ORIGINAL RESEARCH ARTICLE

Does intervention in African indigenous vegetables value chain improve production and welfare outcomes? Evidence from western Kenya

Martins Odendo[1], Christine Ndinya[1], Eunice Onyango[1], Japheter Wanyama[2], Samuel Akollo[3], Noel Makete[1], Suleiman Kweyu[4]

[1]Kenya Agricultural and Livestock Research Organization (KALRO), Kakamega, Kenya
[2]Kenya Agricultural and Livestock Research Organization (KALRO), Kitale, Kenya
[3]Anglican Development Services (ADS), Kakamega, Kenya
[4]AGROKenya, Shianda, Kenya

Corresponding author: odendos@yahoo.com

ABSTRACT

African Indigenous Vegetables (AIVs) are increasingly recognized as essential for sustainable dietary diversification in the predominantly cereal-based staple diets. The AIVs also provide employment opportunities and generate income for the rural populations. Many initiatives by researchers and development agencies have promoted the AIVs value chains in Kenya. However, little evidence exists on impact of the initiatives on farm households. Several studies have examined impact of agricultural interventions based on observational data. The findings from such studies are likely to be influenced by unobserved attributes, resulting in a biased estimation of causal relationships between interventions and impacts. We conducted a cluster-randomized controlled trial to estimate the unbiased impacts of a multifaceted intervention that focused on production, consumption nutrition behavior change communication, and linking farmers to markets in selected AIV value chains (cowpea, spider plant, amaranth, nightshade, and slender leaf) in western Kenya. Using two waves of household panel data (2018 and 2021), we evaluated the impacts of the intervention on land area allocation to AIVs, total leaf production, AIVs income, and household dietary diversity Score (HDDS). The empirical estimation using descriptive statistics and analysis of covariance revealed that households that were exposed to the intervention significantly increased land area under AIVs by 38% ($p < 0.01$) and total leaf production by 46% ($p < 0.05$). At end line, the spider plant had the highest percentage increase (60%) in land area compared to the control group. However, there is no evidence of whether or not the intervention had an impact on AIVs income and HDDS. The study concludes that the hypothesis that the intervention was to have significant impact on AIV production, nutrition security and income had mixed results. We recommend that similar interventions include components to integrate the capacity of households to adapt to risks such as the COVID-19 pandemic and climate change. Further cost-benefit analysis is required for informed resource allocation. Designing and implementing policies that promote household access to input and output markets are likely to improve the performance of the AIV value chains and contribute to income and nutrition.

Keywords: African vegetables, impacts, income, nutrition

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1.0 Introduction

African Indigenous Vegetables (AIVs) are increasingly recognised as essential for sustainable dietary diversification in the predominantly cereal-based staple diets. The AIVs also provide employment opportunities and generate income for the rural populations in Kenya and other countries in sub-Saharan Africa (Maundu et al. 2009; Chweya and Eyzaguirre, 1999; Abukutsa-Onyango, 2010; Ochieng et al. 2016; Ogada et al. 2021). The dominance of carbohydrate-dense diets results in the population suffering from chronic deficiency of essential vitamins and minerals (micronutrients), a condition known as hidden hunger. The clinical symptoms of hidden hunger occur gradually, hence are not easily detected, leading to health problems as well as economic and social burdens, especially among infants, children, and women (Allen, 2000; Tulchinsky, 2010; Yohannes et al., 2014; WHO, 2016). AIVs are important low-cost source of nutrition, providing micro- and macronutrients, fibre, vitamins, and minerals, which are essential components of a balanced and healthy diet. Moreover, AIVs are easy to incorporate into farming systems because they require limited space and fit within short rotations (Schreinemachers et al., 2018; Maundu et al., 2009). The AIVs are also better adapted to local food systems after generations of interactions with humans and the environment than exotic vegetables, according to a large population segment (Chweya and Eyzaguirre, 1999; Abukutsa-Onyango, 2010). The major AIV species grown in Kenya are nightshades *(Solanum scabrum)*, leafy amaranth *(Amaranthus* spp.*)*, spider plant *(Cleome gynandra),* cowpeas *(Vigna unguiculata)*, Ethiopian kale (*Brassica carinata*), Crotolaria *(Crotalaria ochroleuca* and *C. brevidens)*, and pumpkin leaves (*Cucurbita maxima and C. moschata) (*Abukutsa-Onyango, 2010; Odendo et al., 2015).

Despite the fact that AIVs have a high nutritional value among other benefits and are widely grown in western Kenya, production, consumption, and trade in AIVs are still low. Although Kenya has made good progress in many health indicators over the past decade, the nutritional status of the population remains low. Data from the latest Kenya Demographic and Health Survey (GOK, 2015) indicates that 59 percent of the Kenyan population does not consume an adequately diversified diet, indicating a restriction in access to quality diets. Out of 7.22 million children under the age of five, nearly 1.9 million (26%) were stunted, 290,000 (4%) were wasted, and 794,200 (11%) were underweight. However, significant disparities exist across counties. Out of the 47 counties in Kenya, nine (19%) had a prevalence of stunting above 30%, a level categorised as "severe" and of public health significance. As a result, annual costs for malnutrition related to health, education, and labour productivity are estimated to be between 1.9 and 16.5% of GDP (GOK, 2018). Therefore, promotion of interventions to improve AIV value chains could contribute to the achievement of several of the United Nations' Sustainable Development Goals (SDGs), especially No Poverty (SDG #1), Zero Hunger (SDG #2), Good Health and Well-Being, especially for Women and Children (SDG #3), and Gender Equality (SDG #5) (United Nations, 2015). These SDGs resonate well with the economic pillar of the Kenya development blueprint, the Kenya Vision 2030 (GOK, 2007), and its successive five-year Medium Term Plan II (The Big 4 Agenda), of which one of the four pillars is ensuring food and nutrition security (GOK, 2017). Against this backdrop, between 2018 and 2020, the Kenya Agricultural and Livestock Research Organisation (KALRO) and partners tested whether

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interventions in strengthening the AIV value chain in western Kenya could fundamentally contribute to increasing production, encouraging consumption of AIVs and boosting incomes from AIVs.

Many initiatives by researchers and development agencies have promoted the AIV value chains in Kenya (Abukutsa-Onyango, 2010; Odendo et al., 2015). However, there is little evidence on the impact of these initiatives on farm households. Hence, the motivation of this study is to assist in understanding whether or not the intervention accomplished its objectives. This is crucial for accountability, informed decision-making on the scale-up of the pilot project, and efficient allocation of resources to improve the lives of people living in poverty (e.g., Davis et al., 2012; Ragasa and Mazunda, 2018; Kuboja et al., 2021; Abdul and Abdulai, 2021). Several studies have examined impact of agricultural interventions based on observational data. The findings from such studies are likely to be influenced by unobserved attributes, resulting in a biased estimation of causal relationships between interventions and impacts due to selection bias. Selection bias could arise when decisions on project participation are not made randomly but based on some unobserved factors. These factors include participants who may self-select into the project and implementing partners who may specifically target those beneficiaries that are more likely to experience the largest project impacts, which are correlated with the outcomes of interest (McKenzie, 2012; Gertler et al., 2016). Unlike several previous studies that have relied on observational data, this study applied an experimental approach—a cluster-randomized controlled trial (RCT)—to generate credible evidence on causal relationships between interventions and impacts.

RCTs have emerged as a promising way to address the problem of selection bias in evaluating impacts of a wide range of development interventions (Duflo and Kremer, 2008; Gertler et al., 2016; Nobel Committee, 2019). The RCTs have a long tradition in biological and medical research and are considered the gold standard for impact evaluation (ADK, 2011; Gertler et al., 2016). Recent applications of RCTs include interventions in the domains of health, education, microfinance, food production, technology adoption, and institutional reform (Banerjee and Duflo, 2012). RCTs are increasingly seen as the gold standard for scientific evidence in the agriculture field, as they are in medicine. Examples are RCTs in the domain of agricultural intensification in Kenya (Duflo and Kremer, 2008); agricultural extension approaches in Kenya (Fabregas et al., 2017; Ogutu et al., 2018); the impact of new crop varieties in Tanzania (Bulte et al., 2014); and the impact of poultry interventions in Burkina Faso (Leight et al., 2022).

Impact evaluations of interventions similar to our study have used different impact indicators and provided mixed results. For example, Ogutu et al. (2018) report that intensive agricultural training significantly increased technology adoption and nutrition in Kenya. Leight et al. (2022) found that households exposed to a short training-based intervention about household poultry production in Burkina Faso significantly increased their use of poultry inputs, sold more poultry, and earned higher revenue. However, there is no evidence of an increase in profits. Fabregas et al. (2017) find that farmers' attendance at a farmer field day had a statistically

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insignificant impact on the use of agricultural lime, a widely promoted input in Western Kenya. Moreover, they did not find any evidence that receiving agricultural advice through mobile phone messages was effective at increasing knowledge or use of recommended inputs.

This impact evaluation aimed to measure the causal impact of the project interventions on land allocation to AIV cultivation, total leaf production, AIVs income, and household dietary diversity Score (HDDS) in Western Kenya, mimicking as much as possible the real-world context. We hypothesized that intervention in AIV value chains in western Kenya will significantly increase production and consumption of AIVs for improved nutrition and enhanced incomes from sales of AIVs for treatment households compared to control households. To the best of our knowledge, this is the first empirical study to apply RCT to evaluate the impacts of an AIV intervention in Kenya.

2.0. Methodology

2.1 The Study area

This study was conducted in Kakamega, Busia, and Vihiga counties, which are among the main AIVs producing and consuming counties in western Kenya. Agriculture is the main economic activity in all the study counties. Maize is the staple food crop, often consumed as stiff porridge *(ugali).* Cooked leaves of AIVs are traditionally consumed with starchy staple foods as side dishes (Maundu et al. 2009; Odendo et al. 2015).

2.2. The intervention

The intervention consisted of multifaceted trainings and seed provision of selected AIVs (cowpea, spider plant, amaranth, nightshade, and slender leaf) between July 2018 and February 2020 in the three counties. The intervention focused on classroom training sessions, demonstrations and field days on AIVs production practices, preparation and utilization of AIVs, post-harvest management and value addition and linking farmers to markets. The training also focused on nutrition behaviour change communications to alleviate the negative perceptions on AIVs. Other aspects covered include education on nutritive value and health benefits of AIVs, importance of diversified diets and recommended consumption patterns of AIVs. The intervention was implemented across the entire sampled farmer groups in the treatment arm (not just for the households in this evaluation survey), whereas the control group did not receive any intervention.

2.3. Sampling and randomization

Impact of a program or project is considered as the difference in outcomes for the same unit (e.g., person, household, community, firm) with and without participation in the program or project. Yet measuring the same unit in two different states at the same time is impossible. At any given moment in time, a unit either participated in the programme or did not participate. The unit cannot be observed simultaneously in two different states (with and without the programme) (Gertler et al. 2016). However, because the hallmark of impact evaluation focuses on causality and attribution, all impact evaluation methods address some form of cause-and-effect question. The central impact evaluation question is: What would have happened to

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those receiving the intervention if they had not received the project? (Hidrobo et al., 2014; Gertler et al., 2016). To answer the central question requires a counterfactual situation to help assess causality and attribution. We developed a good estimate of the counterfactual situation—a group as similar as possible (in observable and unobservable dimensions) to those receiving the intervention—based on random assignment of treatment and control groups into wards (the lowest county administrative unit) through a five-stage sampling procedure.

First, three counties (Busia, Kakamega, and Vihiga) were purposefully selected because they are the main AIV producers in Western Kenya. Secondly, in each of the study counties, cluster sampling was applied to select two spatially separated wards to minimize concerns about not capturing the true project impacts due to contamination (control households directly receiving the treatment) and spill-overs to controls (control households indirectly receiving the treatment from the treated). Since households in the control areas were outside the intervention catchment area, the benefits were less likely to flow to the control areas. Thirdly, in each county, treatment was assigned to one of the two sampled wards, and the control group (counterfactual) was assigned to the other. Fourthly, we obtained lists of 46 farmer groups in the selected wards from intervention implementation partners (Anglican Development Services (ADS) and AGRO Kenya), of which 42 were considered eligible for the implementation of the interventions. Eligibility was based on the following criteria: there were no on-going similar interventions that could confound the intervention; participants had not been exposed to similar interventions in the five years prior to this study; they were in areas designated as rural or peri-urban in the national census; and they had group membership of at least 15. From the 42 eligible groups, we randomly selected 34 groups across the six wards in the three counties. A total of 18 groups were assigned to intervention and 16 to control. Fifth, for each of the sampled farmer groups, lists of group members were provided, which formed the sampling frame from which five to seven individual members were randomly sampled proportionate to the group sizes for inclusion in this study.

The random assignment minimizes systematic differences between treatment and control and reduces the risk of bias in the impact estimates due to "selection effects" (McKenzie, 2012; Hidrobo et al., 2014; Gertler et al., 2016) and assures that, on average, households had similar baseline characteristics across treatment and control groups; that is, treatment and control groups are on average statistically identical in the absence of the project. Therefore, the comparison allows for the establishment of definitive causality—attributing observed changes in welfare to the program while removing confounding factors (Gertler et al. 2016): Any differences in outcomes between the groups can, therefore, be attributed to project or program interventions.

2.4. Data collection

This impact evaluation, which is part of a larger study, comprised two waves of panel data. The data were collected using an identical quantitative data survey instrument—at baseline and endline. Before each of the surveys, enumerators were trained to ensure that they had a good and common understanding of the questionnaire. The actual survey started immediately

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after the training. A baseline survey was conducted in June and July 2018. This was immediately followed by the rollout of the interventions. An endline survey of the same set of households was conducted between April and May 2021. Data were collected from a sample of 324 households (control n = 155 and treatment n = 169) at baseline. The baseline sample attrited (was not re-interviewed at endline) by 17% to 269 households (control n = 139 and treatment n = 130). Incidentally, a higher proportion (23%) of the households in the treatment arm attrited compared to 10% in the control group (Table 1).

Table 1: Baseline and endline sample sizes

Treatment	Baseline	Endline	Responded	Attrition rate (%)
Control	155	139	89.7	-10.3
Treatment	169	130	76.9	-23.1

The attrition was mainly attributed to respondents not being found at home at the time of the survey despite at least one repeat visit or appointment. The main reasons included involvement of potential respondents in off-farm businesses, attending social functions such as funerals and community meetings, marital issues (separation or divorce), migration, fall-out of members from their groups, and death.

The endline survey was delayed due to the COVID-19 pandemic. This slight delay in the endline survey resulted in a seasonality shift, which could influence agricultural outputs. However, the comparison with the control-arm households and the passage of time still permit a meaningful assessment of the impacts.

We collected data on households' demographics, farm size, land area allocated to AIVs production, quantities of AIVs produced, marketing of AIVs and amount of income derived from AIVs. For purposes of evaluating nutrition impacts of AIVs, the respondents were asked to state whether or not their household members had eaten the listed food groups within the last 24 hours prior to this survey. The 12 food groups are: 1 = cereals; 2 = roots and tubers; 3 = vegetables; 4 = fruits; 5 = meat, poultry, offal; 6 = eggs; 7 = fish and seafood; 8 = pulses, legumes, nuts; 9 = milk and milk products; 10 = oil and fats; 11 = sugar and honey; and 12 = miscellaneous.

2.5. Data processing and analysis

Endline and baseline data were matched using unique household identification codes. Data were cleaned, organized, and analyzed in Microsoft Excel, STATA, and SPSS softwares. Descriptive and inferential statistics were used to analyze the data. Chi-square and t-tests were employed to test the statistical significance of dummy variables and the mean value of continuous variables, respectively. An analysis of covariance (ANCOVA) regression was used to estimate the impacts of the interventions. The analyses disaggregated the results by treatment.

We used the Household Dietary Diversity Score (HDDS) as a metric for nutrition security. The

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HDDS gives a simple qualitative measure of food consumption that reflects household access to a variety of foods (FAO, 2011). HDDS counts the number of different food groups the household consumes out of a maximum of 12 food groups. Each food group receives a score of 1 if consumed, thus HDDS ranges from 0 to 12 (Swindale and Bilinsky, 2006). Compared to income-based measures of household food security, consumption-based food security measures such as HDDS are preferred because they tend to reflect households' ability to meet their basic needs, are less vulnerable to measurement errors, and are closely associated with the utility that people effectively extract from their income.

Impact estimates were based on intent-to-treat (ITT) estimates. We define treatment simply as being a member of a farmer group that was randomly assigned to a treatment arm, resulting in the ITT effect. The ITT effect does not account for possible non-compliance, meaning that not all farmers who were offered certain intervention sessions also participated in these sessions (Angrist, 2006; Ogutu et al. 2018). Non-compliance is better accounted for by the treatment-on-the-treatment (TOT) effect, which is also known as the local average treatment effect (LATE). The TOT measures the actual effect of intervention participation. Though the TOT estimates offer an appealing alternative representation of the impacts, their estimation requires an accurate measure of exposure to the intervention to be valid. We were reluctant to rely heavily on the self-reported measures of exposure to the interventions or tell the difference between households that were exposed to different numbers and types of interventions. Hence, we preferred ITT estimates of impacts for this study because they rely only on the random treatment assignment to accurately characterize intervention outcomes. It is important to note that the ITT effects are still relevant for policymakers because most development programs offer training or other types of services without the ability to enforce full compliance. Therefore, the ITT shows how the development impact may look without full compliance.

We estimated ITT using the Analysis of Covariance (ANCOVA) estimator specification described by McKenzie (2012) and applied by Barrett et al. (2021) and Leight et al. (2022), amongst others. This estimator is operationalized using least squares to estimate regression equation (1) for the base model:

$$Yh = \propto + \beta Th + \gamma Yh, base + \varepsilon h \tag{1}$$

where Yh is the outcome of interest (land area under AIVs, total AIVs harvest, income earned from AIVs, and HDDS) for farm household h at endline, $\propto$ is the scalar, and $Y_{h,\ base}$ is the outcome of interest at baseline. T is an indicator for whether household h is in the treatment group (treatment = 1, control = 0), β is the ANCOVA impact estimator, and ε_h is an error term. In other words, β represents the amount of change in outcome, ***Y***, which is due to household h being assigned to the treatment group.

We used ordinary least squares (OLS) estimators when the outcome of interest (Y_h) was a continuous variable (land allocated to AIVs, leaf production, and a, income from AIVs); and

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Poisson regression for count data (number of different food groups consumed a day prior to this study) (Gujarati, 2004; Ahmed et al., 2020). A cluster effect was added to all regression models because farmer groups were the unit of intervention but individual farmers were the unit of observation. Standard errors and p-values were also cluster-adjusted.

3.0 Results and discussion

3.1. Descriptive statistics and results

3.1.1. Attrition test

To allay concerns of whether the households that attrited were somehow different from those we re-interviewed, attrition bias was assessed by comparing baseline characteristics of the attritors and non-attritors, and the results show that mean comparisons on all characteristics did not differ significantly, except household size, which differed marginally at ($p < 0.10$) as shown in Table 2. Attrition in the sample was therefore more random than non-random. The implication is that, generally, the endline sample, despite attrition, is still similar to the baseline sample, and any inference from it can be generalised to the original population.

Table 2: Attrition bias test of sample households

	Non-attritors		Attritors			p -value
Variable	Mean	SD	Mean	SD	Difference	
Age of household head (years)	53.30	0.83	54.45	1.93	-1.15	0.573
Male household head (1=male)	0.79	-	0.80	-	0.01	0.700
Household size (Count)	5.88	0.15	6.53	0.41	-0.65	0.089*
Dependency ratio (ratio)	0.62	0.04	0.67	0.10	-0.05	0.575
Farm size (Acres)	1.17	0.33	1.76	0.24	0.59	0.645

***Note**:

i. *SD = standard deviations.*
ii. *Dependency ratio: The age-based dependency ratio is computed as the ratio of household members who are non-earning young (< 15 years) and old-aged (> 65 years) to active earners (15–65) in a household. A lower value for the dependency ratio, i.e., (0–14 + 65 above)/15–64) × 100), indicates a smaller number of dependents, and vice versa, in a particular household.*
iii. *The reported p-values are from the two-tailed test with the null hypothesis that the group means and percentages are equal.*
iv. *Significant level: * p < 0.1*

3.1.2. Baseline characteristics and balance test for indicators of interest

To verify the efficiency of the random assignment and assure comparability between the treatment and control groups in terms of observable characteristics, we tested for balance between the treatment and control groups using selected explanatory variables. The results of the balance tests are shown in Table 3. The statistical tests provide strong support for the

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success of the RCT design in being able to balance the groups across many characteristics. The sample looks balanced across the treatment and control groups, as only two variables were significantly different between treatment and control. The mean farm size was significantly higher in the treatment arm (2.1 acres) than the 1.6 acres in the control arm ($p < 0.05$), and the land area allocated to AIVs was significantly higher in the treatment arm than the control ($p < 0.1$). This gives credibility and strong internal validity to the claim that the interventions are attributable to the observed changes in the outcomes presented in this paper.

Table 3: Baseline household characteristics by treatment status and balance test

	Control (n=155)		Treatment (n=169)		p- value
Variable	Mean	SD	Mean	SD	
Male household head (1/0)	0.79	0.41	0.80	0.40	0.734
Age of household head (years)	54.05	13.38	52.98	13.67	0.243
Education attainment (1=primary+)	0.80	--	79.13	--	--
Farming is main occupation (1/0)	0.66	--	0.61	--	0.330
Household size (count)	6.15	2.72	5.86	2.43	0.160
Dependency ratio	0.66	0.73	0.60	0.53	0.179
Farm size (Acres)	1.62	.100	2.13	0.144	0.0043**
Percent sold AIVs (1=sold)	0.21	-	0.22	-	0.423
Annual income from AIVs (KES)	10,056	20,532	8,800	25,456	0.352
HDDS	7.89	2.34	7.57	1.94	0.265

*Significant level: ** $p < 0.05$*

3.1.3. Main African Indigenous Vegetables species grown in Western Kenya

Farmers grew a wide range of AIVs, and the most popular AIVs at both baseline and endline were cowpea, grown by 78 percent for the control group at baseline, which was 9% lower than the treatment arm (85%) (Table 4). This was followed by nightshade, which was grown by 61% and 52% of the households in control and treatment groups at baseline, respectively. Ethiopian kale was grown by the smallest proportion (4 – 7%) of the households. The percentage of households that grew jute mallow was significantly higher in the treatment group than in the control group at both baseline and endline ($p < 0.05$). However, the percentage of households that grew Slenderleaf at endline was significantly higher in the treatment group than the control group (< 0.05) at endline. The percentage of households that grew kale was significantly higher in treatment than in control at both baseline and endline.

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Table 3: Percent of households growing different AIVs species

AIV species	Baseline			Endline		
	Control (n 155)	Treatment (n=169)	p-value	Control (n=139)	Treatment (n=130)	p-value
Cowpea	78	85	0.136	86	82	0.460
Nightshade	61	52	0.109	67	66	0.896
Slenderleaf	41	48	0.207	55	67	0.040**
Spider plant	33	32	0.794	35	43	0.189
Jute mallow	28	39	0.039**	24	38	0.019**
Pumpkin leaves	26	27	0.946	2	19	0.851
Amaranth	21	21	0.863	33	32	0.785
Ethiopian Kale	04	05	0.694	7	5	0.372
Kale§	41	57	0.004**	28	38	0.092*
Number of AIVs grown	3.33	1.71	0.134	3.55	3.90	0.142

§*Kale is not an AIV but was included for comparison because it is the most popular exotic vegetable in Western Kenya*
*Significant level: ** p < 0.05; * p < 0.1.*

Our findings confirm previous findings (e.g., Odendo et al., 2015; Abukutsa-Onyango, 2010), which found that similar AIV species were the most popular in western Kenya. On average, households in the control arm increased the number of AIV species they had from three at baseline to four at endline, while those in the treatment arm doubled from two AIV species to four. This could be attributed to promotion of diverse AIV species by the project to households in the treatment group.

3.1.4. Allocation of land to different AIVs species cultivation

At both the baseline and endline surveys, households allocated small proportions of their farms to AIV production per season. The mean land area allocated to the production of AIVs at baseline was 0.08 acres for control and 0.11 acres for treatment. At endline, the mean area allocated to AIVs was significantly higher (0.25 acres) in the treatment group relative to the control group (0.17 acres) ($p < 0.05$). The spider plant was allocated the largest land area at baseline for both the control and treatment arms. At endline, spiderplant had the highest percentage increase (60%) in land area compared to the control group (Table 5), which implies the importance of spiderplant in the study area.

The results mirror those of a recent study conducted by the National Museums of Kenya (NMK, 2020) in five counties in Kenya: Kiambu, Nairobi, Kirinyaga, Kisumu, and Vihiga, which showed that AIVs in Kenya are grown intensively on small plots of land (less than 0.1 ha) and are mostly grown by women, mainly for home consumption with surpluses sold at the local markets.

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Table 4: Mean area of farm allocated to AIVs (acre)

AIV species	Baseline Control	Treatment	p-value	Endline Control	Treatment	p-value
Amaranth	0.02	0.04	0.837	0.05	0.04	0.357
Nightshade	0.01	0.01	0. 462	0.07	0.06	0.309
Spider plant	0.05	0.07	0.7519	0.05	0.08	0.838
Cowpea	0.04	0.05	0.492	0.06	0.07	0.156
Jute mallow	0.02	0.04	0.154	0.03	0.04	0.927
Slenderleaf	0.02	0.04	0.626	0.05	0.06	0.445
Pumpkin leaves	0.02	0.04	0.807	0.04	0.04	0.219
Ethiopian Kale	0.02	0.01	0.149	0.04	0.03	0.219
Mean area-AIVs	0.08	0.11	0.585	0.17	0.25	0.041**

***Significant level: $p < 0.05$*

3.2. Impact on primary outcomes: AIVs area, production and income

The ITT estimation using ANCOVA regression shows statistically significant positive impacts of the interventions on total land area allocated to AIVs and total AIV harvest (production) per season, but no evidence of an impact on income received from AIV sales. Households in the treatment arm are 38 and 46 percent more likely to increase area under AIVs and total harvests per season, respectively, relative to farmers in the control group ($p < 0.01$) (Table 6). Expansion of the area covered by AIVs during the project's lifespan is the first step towards households realising the importance of AIVs. However, because farm sizes per household are declining in the study area, the most plausible and sustainable means to increase production are through the adoption of improved technologies, especially seed and agronomic practises.

Table 5: Impacts on land allocation (acres) to all AIVs grown, total AIVs harvest (kg) and income

Treatment	Area under AIVs Coefficient	AIVs total harvest Coefficient	AIV income Coefficient
Treatment arm=1, Control=0	0.380***(0.041)	0.462***(0.05)	-0.0329 (0.022)
Constant	0.029 (0.018)	78.916 (13.33)	8,693(1941.17)
Baseline value	0.08	178	10,056

Note: Figures in parentheses are standard errors
*Significant level: ***$p<0.01$*

The study, however, did not find any evidence as to whether or not the intervention had an impact on income from AIV sales because the results show no significant difference in AIV income ($p > 0.1$) between the treatment arm and control group. This result is consistent with the finding that only about 20% of the households sold AIVs in both the treatment arm and the control group. The low participation in the AIVs markets could be associated with low production of AIVs due to farmers' limited access to inputs, especially improved seeds, and

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poor linkages to AIVs markets. Most of the AIVs produced are, hence, for subsistence.

3.2.1 Impact on nutrition

Poisson regression analysis shows no significant effect on HDDS (Table 7). The result implies that nutrition knowledge, like the one that was part of the intervention, is not the only factor that can influence eating behaviour. Other factors, such as food availability, physiological needs, food preferences, peer pressure, social norms, and personal experiences (Farthing 1991), contribute to influencing eating behaviour.

Table 6: Impact on secondary outcomes: food security and nutrition

Treatment	HDDS Coefficient
Treatment arm=1, Control=0	-0.016 (0.027)
Baseline HDDS	-0.003 (0.004)
Constant	2.060 (0.038)
Baseline value	7.89

Note: Figures in parentheses are standard errors

This finding adds to the limited research data on the relationship between nutrition knowledge and eating behaviour. It is important to note that a major drawback of the HDDS is that its computation utilizes data collected at the household level. As such, HDDS does not provide any information on the consumption of different food groups or overall dietary diversity by individuals, such as children in the household, who have unique requirements. While we acknowledge these limitations of HDDS, it is very easy to construct, which may explain why it is widely adopted in food security studies. Moreover, empirical studies have shown that dietary diversity is highly correlated with anthropometric measures, which are examples of indicators that take into account dietary quantity and quality (Marshall et al., 2014; Hoddinott and Yohannes, 2002; Nkonya et al., 2020) and are positively associated with nutrient adequacy (Torheim et al., 2003). Additionally, dietary diversity is associated with other positive health outcomes, including greater birth weight, child anthropometric status, hemoglobin concentration, and reduced hypertension, cardiovascular disease, and cancer (Hoddinott and Yohannes 2002).

4.0 Conclusions and recommendations

The intervention had mixed results. Whilst the intervention had a significant positive impact on the land area allocated to AIVs and the total AIVs harvested per season, the impact was not significant on AIVs income and nutrition measured by the household dietary score (HDDS). Households in the treatment arm were at 38% and 46%, respectively, more likely to increase area under AIVs and total harvests per season relative to households in the control group. The mean land area allocated to AIV's production was 0.08 acres for control and 0.11 acres for treatment at baseline, which increased to 0.17 acres for control and 0.25 acres for treatment at endline. Spiderplant was allocated the highest area at baseline for both the control and treatment arms.

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We recommend that similar future interventions include components that integrate the capacity of households to adapt to risks such as COVID-19 and climate change. Further, cost-benefit analysis is required as an integral component of impact analyses to help policymakers, donors, managers, and researchers reliably identify the projects that will maximize the research benefits under tightening budgets. The lack of evidence that the intervention had any impact on nutrition requires further research to better understand both the drivers of dietary diversity and the barriers to behaviour change. Given that area under AIVs and leaf production significantly increased due to the intervention, designing and implementing policies that promote household access to inputs (seed, fertilizers, knowledge) and improving household access to markets are likely to improve the performance of the AIV value chains and contribute to income and nutrition.

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5.1 Conflict of interest

The authors declare no conflict of interest.

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