.1853	0.1162	0.1492	0.1626	0.1165	N/A	N/A
Prob>chi^2	0.000	0.000	0.000	0.000	0.000	0.000	N/A	N/A
Obs	522	522	522	522	522	522	N/A	N/A

*Notes: Values in parentheses are standard errors. *Significant at 10%; ** significant at 5%; *** significant at 1%.*

The conditional probability of any intervention (in our case, sludge manure adoption) can be estimated using a standard logit model to predict the propensity score of adopters and nonadopters in the sample (Awotide et al., 2016; Danso-Abbeam &Baiyegunhi, 2019; Diiro et al., 2015; Melesse, 2015). From Table 4, several key conclusions can be drawn. First, the likelihood of adopting sludge manure by households that grow sweet potatoes, beans, coffee and cassava increases with the age of the household head. Second, as the number of people living in a particular household increases, the likelihood of adopting sludge manure to grow bananas, maize and cassava also increases. This is attributed to a household having more labor force to help in the distribution of manure. This result is supported by Ajewole, (2010); Ayenew et al., (2020), Endale, (2011) and Mebrate et al. (2022) which demonstrate a positive association between family size and fertilizer adoption.

Turning to land size, the logistic regression results indicate a high likelihood of adopting sludge manure when a household uses a large piece of land for growing bananas, maize and cassava. Bananas and cassava varieties are key staple foods in central Uganda. By implication, the result of a positive association between land size and bananas and cassava growing is not surprising. Pan et al. (2021) finds land to be a key constraint for the adoption of sustainable manure management technologies by large-scale farmers, which was also supported by Djibo and Maman., (2019).

Additionally, farmers who use composite manure have a greater likelihood of adopting sludge manure for growing bananas, maize and cassava. This can be attributed to farmers' past experience with the use of organic manure. Experience in the use of specific manure matters greatly for farm production. Hou et al. (2018) finds farmers with experience in the separating manure to easily make decisions or even assist in making decisions for technological adoption. Nevertheless, the results reveal a lower likelihood of adopting sludge manure when the distance to the market is long. However, farmers who live closer to the market are more likely to have access to agricultural information via various channels that aid adoption of modern technologies. This is more likely for growers of beans and sweet potatoes. This finding supports Iresso and Abebe, (2024) which finds adopters of inorganic manure to be closer to the market. However, the results also suggest a less likelihood of adopting sludge manure by banana growers.

Furthermore, households that irrigate maize and bananas have a lower likelihood of adopting sludge manure. The possible explanation for this result, is that our study focused on rural based farmers who are characterised by low incomes to finance adoption of multiple technologies. However, our results contradict the findings of Datar and Del Carpio (2009), which suggests that the use of irrigation practices is an important breakthrough in the adoption of manure and production of high-yielding and profitable crops.

Furthermore, bananas, beans and sweet potatoes growers are less likely to adopt sludge manure when they have a higher household monthly income. These results are in line with Saliem et al. (2020), which reports that higher household income may decrease farmers' dependence on agriculture. However, these results contradict Langyintuo and Mungoma, (2008) which finds household income to have a negative correlation with adoption. Langyintuo and Mungoma attribute that result to households spending on other inputs which constrains their ability to deploy manure.

Finally, if a household head is a member of at least a farmers' group, there is a lower chance of adopting sludge manure. This result supports Mwaura (2014), which demonstrates that being a member of a farmer's group has a negative relationship with inorganic fertilizer adoption in Uganda.

4.1.1 Effect of Sludge Manure Adoption on Crop Yields

Table 5: Average Treatment Effect using the Nearest Neighbor Algorithm[9]

Matched Crops	Adopters	Nonadopters	ATT
Banana (bunches)	154.372	35.038	119.334 (14.492)***
Maize (sacks)	16.978	8.741	8.236 (4.018)***
Beans/soya (sacks)	2.113	1.678	0.435 (1.153)
Swtpotato (sacks)	2.560	1.968	0.592 (1.210)
Coffee (kgs)	513.281	152.572	360.708 (151.418)***
Cassava (sacks)	2.875	1.115	1.76 (0.547)***

Source: *Author's computation using survey data*

The estimates of the impact of sludge manure adoption on farm yields are shown in Table 5. First, compared to nonadopters, bananas growers harvest 119 more bunches. This difference is statistically significant at the 1% level. Furthermore, comparing nonadopters and adopters, growers of coffee and cassava also significantly harvested more output when they used sludge manure. Specifically, coffee and cassava growers harvested an extra 361 kg and 1.76 sacks, respectively, when they used sludge manure compared to nonadopters. Additionally, the results in Table 5 reveal 8.2 sacks in the form of an extra harvest for maize. This result is in line with those of Andersson (2011) and Guzha (2005), who reported a positive effect on maize production after using faecal sludge in Zimbabwe and South Africa, respectively. However, as reported by Andersson (2015), maize yields increased by up to 120% among smallholder farmers in the Tororo district in eastern Uganda after the application of urine collected from their households.

For beans, the adopters harvested an extra 0.435 sacks, and this finding is in line with (Moya Diaz-Aguado et al., 2017), who reported an increase in farm yields after farmers adopted sewage sludge, while Yanggen et al. (1998) documented an average increase in cereal production as a result of using human excreta. However, an extra 0.592 sacks for sweet potatoes were produced by adopters compared to nonadopters, but this difference is statistically equal to zero. Therefore, the key finding of this study is the contribution of sludge manure to the yield of banana, cassava and coffee crops. These crops have not been studied before in relation to sludge manure. A crucial diagnostic marker of the effectiveness of matching power is the number of adopters used in estimating the ATT after matching, which is 185 (out of 199 adopters). Since only 14 adopters have left the support region, the information loss is rather small. Although the estimated results support the notion that the adoption or application of sludge manure to various crops affects yields for adopting households, our results reveal that the effect is not always significant across crops.

[9] Results from radius calliper Algorithms are presented in appendix 2.

Generally, the influence of the adoption to sludge manure on farm production can be explained by a number of factors, including enhancing farm yields, environmental protection and mitigation of health hazards. In the previous discussions, we demonstrated how sludge manure positively impacts the yields of banana, maize, coffee and cassava. In regard to environmental protection, Burducea et al., (2022); Li et al. (2017) and Khalid et al. (2017) confirm that organic manure revitalizes the health of the soil and improves its physical properties. According to Agbede et al., (2019) and Sarka & Siegh, (2003) organic manure increases soil bulk density, organic matter, and critical soil elements such as nitrogen and phosphorus. In contrast, the use of inorganic manure is associated with environmental destruction (Carvalho, 2006; Rahman & Zhang, 2018; Walsh et al., 2012) and contamination of water sources (Deknock et al., 2019). Furthermore, various researchers have proven that the excessive use of chemical fertilizers causes various diseases in farming systems (Boone, et al. 2019; Jayakumar, et al., 2023). Comparing synthetic fertilizers and organic manure, the concentrations of dangerous or contaminating compounds such as heavy metals and pesticide residues are often lower in organic manure (Jönsson, et al., 2004).

In regard to health, because humans are greatly dependent on soil and water for survival, they are exposed to health risks if synthetic fertilizers are applied on crop. This mostly occurs through the food chain. Consuming contaminated groundwater can result into human health issues, including hormone disruption, reproductive abnormalities, and cancer (Hossain et al., 2022). However, application of treated manure can lessen threats to human health via the food chain and drinking water (Goss et al., 2013). In conclusion, in this study, we examined the effect of well-treated sludge manure on crop yields, and the results reveal a positive effect on the production of bananas, maize, coffee, and cassava. This finding, implies that sludge manure has provide an excellent potential to reduce the overdependence on inorganic fertilizers, which are environmentally unfavourable and hazardous to humans.

4.2 Assessing Matching Quality

4.2.1 Conditional Independence Assumption

To validate the efficacy of PSM in terms of removing discrepancies in observables between adopters and nonadopters, the matching quality needs to be assessed. PSM credibility is founded on two distinguishing assumptions: the conditional independence assumption (CIA) and the common support condition. We explore whether the propensity score appropriately balances the distribution of key variables in the matched adopter and nonadopter groups for CIA. We use a two-sample t test to compare the means of adopters and nonadopters on each observable before and after matching, and a chi-square test is used to compare the joint significance of all variables in the logit model before and after the match. Tables 5 and 6 contain the outcomes of the tests. According to Rosenbaum and Robin (1983), a balancing test should involve balancing across the inferior bounds and running mean equality tests across the covariates. The results of the balancing tests of mean equality across covariates are presented in Table 6. The results reveal that the number of farm households adopting sludge manure and the corresponding nonadopting farm households are equivalent since there is no significant difference in their mean variables after matching. With the exception of hybrid seed usage, the two groups are identical across all other variables.

Table 6: T tests for the equality of means for each variable before and after the match

Variable	Sample	Mean (Adoption)	Mean (Nonadoption)	%reduction |bias|	T test p>|t|
Age_household head	U	44.412	46.861		
	M	44.946	44.824	95.0	0.917
household_size	U	6.432	6.210		
	M	6.367	6.784	-88.3	0.184
Distance market	U	3.378	4.031		
	M	3.477	4.286	-24.0	0.290
Income _household	U	3.2e+05	4.1e+05		
	M	3.3e+05	3.3e+05	96.6	0.939
Hired_labor	U	0.623	0.412		
	M	0.594	0.599	98.0	0.933
Synthetic_fertilizer	U	0.100	0.613		
	M	0.108	0.121	97.5	0.696
Compost_manure	U	0.155	0.359		
	M	0.167	0.155	94.2	0.757
Hybrid_seeds	U	0.492	0.613		
	M	0.502	0.635	-10.3	0.010
Government_support	U	0.155	0.148		
	M	0.140	0.149	-20.6	0.814
Credit_access	U	0.402	0.498		
	M	0.416	0.352	33.9	0.208
Education_household head	U	0.889	0.916		
	M	0.891	0.869	15.8	0.502
leadership	U	0.201	0.269		
	M	0.210	0.215	93.7	0.919
Grp_member	U	0.201	0.247		
	M	0.2	0.145	-15.8	0.170
irrigation	U	0.125	0.247		
	M	0.135	0.138	97.3	0.928
landsize	U	5.015	4.381		
	M	5.054	4.440	3.1	0.416

Source: *Author's computation using survey data (U= unmatched M= matched)*

Key results from table 6 are summarised in table 7 below.

Table 7: Chi-square test for joint significance of all variables before and after the match

Sample	Pseudo R^2	p> chi^2
Unmatched	0.322	0.000
Matched	0.029	0.452

The results are presented in Table 7 show that the chi-square test of all the variables in the logit model are not jointly significant after matching (prob > $_{\chi}2$ = 0.452). In contrast, the same test is rejected before the match (prob > $_{\chi}2$ = 0.000). This is supported by the pseudo R^2 values of the model before and after matching. There were no systematic differences in the distribution of covariates between adopters and nonadopters after matching. Second, the pseudo R^2 is fairly low compared to its value before matching which satisfies the post estimation requirement.

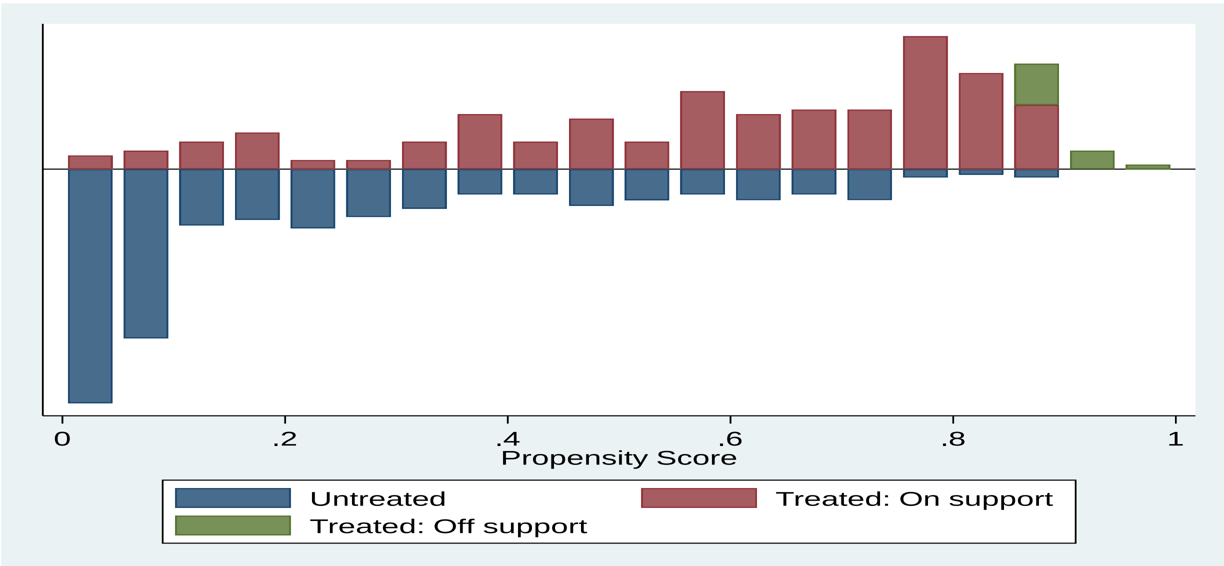
4.2.2 Common Support Assumption

Table 8: **Number of Farmed Hospitals with Nearest Neighbor Matching in Terms of Common Support**

	On Support	Off Support	Total
Sludge manure nonadopters	323	0	323
Sludge manure adopters	185	14	199
Total	**508**	**14**	**522**

The matching quality tests in Table 8 show that sludge manure adopters and nonadopters are equivalent. The matching process produced samples of nonadopters that are sufficiently similar to adopters, which allows for the building of counterfactuals for the ATT estimates. Furthermore, Figure 2 depicts the density distribution of the propensity score for adopters and nonadopters, demonstrating that there is significant overlap in the distribution for both users and nonusers of sludge manure. By implication, this indicates that the common support requirement has been met. The upper and lower sections of the histogram represent the adopters' and nonadopters' propensity score distributions, respectively.

Figure 1: **Histogram distribution of propensity score distributions and common support for adopters and nonadopters using nearest neighbouring matching**



Notes: "Treated: on support" indicates that sludge manure adopters constitute a suitable comparison group to nonadopters. "Treated: off support" represents the sludge manure adopters that did not have a suitable comparison group (nonadopters)

4.3 Sensitivity of ATT estimates to alternative algorithms

4.3.1 Estimates from the Kernel Algorithm

One of the significant shortfalls in PSM methodology is that selection into treatment is based on observed variables. Caliendo and Kopeinig (2008) noted that matching estimators are not robust to hidden bias due to unobserved variables. This study, therefore, checks the robustness of the estimates obtained from the nearest neighbor algorithm. First, the kernel algorithm results are used, and second, the Rosenbaum bounds sensitivity test is used. In the kernel algorithms, every treated subject is matched with the weighted average of the control subjects. The weights are inversely proportional to the distance between the propensity scores of the treated and control groups.

Table 9: Average Treatment Effects using Kernel Algorithms[10]

Matched Crops	Adopters	Nonadopters	ATT
Banana (bunches)	153.909	32.807	121.101 (14.908)***
Maize (sacks)	17.479	9.710	7.769 (3.355)***
Beans (sacks)	2.113	1.584	0.529 (0.913)
Swtpotato (sacks)	2.560	2.030	0.529 (2.212)
Coffee (kgs)	508.093	187.635	320.458 (145.752)***
Cassava (sacks)	2.762	0.900	1.861 (0.594)***

*Notes: Values in parentheses are standard errors. ** Significant at 5%; *** significant at 1%.*

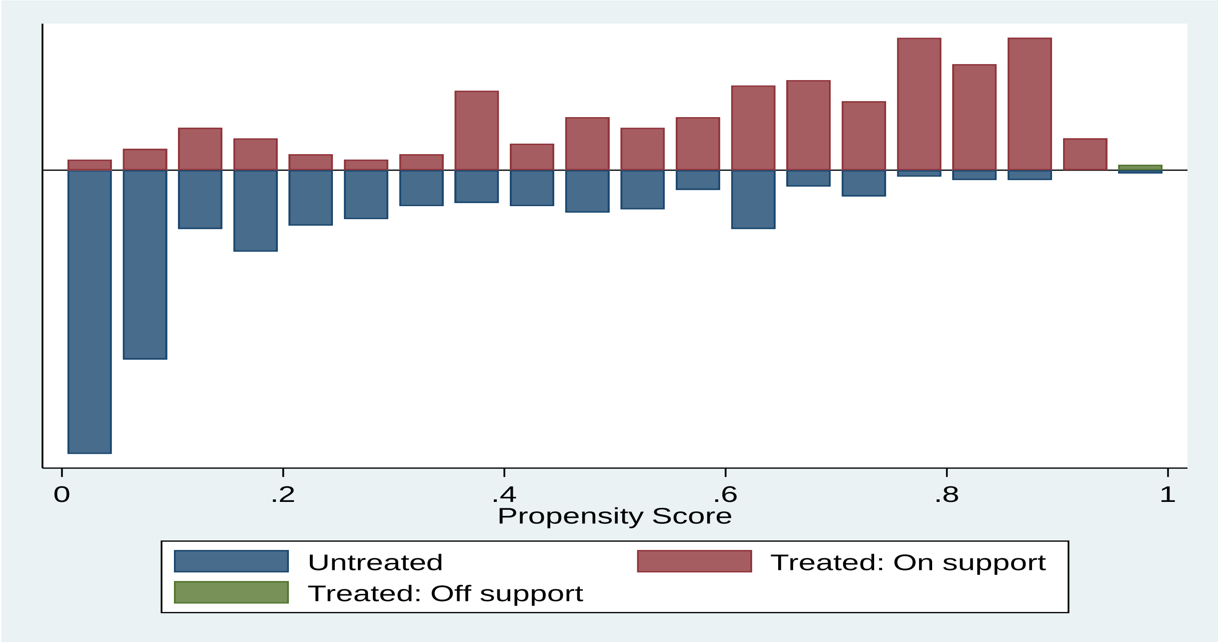
The results in Table 9 estimated using kernel algorithms remain robustly similar to those estimated using the nearest neighbor algorithm estimates in Table 5. For example, the results show that adopters experience an increase in bananas harvested by 121 bunches compared with nonadopters, 7.76 sacks of maize, 320 kgs of coffee and approximately 1.86 sacks of cassava. The robust resemblances of the kernel estimates to the nearest neighbor estimates also remain consistent with the kernel weight matching on common support and the score distributions and common support for adopters and nonadopters (see Table 10 and Figure 3).

Table 10: Farm Households with Kernel (Biweight) Matching on Common Support

	On Support	Off Support	Total
Faecal sludge nonadopters	323	0	323
Faecal sludge adopters	198	1	199
Total	521	1	522

[10] The results from adoption selection model for all crops remain robustly similar to those of Nearest Neighbor algorithms.

Figure 2: **Histogram distribution of propensity score distributions and common support for adopters and nonadopters (kernel matching)**



4.3.2 Sensitivity Analysis Using Rosenbaum Bounds

From the analysis, the rbounds "r" are greater than 3 (gamma > 3), which implies that the results are insensitive to hidden bias that would double (gamma = 2)–the odds of participation (self-selection) in the adoption of sludge manure but sensitive to bias that would triple the odds (gamma = 3). This is the magnitude of hidden bias that would make our findings of positive and significant effects of sludge manure adoption on farm production of the studied crops questionable. Hence, we conclude that the strength of the hidden bias should be sufficiently high to undermine our conclusion based on both nearest neighbor and kernel matching analysis.

5. Conclusion and recommendations

With increased soil salinity and reduced soil fertility in many agro-based countries, enhancing farm production requires the application of agricultural supplements. Both organic and inorganic supplements have been used by farmers over time, but some evidence related to the use of inorganic supplements has pointed to detrimental effects on the environment (Rahman & Zhang, 2018; Walsh et al., 2012), which puts organic supplements such as sludge manure at limelight. However, promoting the use of organic supplements requires a deeper understanding of their potential impacts on farm production.

In this paper, we examine the impact of sludge manure adoption on farm production, focusing on bananas, maize, beans, sweet potatoes, coffee and cassava. We studied sludge manure in the context of a formal arrangement under which the Lubigi Sewerage Treatment Plant (a government-managed facility affiliated with the National Water and Sewerage Corporation (NWSC)) collects faecal sludge (human waste) and processes it to sludge manure that it supplies to interested farmers.

Our main results indicated a positive and significant impact of sludge manure on bananas, maize, coffee and cassava. These results remain robustly similar when subjected to different estimation algorithms of propensity score matching. From a policy perspective, our results suggest that the design of agricultural productivity enhancing programmes, especially for farm households, requires leveraging organic technologies to promote agricultural production.

6. Limitations of the study and areas for future research

For logistical reasons, this study excluded urban farmers, yet information obtained from the LSTP indicates that sludge manure is also used by urban farmers to support urban farming, which is more intensive. Moreover, the study does not disaggregate the impact of sludge manure on farm production along the various dimensions of gender, e.g., education, marital status, etc. We only considered one gender dimension of whether the household head is male or female.

Furthermore, this study focused on the central region (Lake Victoria Crescent agro-ecological zone), but Uganda is characterized by seven agro-ecological zones, i.e., South-Western Grass Farmlands (SWGF), Western Medium-High Farmlands (WMHF), Western Mid-Altitude Farmlands and the Kyoga Flats (WMFKF), Lake Victoria Crescent and Mbale Farmlands (LVCMF), and North-Western Farmland Wooded Savannah (NWFWS). Therefore, our results may not be generalizable across all the agro-ecological zones of Uganda. As such, further studies that are inclusive of all agro-ecological zones are needed. Still, a gender-based study is important for providing more evidence on how sludge manure impacts farm production along various gender dimensions. This is important for enhancing women's empowerment.

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Appendices:

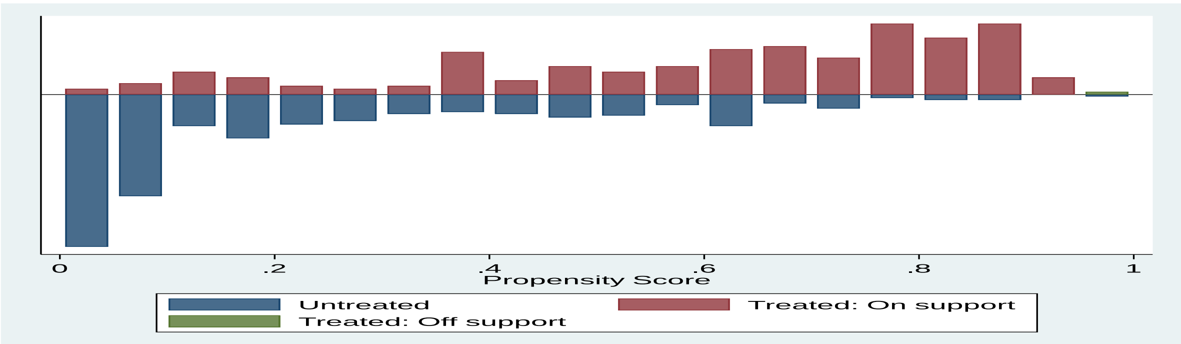
Appendix 1: Average Treatment Effects of Radius Callipers (0.1)[11]

Matched Crops	Adopters (treated)	Nonadopters (control)	MDE
Banana_bunches	153.909	38.392	115.517 (14.016)***
Maize_sacks	17.479	9.618	7.861 (3.012)***
Beans_sacks	2.113	1.670	0.443 (0.811)
Swtpotato_sacks	2.560	1.985	0.574 (1.950)
Coffee_kgs	508.093	179.185	328.908 (133.085)***
Cassava_sacks	2.762	0.960	1.802 (0.563)***

Appendix 1.2: Matching of Farm Households with Radius Callipers (0.1) for Common Support

	On Support	Off Support	Total
Faecal sludge nonadopters	323	0	323
Faecal sludge adopters	198	1	199
Total	521	1	522

Appendix 1.3: Histogram distribution of propensity score distributions and common support for adopters and nonadopters (radius calliper matching)



[11] Estimating the adoption selection model for ATT using Radius Calliper gives robustly similar results like the Nearest Neighbour and Kernel algorithms.

Appendix 2: T test for adopters and nonadopters of sludge manure (N=399)

Variables	Adopters (N=199)	Nonadopters (N=200)	Mean Difference	P Value
Age_household head	44.261	47.06	2.798	0.011
household_size	6.432	6.265	-0.167	0.712
Distance market	3.440	3.502	0.124	0.406
Income_household	319598	393675	74077	0.061
Hired_labor	0.623	0.42	-0.203	1.000
Synthetic_fertilizer	0.155	0.36	0.204	0.000
Compost manure	0.100	0.585	0.484	0.000
Hybrid_seeds	0.492	0.57	0.077	0.060
Government_support	0.155	0.155	-0.000	0.508
Credit_access	0.402	0.555	0.152	0.001
Education_household head	0.889	0.935	0.045	0.054
Leadership	0.201	0.245	0.043	0.146
Group member	0.201	0.25	0.048	0.121
Irrigation	0.125	0.265	0.139	0.000
Landsize	5.270	3.780	-1.489	0.999

Appendix 3: Processing of sludge manure at LSTP