Research article

Socio-economic determinants and impact of adopting climate-smart Brachiaria grass among dairy farmers in Eastern and Western regions of Kenya

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ABSTRACT

The sustainability of the livestock sector in sub-Saharan Africa is negatively affected by limited access to high-quality fodder in adequate quantities. The effects of climate change further exacerbate feed availability. Therefore, there is a need to develop feasible cost-effective strategies for improving the year-round feed supply. Improved planted forages such as Brachiaria grass have been recommended as one of the strategies of alleviating feed scarcity, especially in drier agro-ecological zones. This study analyses the socio-economic determinants of adoption and the impact of adopting Brachiaria grass for feed sufficiency and increased milk production. Propensity Score Matching (PSM) method was used to assess the determinants and impact of the adoption of Brachiaria grass. Empirical results indicate that the adoption of Brachiaria grass led to a significant increase in milk production by 27.6% and feed sufficiency by 31.6%. The positive impact of Brachiaria grass is consistent with the role of agricultural technologies in improving the productivity, income, and welfare of smallholder farmers. The adoption of Brachiaria grass is influenced by age of farmer, tropical livestock unit (TLU), type of animal breed, perceived benefits of the technology, access to extension, and farmer group membership. The study recommends holistic policy approaches that promote the widespread adoption of Brachiaria grass. There is also a need for an effective information dissemination pathway for Brachiaria grass.

1. Introduction

Population growth, urbanization, and increasing consumer demand on livestock are re-shaping the livestock systems globally (White et al., 2013). In 2015, the United Nations estimated that by 2050, Africa would account for more than half of the world's projected growth in population to 9.7 billion (United Nations, 2015). The growth in population is expected to double the demand for milk and meat products in Africa by 2050 (Holechek et al., 2016). This raises concern on the capability of African countries to feed the projected population growth.

Livestock production is a major source of food and income for rural households in sub-Saharan Africa (Thornton, 2010; Thornton et al., 2003). The dairy sub-sector is a major income earner and a source of employment for the farming community. Estimates from Kenya's Economic Survey of 2017 indicated that the sub-sector contributes about 14% to the agricultural gross domestic product (GDP). Additionally, dairy contributes to the nutritional status of households by providing calcium and vitamin B12 (FAO, 2015). Despite this contribution, the productivity of livestock is more than often constrained by the availability of quality fodder (Lugusa et al., 2016). Increasing temperatures coupled with prolonged drought negatively affect forage quantity and quality; and consequently reduces livestock productivity (Dawson et al., 2014). Constant seasonal variation in forage availability increases the cost of feed thereby threatening the sustainability of the livestock sector (Fallis, 2015; Gachuiri et al., 2017; Lukuyu et al., 2009). Moreover, the scarcity of feed increases labour demands on all household members especially women[1] and children below 18 years (Tangka and Jabbar, 2010).

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[1] Emphasis has often been put on women owing to the major responsibilities they have in agricultural production as well as household activities (Tangka and Jabbar, 2010). In dairy production systems, women are responsible for feed related activities, milking and milk processing.

Climate-Smart Agriculture (CSA) is designed to implement sustainable agricultural development strategies that address challenges in climate change and food security (FAO, 2015). However, scarcity of climate-smart fodder varieties, inadequate rainfall, recurrent and prolonged drought are major factors contributing to insufficient quality and quantity of feed. Fodder production systems in Kenya are mainly rain-fed and farmers have limited ability to prepare for dry periods and appropriate feeding regimes. Therefore for most farmers, the production and sales activities are suboptimal (Netherlands Development Organization SNV, 2013). Increased population growth and loss of pastoral land to competing alternative enterprises such as crop production and non-agricultural uses (e.g. real estate development), has aggravated the feed scarcity situation (Njarui et al., 2016). Therefore, the scarcity of quality fodder is of great concern, especially for resource-poor dairy farmers given the prolonged dry season. It is against this backdrop that there is a need to improve the quality and reliable availability of year-round fodder. It follows that adoption and use of improved planted forages is one of the main alternatives available to improve the productivity of the dairy sector. Improved planted forages such as Brachiaria grass (*Brachiaria decumbens*) can contribute to alleviating feed scarcity (Kabirizi et al., 2013).

Brachiaria grass is nutritious and gives high biomass production and hence has the potential to increase the productivity of livestock (Holmann et al., 2004; Kabirizi et al., 2013; Rivas and Holmann, 2005). Low (2015) notes that Brachiaria is common in South America and parts of South East Asia due to its adaptation to different soil types and environments. Kabirizi et al. (2013) and Rao et al. (2014) also note that Brachiaria grass tolerates prolonged drought periods and adapts well to soils with low fertility. Additionally, it can increase nitrogen use efficiency as well as sequester carbon through its large root system (Arango et al., 2014; Rao et al., 2014; Subbarao et al., 2009). Several experimental field trials have shown the potential of integrating Brachiaria in different agro-ecological zones and the potential to increase livestock productivity (Gatheru et al., 2017; Maass et al., 2015; Moreta et al., 2014; Nguku, 2015; Njarui et al., 2016; Rivas and Holmann, 2005). Despite the potential benefits of Brachiaria, little is still known about the drivers and impacts of adoption. Gatheru et al. (2017) and Nguku (2015) used participatory on-farm evaluations to assess the agro-ecological adaptability of Brachiaria cultivars. These studies concluded that Brachiaria can adapt to low fertility soils as well as different drier agro-ecological zones. Similarly, Muinga et al. (2016) used an on-farm feeding trial to assess the effect of Brachiaria on lactation performance of cows. The study concluded that in comparison to local feed, Brachiaria can increase milk production by 15–40%. Murage et al. (2015b) used a Tobit model to evaluate the factors influencing the extent of adopting climate-smart push-pull technology that utilizes Brachiaria. Additionally, Kassie et al. (2018) used a combination of economic surplus and econometric methods to assess the economic and social welfare effects of push-pull technology. However, the studies focused on the adoption of Brachiaria as part of a technology package that involves intercropping of cereal crops with perennial fodder legumes and perennial fodder grass such as Brachiaria. Therefore, the studies could not isolate the determinants of adopting Brachiaria as a fodder crop as well as its effect on milk productivity and feed sufficiency. Thus, empirical evidence on the drivers of technology adoption and possible impacts on livelihoods is crucial in developing effective policy interventions that promote the uptake of new technologies (Kassie et al., 2011).

This study, therefore, seeks to fill in the gap in the literature on the determinants of adoption of Brachiaria using household socio-economic characteristics and institutional support factors. The specific objective of this study was to assess the factors that influence the adoption of Brachiaria and the impact of adoption on milk productivity and feed sufficiency. In the present study, milk productivity was measured as annual milk production per household. This was achieved by estimating the lactation curve of the cow and accounted for the different breed types. Feed sufficiency refers to the extent to which farmers can adequately meet demand on feed throughout the year. Feed sufficiency was, therefore, measured by considering the man-hours dedicated to feeding-related activities (feed sourcing and preparation) by the primary woman in the household.

The following section of this paper comprises Section 2 that describes the methodology of the study including research design and sampling techniques. Section 3 presents key results and discussions; Section 4 makes a conclusion on key findings and their policy implication.

2. Methodology

2.1. Theoretical analysis of farmers adoption process

There is potential for households to increase dairy productivity (milk yield), improve the household living standards, and conserve the environment through the adoption of Brachiaria grass. It is evident in literature that uncertainty and risk play a critical role in the adoption of new agricultural technologies (Mercer, 2004). Following the theory of expected utility, the assumption is that a farmer's decision, whether to adopt or not to adopt a technology such as Brachiaria grass given the risk and uncertain prospects, is based on the comparison of expected utility from maximizing profit (Mercer, 2004; Schoemaker, 1982). Joao et al. (2015) note that since it is difficult to measure utility, profit can be used as a proxy and if combined with attitude to risk, farmers are described as maximizing the expected utility of profit rather than expected profit. For example, if farmers expect that Brachiaria would lead to an increase in milk output, they will adopt the fodder. Kassie et al. (2015) note that farmers will adopt a technology if the expected utility from adoption (U_a) is greater than that derived from non-adoption (U_n).

Following Greene (2003), the utility derived from the adoption of Brachiaria will have a dichotomous choice component determined by observable characteristics Z_i and a stochastic error term ε_i which is unobservable. Such that:

$$I_i^* = \beta Z_i + \varepsilon_i, \quad I_i = 1 \, if \, I^* > 0, and \, 0 \, if \, otherwise \tag{1}$$

where I_i is a binary choice variable for the adoption of Brachiaria that equals 1 if household i adopts Brachiaria and 0 if otherwise, β is a vector of parameters to be estimated, Z_i is a vector of household socio-economic characteristics and ε_i is the error term.

Thus, farmers will adopt Brachiaria if $I_i^* = U_a - U_n > 0$. The probability of adopting Brachiaria can then be estimated as follows:

$$\Pr(I_i = 1) = \Pr(I_i^* > 0) = 1 - D(-\beta Z_i) \tag{2}$$

where $\Pr(I_i = 1)$ is the probability of adoption, D is the cumulative distribution function for ε_i. The assumption on the functional form for D differentiates the models used in estimation. The probit model is applied when the distribution is assumed to be normal and the logit model is used for logistic distribution (Greene, 2003).

2.2. Analytical framework

2.2.1. Impact evaluation

The conventional approach in impact evaluation such as the adoption of Brachiaria grass on milk productivity and feed sufficiency would be to obtain a reduced-form equation showing the relationship between fodder choice and the outcome variable and subsequently applying OLS regression. The relationship can be specified as:

$$Y_i = \alpha Z_i + \beta I_i + \varepsilon_i \tag{3}$$

where Y_i is a continuous outcome variable representing milk productivity and feed sufficiency for the ith household, I_i is a dummy for adoption; $I_i = 1$ if a household adopted Brachiaria and $I_i = 0$ otherwise. Z_i is a vector of household socio-economic characteristics. ε_i is the error term that is

normally distributed reflecting unobservable factors such as farmer managerial skills that also affect the outcome (Y_i).

This approach, however, leads to biased estimates due to the correlation of the error terms in Eqs. (1) and (3) as a result of unobservable factors (selection bias). Researchers have, therefore, employed various approaches to correct for selection bias. Heckman's two-stage (Heckman et al., 1998) and the instrumental variable (IV) approach (Khandker et., 2010) have been used to address selection bias. However, the procedures are dependent on the distributional assumption of the normality of the unobservable. Following Jalan and Ravallion (2003), the assumption may not hold. Moreover, the instrumental variable approach (IV) requires instruments that are difficult to identify in empirical studies.

The Difference in Difference Method can be used to eliminate selection bias as it allows time-invariant differences in outcomes between adopters and non-adopters. Nevertheless, it requires two sets of data for the pre-treatment period (Conley and Taber, 2011) which were not available. Therefore, the current study used propensity score-matching approach (PSM) to control for selection bias.

2.2.2. Propensity score matching approach

The PSM method compares observable outcomes between adopters and non-adopters of Brachiaria. Moreover, it does not rely on assumptions of distribution and functional form of the error terms making it appealing (Heckman et al., 1998). For this study, the outcome variables are milk productivity (yield per lactation year) and feed sufficiency measured by time spent (by the primary woman in a household) in sourcing and preparing feed. Feed sufficiency refers to the availability of fodder in adequate quantities. The primary woman in a household herein refers to the specific woman in a household aged above 18 years who undertakes feed-related activities. The proxy for feed sufficiency follows Ashley et al. (2016) in their study on the socio-economic impact of forage technology adoption by smallholder cattle farmers in Cambodia.

PSM has been used in previous studies to correct the self-selection bias and to estimate the average treatment effect (ATE) of technology adoption (Haji and Legesse, 2016; Mwansakilwa et al., 2017; Rosenbaum and Rubin, 1983, 2006). PSM can be used to identify the impact of adopting Brachiaria if the assumptions of conditional independence (unobserved factors do not affect participation) and common support (significant overlap in propensity scores between adopters and non-adopters) hold (Khandker et al., 2010). The main idea for the PSM approach is to find in the group of farmers, those individuals who are similar to adopters in all relevant pre-treatment observable characteristics. This means finding a control group similar in characteristics to adopters. The assumption is that after controlling for all pre-adoption observable characteristics correlated with adopting Brachiaria and the outcome variables, farmers who have adopted have similar average outcomes as non-adopters would have had, had they adopted.

Differences in outcomes between the treated and control group are attributed to the adoption of Brachiaria.

Propensity score can be estimated using binary choice models such a logit or probit, where adoption is regressed against pre-intervention characteristics to derive the predicted probability of adoption (propensity scores). A probit model was used to estimate the propensity scores. Following empirical studies on the adoption of agricultural technologies (Ashley et al., 2016; Kassie et al., 2011, 2018, 2015; Murage et al., 2015a; Ndiritu et al., 2014; Shiferaw et al., 2014; Teklewold et al., 2013) variables hypothesized to influence adoption are presented in Table 1.

The second step involved is matching the estimated propensity scores using the best matching estimator. The most widely used matching algorithms in literature include Kernel Matching, Radius matching (RM), and nearest-neighbour matching (NNM). Baser (2006) notes that the best matching algorithm is one that reduces selection bias by increasing the balance between adoption and non-adoption. In the current study the best matching algorithm was selected because it had large matched samples, a large number of insignificant variables, a small pseudo- R^2 after matching, and a small mean standardized bias (Abadie and Imbens, 2008). The methods were tested based on the aforementioned criteria. Matching was restricted to the region of common support between the treated and control groups. Imposing this restriction helps to improve the quality of the matches used in the estimation of the average treatment effects on the treated (ATT) (Caliendo and Kopeinig, 2008; Kiiza et al., 2011).

Following Rosenbaum and Rubin (1983) and Caliendo and Kopeinig (2008), the ATT was estimated as follows:

$$ATT = E(Y_1 - Y_0 | I = 1) = E(Y_1 | I = 1) - E(Y_0 | I = 1) \qquad (4)$$

The ATT can be estimated by $E(Y_0 I = 0)$ since the counterfactual outcome ($E(Y_0 | I = 1)$ for a given household is unobserved. However, the approach may lead to a biased ATT. The non-adopters and adopters may be different before adoption; therefore, the expected differences in the outcome may not entirely be attributed to adoption.

Based on the assumption of conditional independence and common support, it is observed that the PSM approach will have similar conditions as those of randomized experiments (Ali and Abdulai, 2010). The propensity score under the assumption of conditional independence is given by:

$$p(Z) = pr(I = 1 | Z) = E(I | Z) \qquad (5)$$

where $I = 1$ or 0 is a binary choice for adoption or non-adoption; Z is a vector of household characteristics. Thus, the conditional distribution of Z given p(Z) is the same in both groups of adopters and non-adopters. Therefore, under this assumption estimation of the propensity score

Table 1. Description of explanatory variables influencing adoption of Brachiaria Grass.

Variable	Description	Type of Variable
Sex of HH	Sex of the household head	Dummy (1 = male, 0 = female)
HH Size	Number of people in a household	Continuous
Perception of milk productivity	Perceived effect of Brachiaria grass on milk production	Continuous (measured as a factor score)
Age of HH	Age of household head in years	Continuous
Farming experience	Years that a household head has practiced dairy farming	Continuous
Education (years completed)	Number of years completed of formal education by the household head	Continuous
Farm Size	Size of the farm in acres	Continuous
Group Membership	Subscription to a social group/society by the household	Dummy (1 = yes, 0 = no)
Source HH income	Main source of income for the household	Dummy (1 = Off-farm, 0 = farm)
TLU	Tropical Livestock Unit	Continuous
Extension	Access to extension by the farmer	Dummy (1 = yes, 0 = no)
Breed type	Type of dairy cow that a farmer keeps	Dummy (1 = exotic breed 0 = otherwise)
Credit Access	Access to finance by the household Head	Dummy (1 = yes, 0 = no)

tries to balance the observed distribution of the covariates across the two groups (Khandker et al., 2010).

The assumption of common support is expressed as:

$$0 < pr(I = 1|Z) < 1 \qquad (6)$$

This assumption ensures that every person has a positive probability of adopting Brachiaria.

Based on the two assumptions in Eqs. (5) and (6), the ATT can then be estimated as:

$$
\begin{aligned}
ATT &= E\{Y_1 - Y_0|I = 1\}, \\
ATT &= E[E\{Y_1 - Y_0|D = 1, p(Z)\}], \\
ATT &= E[E\{Y_1|D = 1, p(Z)\} - E\{Y_0|D = 0, p(Z)\}|D = 1]
\end{aligned} \qquad (7)
$$

2.3. Study area and sampling design

The study collected household data from Siaya and Makueni counties in the Western and Eastern regions of Kenya. The study sites were purposively selected to represent non-traditional dairy production areas within the sub-humid and mid-altitude agro-ecological zones in Kenya. Additionally, the sites selected have larger proportions of dairy farmers within the agro-ecological zones of interest. The study sites are characterized by low soil fertility and feed scarcity (Fallis, 2015; Gatheru et al., 2017; Njarui et al., 2016). Further, the government of Kenya through Kenya Agricultural and Livestock Research Organization (KALRO) in collaboration with the International Livestock Research Institute (ILRI) have been implementing feed and dairy interventions through projects such as Feed The Future Kenya: Accelerating Value Chain Development (AVCD).

The study adopted a multi-stage sampling technique to select respondents. The first stage involved the purposive selection of two counties (Siaya and Makueni). Siaya County has six sub-counties, namely; Ugenya, Ugunja, Gem, Rarieda, Bondo, and Alego-Usonga.

Makueni County also has six sub-counties namely; Kilome, Kaiti, Mbooni, Makueni East, and Makueni West. Before randomly selecting two sub-counties in each County, four sub-counties were dropped. First, Rarieda and Bondo sub-counties were eliminated since they are closer to the shores of Lake Victoria. Additionally, they have lower densities of smallholder dairy farmers; thus, their inclusion would have resulted in increased data gaps. Secondly, Makueni East and Makueni West were also dropped since they fall under the dry mid-altitude agro-ecological zones; thereby, ensuring uniformity of the agro-ecological zones for the study sites. In the second stage, due to budgetary and time constraints, two sub-counties were randomly selected. Ugunja and Alego-Usonga sub-counties in Siaya County and Makueni and Kaiti sub-counties in Makueni County were selected. Data were collected from the four sub-counties as shown in Figure 1:

With the help of extension officers and contact farmers, two clusters of wards and villages were identified. The first cluster focused on villages with a larger proportion of Brachiaria adopters. In the second cluster for non-adopters, neighbouring villages where farmers utilized improved Napier grass (*Pennisetum purpureum*) varieties such as Kakamega I and II were considered in order to minimize the incidence of spillovers. This criterion has been considered in other impact assessment studies to control for any influence (bias) resulting from close proximity with adopters (Gitonga et al., 2013; Marwa et al., 2020). Eight villages were then selected in each sub-county. From each village in the identified clusters, a list of dairy farmers was generated followed by a random selection of respondents using proportionate to size approach. Meaning more respondents were sampled from the list with more names. The procedure resulted in a sample size of 237 respondents. The low sample size is attributed to the fact that the study sites are non-traditional dairy production zones with lower proportions of smallholder dairy farmers. Makueni County had 132 respondents (50 adopters & 82 non-adopters) whereas Siaya County had 105 farmers (56 adopters & 49
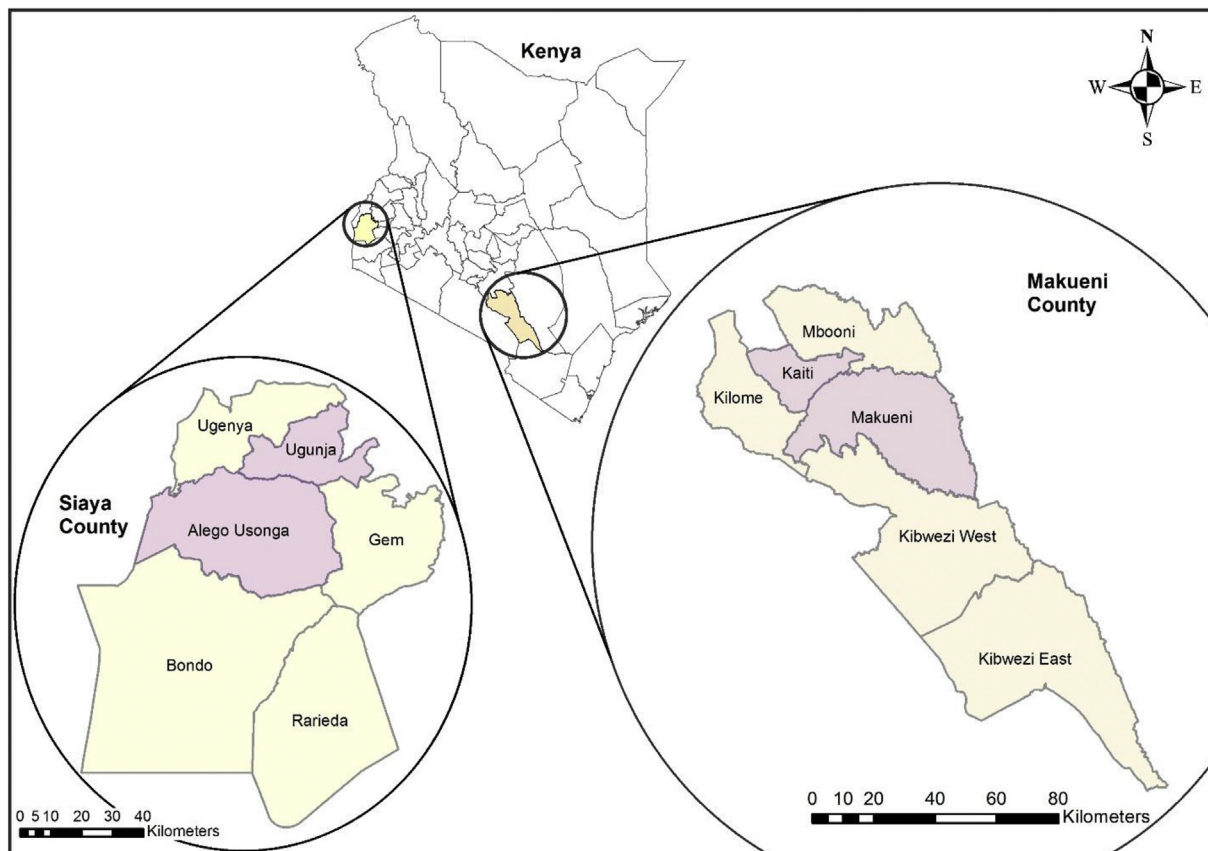

Figure 1. Map of the study area.

non-adopters). To ensure completeness of data, farmers who had lactating cows for the last one year (12 months) were considered in the survey. Data were collected and entered using computer-aided personal interviews application CS Pro version 7.1 program.

3. Descriptive results

3.1. Household demographics and social characteristics

Table 2 shows the summary statistics of selected socio-economic characteristics of dairy farmers that were sampled in Makueni and Siaya counties. Most of the households were male-headed (77%). The average age of the household head was 54–58 years. The household head for adopters was significantly older than for non-adopters. The average number of years of formal education completed by the household head was 10 years and was not significantly different between adopters and non-adopters. Farming experience in dairy was 12 years for adopters and 11 years for non-adopters. The average household size was six people for both adopters and non-adopters.

Adopters derived more income from off-farm activities (76%) compared to non-adopters (66%). The average farm size for adopters (4.37 acres) was significantly higher than for non-adopters (2.96 acres). Additionally, adopters had an average tropical livestock unit (TLU) of 9.36 units, which is significantly higher than for non-adopters (6 units). Larger proportions of adopters (84%) significantly had more access to extension compared to non-adopters (60%). Consequently, adopters had significantly higher perception scores (4.27) on milk productivity compared to non-adopters (3.45). A significant proportion of adopters belonged to a social/agricultural group (87%) compared to non-adopters (60%). Moreover, more adopters reported having accessed credit (40%) compared to non-adopters (30%).

4. Model results

4.1. Factors influencing adoption of Brachiaria

The results of the probit model shown in Table 3 were used to estimate the propensity scores for participation in Brachiaria production using factors that drive the adoption of the grass. The probit model was subjected to a test of normality using the Jarque-Bera test. The calculated Chi^2 probability was greater than the stated (prob $> Chi^2 = 0.432$) at 1% level of significance (Table 4). Hence, the study failed to reject the null hypothesis and concluded that the error terms are normally distributed. Therefore, it was fit to estimate the propensity scores using a probit model.

Empirical results in Table 3 indicate that older farmers were more likely to adopt Brachiaria grass. Kassie et al. (2009) and Teklewold et al. (2013) note that older farmers are perceived to be more experienced than younger farmers and thus are more likely to adopt new agricultural technologies. The findings are similar to those of Asfaw et al. (2012) who found that older and experienced farmers were more likely to adopt improved pigeon pea in Tanzania. Moreover, monetary benefits from fodder production are not immediate compared to flexible crops such as maize. A substantial amount of time is required for a farmer to realize them (Holmann et al., 2004; Rivas and Holmann, 2005). Kanyenji et al. (2020) noted that older farmers were less likely to adopt the use of inorganic fertilizer compared to younger farmers starting farming. The study alluded to the fact that younger farmers are willing to invest in farming enterprises that have a higher rate of turnover. Therefore, older farmers are willing to invest in long-term farm enterprises such as the establishment of Brachiaria and wait for the anticipated benefits.

Households with higher tropical livestock units and own improved breeds are more likely to adopt Brachiaria grass. Households with larger herd sizes have higher demands for animal feed requirements. This results in farmers sourcing for alternative feed sources. Kanyenji et al. (2020) observed that households with higher tropical livestock units utilized more crop residue as animal feed and thus more likely to adopt agricultural technologies that yield more animal feed. Similar observations were made by Kassie et al. (2018); Murage et al. (2015a) and Khan et al., 2014 who found that ownership of productive resource such as dairy cows increased the adoption of climate-smart push-pull technology as they would utilize the fodder produced.

Farmers who perceived Brachiaria grass could increase milk production were more likely to adopt Brachiaria. The findings are similar to those of Murage et al. (2015b) who note that farmers adopted climate-smart push-pull technology that utilizes Brachiaria because they

Table 2. Selected characteristics of adopters and non-adopters of Brachiaria grass in Siaya and Makueni counties.

Explanatory Variables	Description of variables	Overall sample n = 237			
		Mean		t-test	
		Non-adopters n = 126	Adopters n = 111	Sig. (2-tailed)	χ^2-value
Socio-economic characteristics					
Sex of HH	% of male HH	77%	77%		0.01
Age of HH	Age of household head in years	54.2 (13.94)	58.85 (13.12)	2.70***	
Education	Number of years completed of formal education by the household head	10.33 (8.93)	10.71 (3.62)	0.43	
Farming experience	Experience of the household head in dairy farming in years	11.04 (13.94)	12.65 (11.16)	1.01	
HH size	Number of people in a household	5.58 (2.4)	5.9 (2.91)	0.9337	
Source HH income	% of HH whose main source of income is off-farm income	66%	76%		2.72
Farm characteristics					
Farm size	Size of the farm in acres	2.96 (2.82)	4.37 (5.22)	2.62***	
TLU	Tropical livestock unit	6 (4.2)	9.36 (9.20)	3.68***	
Breed type	% of household whose main breed type is exotic	61%	91%		28.18***
Farmer perception					
Perception on milk productivity	Perception effect of Brachiaria grass on milk productivity	3.45 (0.68)	4.27 (0.55)		100.30***
Institutional characteristics					
Group Membership	% of HH belonging to a social group/society	60%	87%		21.94***
Credit Access	% of HH that has access to credit	30%	40%		5.60**
Extension	% of HH that have access to extension	60%	84%		47.88***

Note: HHH refers to household head, HH refers to HH.

*** and ** represent significance at 1% and 5% probability levels, respectively. (Standard deviation) in parentheses.

Table 3. Jarque-Bera test of normality of the error terms.

kewness-Kurtosis test (Jarque-Bera)
Ho: Normal Distribution
Chi^2 (2) = 1.558
Prob > Ch^2 = 0.432

perceived that Brachiaria provided fodder during drought period and it increased milk production. Therefore, the perceived benefits of a specific technology influence adoption decisions made by farmers. Mishra et al. (2018) and Meijer et al. (2014) observed that farmers' prior knowledge of the benefits of technology creates a positive attitude on the technology and increases the likelihood of adoption.

Membership to a social or agricultural group increases the probability of adopting Brachiaria grass. Similar findings were observed by Kanyenji et al. (2020), Kassie et al. (2011), Kassie et al. (2015), and Marwa et al. (2020) who observed that membership to an agricultural group increased the likelihood of adopting an agricultural technology. Membership to a group is a proxy for social capital. These social networks facilitate the flow of information and provide avenues for peer learning among farmers (Kassie et al., 2011). Quisumbing (2003) indicates that social groups also act as informal insurance in crisis periods. This implies that the dissemination of new technologies such as Brachiaria can reach more farmers when channeled through agricultural groups such as cooperatives.

Farmers that had access to extension services were more likely to adopt Brachiaria grass. The findings are similar to those of Ali and Abdulai (2010) who indicated that extension visits facilitated the adoption of genetically modified cotton in Pakistan. Similarly, Kassie et al. (2015) found that access to quality extension services increased the adoption of water and soil conservation technologies in East and Southern Africa. Extension services facilitate the flow of information and farmers are more aware of emerging technologies. Extension services also provide avenues for farmers to observe potential benefits either by demonstration or by linking farmers with early adopters.

4.2. Choosing the matching method

In order to minimize selection bias from the unobservable factors and estimate the impact of adopting Brachiaria grass, it was necessary to match participants and non-participants in Brachiaria production. Kernel matching bandwidth 0.25 was chosen to estimate the impact (ATT). Heckman et al. (1998) notes that kernel-matching estimators perform better in reducing the standardized mean bias between adopters and non-adopters compared to other estimators. Haji and Legesse (2016) point out further that kernel matching has a lower variance and uses more information in the matching of propensity scores.

4.3. Inspecting the matching quality of kernel method on the propensity scores

Verification of the performance of the matching estimator is accomplished by verifying the assumption of common support. According to
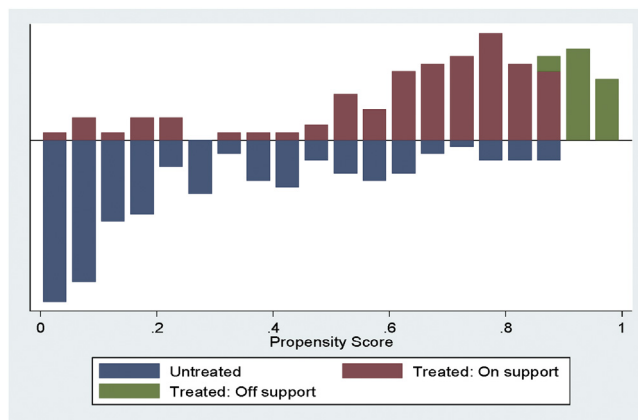

Figure 2. Propensity score distribution and common support area for milk productivity by pairwise comparison of adopters and non-adopters. Source: Survey data 2018, plotted using psgraph.
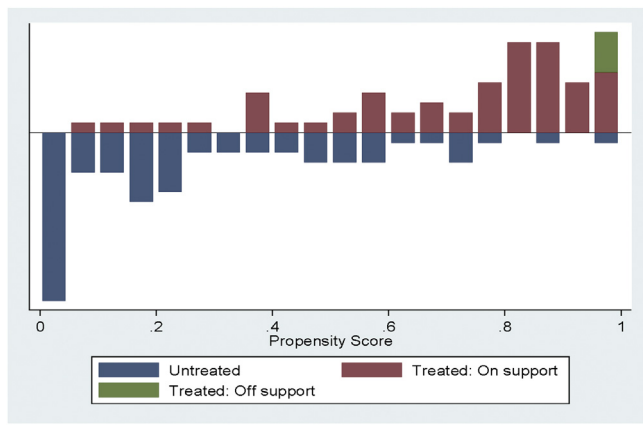
Table 4. Determinants of adoption behaviour of dairy farmers in Siaya and Makueni Counties.

Variables	Coef.	Std err	Marginal Effects
Socioeconomic characteristics			
Sex of HH (1 = male 0 = female)	-0.0082	0.254	-0.0032
Age of HH (years)	0.0211**	0.0092	0.0083
Education (years completed)	-0.0242	0.0173	-0.0096
Farming experience (years)	-0.0111	0.0097	-0.0044
HH size (count)	-0.0046	0.0419	-0.0018
Source HH income (1 = off-farm 0 = Farm)	-0.0406	0.2339	-0.0161
Farm characteristics			
Farm size (acres)	-0.021	0.0419	-0.0083
TLU (Tropical Livestock Unit)	0.0633***	0.0238	0.025
Breed type (1 = exotic breed 0 = otherwise)	0.7051***	0.1889	0.2782
Farmer perception			
Perception on milk productivity	1.0204***	0.1653	0.4026
Institutional characteristics			
Group Membership (1 = yes 0 = no)	0.5440**	0.2715	0.2067
Credit Access (1 = yes 0 = no)	0.133	0.2174	0.0526
Extension (1 = yes 0 = no)	0.5049**	0.2431	0.1948
Number of observations	237		
LR Chi^2 (13)=	131.2		
Prob. > Chi =	0		
Log pseudo-likelihood=	-98.19943		
Pseudo R^2=	0.4005		

*** and ** represent levels of significance at 1% and 5%, respectively.
Source: Survey Data 2018

Figure 3. Propensity score distribution and common support area for feed sufficiency by pairwise comparison of adopters and non-adopters. Source: Survey data 2018, plotted using psgraph.

this assumption, the probability of adopting Brachiaria grass conditional on observed covariates should lie between 0 and 1. This assumption ensures that households with the same characteristics have a positive probability of being both adopters and non-adopter (Caliendo and Kopeinig, 2008). The distribution of the propensity scores and the region of common support between adopters and non-adopters is illustrated in Figures 2 and 3.

The common support region can be verified through visual inspection of the density distribution of the propensity scores for the two groups.

Figures 2 and 3 indicate that condition for common support was satisfied, as there is substantial overlap in the distribution of the estimated propensity scores for adopters and non-adopters.

4.4. Testing for hidden bias

Sensitivity analysis was conducted using Rosenbaum bounds (rbounds) to check for the influence of hidden bias (Table 5). Since sensitivity analysis for insignificant effects is not meaningful, rbounds were calculated for treatment effects that were statistically significant (Hujer et al., 2004). Under the assumption that the treatment effect was underestimated, the results are insensitive to unobserved bias. Considering lower bound significance level (sig-) for underestimation, Gamma (hidden bias Γ) would have to increase three folds (a factor of 1.3) for the conclusion on the level of significance for total milk yield per household per year to be different. Therefore, the estimated average treatment effect of adopting Brachiaria grass on milk productivity measured by annual milk production per household and feed sufficiency measured by man-hours dedicated to feeding activities by the primary woman in the household remains robust in the presence of unobserved bias.

4.5. Impact of Brachiaria grass

Table 6 presents the average treatment effect of the adoption of Brachiaria grass on milk productivity and feed sufficiency. The adoption of Brachiaria grass resulted in an increase in milk yield by 27.6%. After matching, adopters had significantly higher milk yield (3302.47 L) than non-adopters (1872.32 L). Further, this difference translates to an average daily increase of 3 L. This is consistent with the findings of

Table 5. Sensitivity analysis for hidden bias on the outcome variables with Rosenbaum bounds.

Gamma (Γ)	Total Milk Yield per HH Hold Per year (litres)		Average Milk Production (per day per Cow)		Hours dedicated to feeding by primary female HH member (dry season)	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
1	0.00024	0.00024	4.60E-07	4.60E-07	4.50E-11	4.50E-11
1.1	0.00095	0.000051	3.10E-06	5.70E-08	5.00E-12	3.30E-10
1.2	0.002903	0.00001	1.50E-05	6.90E-09	5.60E-13	1.70E-09
1.3	0.007259	2.10E-06	5.40E-05	8.30E-10	6.20E-14	7.20E-09
1.4	0.015517	4.20E-07	0.000164	1.00E-10	7.00E-15	2.40E-08
1.5	0.029273	8.20E-08	0.000424	1.20E-11	7.80E-16	7.00E-08
1.6	0.049913	1.60E-08	0.000966	1.40E-12	1.10E-16	1.80E-07
1.7	0.078345	3.00E-09	0.001976	1.70E-13	0	4.00E-07
1.8	0.114838	5.80E-10	0.003699	2.00E-14	0	8.30E-07
1.9	0.158986	1.10E-10	0.006428	2.30E-15	0	1.60E-06
2	0.209791	2.10E-11	0.010483	2.20E-16	0	2.90E-06

gamma – Log odds of differential assignment due to unobserved factors.
sig+ – Upper bound significance level (overestimation of treatment effect).
sig – Lower bound significance level (underestimation of treatment effect).

Table 6. Impact of Brachiaria on milk productivity and feed sufficiency.

Outcome Variable	Sample	Adopters	Non-adopters	ATT	S.E.	t-value
Total Milk Yield per HH Hold Per year (litres)	Unmatched	3444.82	1728.46	1716.36	350.53	4.90***
	ATT	3302.47	1872.32	1430.14	456.86	3.11***
Average Milk Production (per day per Cow)	Unmatched	8.25	4.81	3.44	0.67	5.15***
	ATT	7.91	4.55	3.35	0.82	4.07***
Hours dedicated to feeding by the primary woman in a household (rainy season)	Unmatched	2.11	2.24	-0.13	0.17	-0.73
	ATT	2.07	2.38	-0.31	0.25	-1.21
Hours dedicated to feeding by the primary woman in a household (dry season)	Unmatched	2.07	4	-1.94	0.16	-12.05***
	ATT	2.06	3.92	-1.89	0.26	-7.25***

***, ** and * represent significance at 1%, 5% and 10% probability levels, respectively. (Standard deviation) in parentheses.
Source: Survey Data 2018

Muinga et al. (2016) and Kabirizi et al. (2013) who noted that cows fed on Brachiaria increased their milk yield by 15–40%. Similarly, Hare et al. (2013) indicated that Mulato II, a hybrid Brachiaria variety, increased milk yields by 11% during dry periods and by 23% during the rainy season. Kassie et al. (2018) noted that adopters of climate-smart push-pull technologies that utilize Brachiaria had significantly higher milk yield than non-adopters. Therefore, Brachiaria is able to provide year-round quality feed and increase the productivity of livestock. As noted by do Valle et al. (2013), beef cattle in Brazil gained daily weight by 0.44 Kg/head when fed on Brachiaria grass.

Adoption of Brachiaria is estimated to have increased feed sufficiency by 31.6% during feed stress periods. After matching, adopters of Brachiaria significantly spent fewer hours in feeding (2 h) compared to non-adopters (4 h) during dry the season. The findings are consistent with those of Ashley et al. (2016) who noted that adoption of improved forage technology resulted in a significant reduction in time spent on feeding and further reduced involvement of women and children in sourcing for feed. These results imply that programs aimed at promoting the adoption of Brachiaria can improve livestock productivity and improve household welfare.

5. Summary and conclusions

Dairy farmers in the non-traditional medium potential agro-ecological zones in Kenya are faced with limited forage options as a result of poor soils and infrequent weather patterns. This study analysed the socio-economic drivers of the adoption of Brachiaria grass and the impacts on milk productivity and feed sufficiency. Empirical results have shown that the adoption of Brachiaria grass resulted in increased milk production and improved feed sufficiency. The study revealed that the adoption of Brachiaria grass is influenced by group membership, perceived benefits, and access to extension services. Therefore, promising holistic strategies to boost the uptake of new agricultural technologies should focus on increasing access to information through innovative dissemination pathways. This will help reduce uncertainties among farmers on new technologies. Further, building the capacity of existing farmer groups and increasing on-farm farmer training will increase the uptake of technologies. It will also improve farmers' capacity and skills in forage and dairy management. Key strategies should also focus on strengthening other organizations such as service providers who offer market and input support to farmers.

The adoption of Brachiaria grass is also influenced by the herd size and type of breed reared. Effective strategies should promote farmers' accessibility to AI services. This will help improve breeds even as farmers expand their dairy enterprises. It will also promote the adoption of climate-smart forages such as Brachiaria grass. The study also found that older farmers were more likely to adopt Brachiaria grass. Policies and strategies should reorient to focus on promoting youth participation in fodder and dairy production. This can be done by making the dairy sector attractive through the promotion of value-addition to enhance market access and dissemination of information through social media platforms frequented by the youth.

While rigorous econometric methods have been used to confirm that the adoption of Brachiaria has positive effects on milk production and feed sufficiency levels, the authors acknowledge the limitations in the estimation. First, by using cross-sectional data, the study could not isolate the household dynamic impact of Brachiaria on feed sufficiency. Secondly, the study resorted to the use of time as a proxy to quantify farm-level animal feed sufficiency, which might not be a true indicator of animal feed requirements. In order to overcome this, the study recommends the use of standard computed indices on feed sufficiency observed over time to get more robust results.

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