Assessing the impact of integrated pest management (IPM) technology for mango fruit fly control on food security among smallholders in Machakos County, Kenya

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Abstract

Adoption and extensive use of agricultural innovations is seen as a key avenue for poverty reduction and improved food and nutritional security in developing countries. This paper evaluated the impact of IPM strategy for mango fruit flies suppression on food security with the help of a two-wave panel household survey data collected in Machakos County in Kenya. Using a randomly selected sample of 600, a difference in difference was fitted to the data in order to assess the impact of IPM on food security. The results showed that on average, both IPM participants and non-participants were food secure as measured by per capita calorie intake and Household Dietary Diversity Index (HDDI). The difference in difference estimates indicated that fruit fly IPM had a positive impact on per capita calorie intake but no significant effect on HDDI. Other factors that had an effect on per capita calorie include level of farm income, access to extension services, wealth category and distance to agricultural input market and household size. Our study recommends wider dissemination and upscaling of the fruit fly IPM strategy to facilitate broader impacts on household-level food security.

Key words: integrated pest management, smallholder mango farmers, difference in difference, food security

Section 1: Introduction

The horticulture sector in Kenya accounts for about 36 percent of agricultural GDP and grows between 15 and 20 percent per year (Government of Kenya [GoK], 2012). Of the many tropical fruits grown in Kenya, mango is leading in market share in both local and export markets. In Kenya, mango is ranked third after banana and pineapples in terms of acreage and total production volumes (Economic Review of Agriculture [ERA], 2015). Mango production provides employment many people in both the rural and urban areas who depend on the seasonal labor demands and accounts for 26 percent of fruit exports. Approximately 98 percent of mangoes produced in Kenya go to the domestic market (local consumption or processing), while the remaining two percent go to the export markets (ERA, 2015). In 2014, mangoes earned Kenya

US$98 million (ERA, 2015). Major destinations for export mangoes from Kenya include United Arab Emirates (53 percent), Tanzania (20 percent), and Saudi Arabia (22 percent) (HCDA, 2010).

However, the current mango production is far below its potential. The sub-sector is faced with myriad of challenges, including highly perishability nature of the fruit, inadequate clean and quality planting materials, pest and disease infestation, high cost of inputs, limited adoption of improved technologies, seasonal gluts and poor post-harvest handling techniques, and poor market infrastructure (Irungu, 2011). Among these challenges, insect pests and diseases are ranked highest (Korir et al., 2015). Directly pests and diseases lower the quality and quantity of the mango fruits, while indirectly quarantine restrictions on fruit fly-infested mango limit access to lucrative export markets abroad. For example, Bech (2008) points out that South Africa, Mauritius and Seychelles have banned importation of fruits such as mango and avocado from countries infested by the invasive fruit fly species (*Bactrocera dorsalis*).

Chemical broad-spectrum pesticides have usually been used as the sole method of pest control by mango farmers in the country (Amata et al., 2009; Nyakundi et al., 2010). There use have been shown to be ineffective against some insect pests hence farmers tend to increase the frequency of spraying hoping that it works (Macharia et al., 2005, 2008). In order to reduce losses in mangoes due to fruit flies and cut down the cost of production, the International Center for Insect Physiology and Ecology (ICIPE) and partners has developed an Integrated Pest Management (IPM) strategy which are being promoted across several countries in Africa. The technologies aim to lower the cost of production, reduce mango losses induced by fruit flies, increase producers' income and improve market access to quality mangoes (Muriithi et al., 2016).

The mango fruit fly IPM technology combines different interventions that support each other rather than work as a single management strategy (Ekesi and Billah, 2007; Ekesi et al., 2011; Korir et al., 2015; Muriithi et al., 2016). It comprise of baiting and male annihilation techniques, orchard sanitation, fungal application, use of parasitoids and weaver ant (*Oecophylla longinoda*). An insecticide (spinosad) is combined with a proteinous food bait (DuduLure®) so as to attract the fruit flies. The fruit flies are killed by ingesting the bait along with the toxicant before they invade the mangoes (Ekesi et al., 2014). The male annihilation technique (MAT) involves deployment of trapping equipment consisting of methyl eugenol (a male attractant), combined with Malathion (a toxicant) to trap and kill male flies reducing their population resulting to low mating hence a decline in fruit fly population (Ekesi and Billah, 2007).

The bio-pesticides used are to target the larva stages and emerging adults of the fruit flies. However they have no effect on beneficial parasitoids, instead it complements them in fruit fly suppression (Ekesi et al., 2005). In order to achieve orchard sanitation a tent-like structure refered to as an Augmentorium is used (Klungness et al., 2005). It suppresses any emerging fruit flies from fallen rotten fruits collected from the field and deposited in the structure. At the same time it conserves their biological enemies (parasitoids) to escape from the structure (Muriithi et al., 2016).

The current mango fruit fly IPM technology dissemination and promotional activities by the program have shown success with many farmers taking up the strategy (Korir et al., 2015; Kibira et al., 2015; Muriithi et al., 2016). Since the introduction of the *icipe's* IPM package in Kenya, no research has been done to evaluate the intervention in terms of its effects on smallholder household food security. Kibira et al. (2015) and Muriithi et al. (2016) have shown that use of IPM technology can lead to a reduction in mango losses due to fruit fly invasion, reduced expenditure on insecticide and increased net income. Increase in net income will increase the farmers' purchasing power of food which in turn is hypothesized to increased food security. The current study seeks to fill this gap by assessing the impact of IPM technologies for controlling mango fruit fly on household food security.

Section 2: Conceptualizing mango production, fruit fly IPM and food security nutrition inter-linkages

The effect of IPM technology on household food security is transmitted through four main linkages; (i) introduction of the technology, (ii) adoption of the technology in a farming system, (iii) reallocation of farm resources between enterprises as a result of technology adoption, and (iv) changes in food consumption patterns as a result of changes in income derived from the proceeds of technology adoption. These linkages are anchored upon and shaped by the socio-economic, biophysical, institutional and idiosyncratic influences that the production system operates in.

The principle objective of IPM is to provide farmers with new opportunities to improve their livelihood. In mango production, for example, this is achieved through reduced mango losses at the farm level, reduced pesticide usage and enhanced quality mango supply to the market. Application of IPM techniques may also raise the overall productivity of mango production by encouraging more effective use of other inputs. Ceteris paribus, these effects raise farmers' profit leading to improved welfare measures such as food security, poverty reduction and general wellbeing.

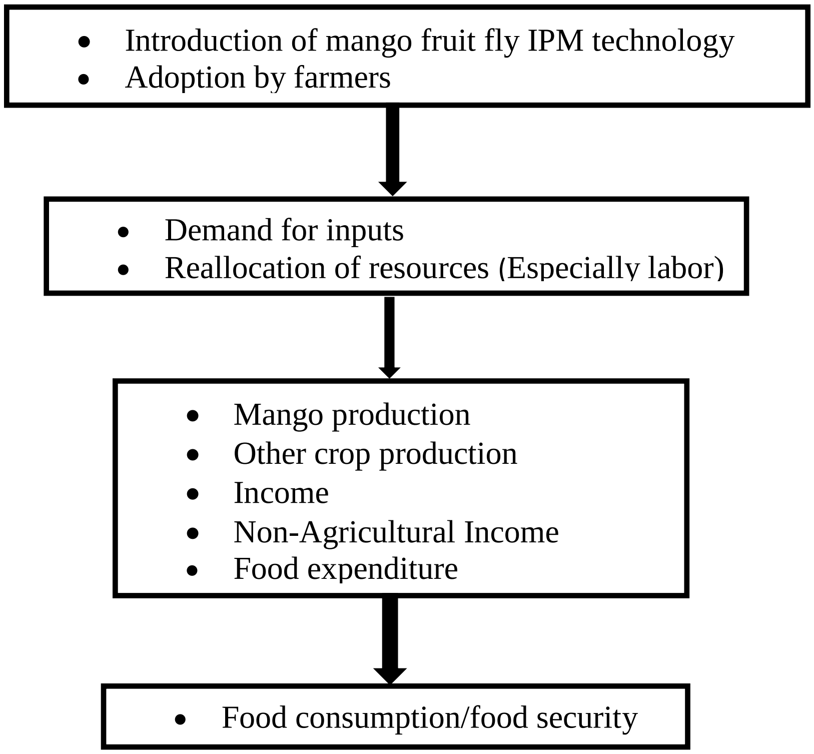

Figure 1: Conceptual framework for assessing impact of IPM technologies on household food security

Source: Adapted from (Von Braun, 1988)

Section 3: Methodology

Study area and sampling technique

This study utilized data collected before and after and with and without fruit fly IPM intervention (analogously referred to treatment and control groups) in Machakos County, which is among the leading Mango producing areas in Kenya. Machakos County is located on latitude 01°14′S and longitude 37°23′E and covers a total area of 5,952.9 km^2. The total population in Machakos County is 1,098,584. The annual rainfall ranges between a mean of 500 to 700mm and is received in two seasons per year. The long rains are experienced in the months of March and May while the short rains are received in October and November. Temperatures range between 9.1^{o}C -26.7^{o}C and lies at an altitude of 1000 to 2100 meters above sea level. These climatic factors have a greater bearing on mango production.

Two stage sampling procedure was followed to select the sample of mango growers. The first stage involved selecting two sub-counties in Machakos County that produces a lot of mangoes. A Sampling frame comprising of a census of mango farmers was compiled by the respective Sub-

County Agricultural Officers namely Mwala (treatment area) and Kangundo (control area). From this list, following the standard procedure outlined by Barlett et al. (2001) the final sample size was computed. Three hundred households were randomly selected from the treatment area (Mwala sub-County) and a similar sample size from the control group (Kangundo sub-County). To reduce location biases in the analysis, both the treatment and control groups have the same average climatic and market potential. In addition, in order to minimize any potential interregional spillover effects of the IPM technology benefits. The control selected site was about 20km away from the treatment area.

Measuring food security

Food security is defined as access to adequate quality and quantity of food by all people at all times for an active and healthy life (FAO, 2002). This definition has four dimensions that constitute the four pillars of food security: food availability, access, utilization and stability. Food availability is achieved when all individuals have sufficient quantities of food, while access is achieved when all members in a household have enough resources to acquire food to meet their nutritional and dietary requirements (Bongaarts, 2007). Food utilization requires a diet that provides sufficient energy and essential nutrients, along with access to portable water and adequate sanitation. Stability, on the other hand, concerns the balance between vulnerability, risk, and insurance to food access and availability, which are often termed as security (FAO, 2006).

Food security situation was measured using two components: (i) household per capita calorie intake and (ii) Household Dietary Diversity Index (HDDI) following Swindale and Bilinsky (2006) and Hoddinott and Yohannes (2002). This was done using a 30-day and 7-day recall data respectively where the two outcome indicators of food availability, access and other underlying factors were developed. Household per capita calorie intake is defined as the amount of food available for consumption per adult equivalent per day measured in kilocalories (Mulugeta and Hundie, 2012). Using the formulae below, the household’s energy consumption levels were calculated (Swindale and Bilinsky, 2006):

$$C_i = \Sigma_1^n W_j B_j \tag{1}$$

where C_i is the total calorie intake for household i, W_j is the weight in grams of intake of food commodity j, B_j is the standardized food energy content of the jth food commodity (from nutrient conversion table). Following (Chege et al., 2015a, 2015b; Mulugeta and Hundie, 2012), C_i was divided by the household’s total adult equivalent to get the per capita calorie intake. Based on the average dietary energy requirement in Kenya, we use a minimum intake of 2250 kcal per adult equivalent and categorize households below this threshold as undernourished (Chege et al., 2015b).

Dietary diversity is an outcome measure of food security mainly at the level of individual or household food access. It can also be used to provide information on food availability and show changes in seasonal dietary patterns. The dietary diversity score is the sum of food groups consumed over a reference period (Hoddinott and Yohannes, 2002; Jones et al., 2014; Savy et al., 2006). HDDI was developed by calculating a simple count of the sum of the different number of food types consumed in the previous day, following the United Nations Food and Agriculture Organization (FAO) food groups which include; Cereals, Root and tubers, Pulses/legumes, Milk and milk products, Eggs, Vegetables, Meat, Oil/fats, Sugar/honey, Fruits, Fish and seafood and Miscellaneous (FAO, 2013).

Empirical approach

The effect of fruit fly IPM strategy on food security was estimated using the double difference method or difference-in-difference (DiD) model. The model combines both with-and-without before and after adopting the technology to estimate the difference between the observed mean outcomes for the treatment (with) and the control (without) groups before and after the technology intervention. The model compares outcome changes over time among treatment and control groups and accounts for selection bias due to time-invariant and other unobservable differences (Glewwe and Jacoby, 2000). To assess the impact of IPM technology for mango fruit fly control on food security, the unconditional treatment effect was expressed as (Khandker et al., 2010) follows:

$$Y_i = \alpha + \theta t_i + \beta T_i + \delta T_i * t_i + \gamma \mathbf{Z} + \varepsilon_i \qquad (2)$$

where Y_i is the outcome of interest for farmer I, in this case food security parameter (per capita calorie intake, or HDDI); *Ti* is a dummy variable, given as 1 if farmer *i* is in the treatment group and 0 if in control group; t_i is a dummy variable, defined as 1 if in post-treatment period (follow-up survey), and 0 if in pre-treatment (baseline) period. The treatment and time interaction term, $T_i * t_i$, represents the actual treatment variable that indicates the impact of the mango fruit fly IPM technology on food security outcomes, which is captured by the coefficient of the interaction, δ. The coefficient for the time dummy, γ, capture the changes that occur over time that are independent of the IPM technology, while the strategy coefficient β, capture the initial average differences between the treatment and control groups.

The unconditional treatment effect of DiD expressed in Eq. (2) assumes that food security is only affected by the intervention, while other factors do not change across time (Ravallion, 2005). However, this is not realistic as farm and household's conditions are expected to vary and may also affect the outcome of interest (Ravallion, 2005). Therefore we estimate conditional treatment effect of DiD as follows:

$$Y_i = \alpha + \gamma t_i + \beta T_i + \delta T_i * t_i + \lambda_i \boldsymbol{X}_i + \varepsilon_i \tag{3}$$

Where $\boldsymbol{X}_i$ represents a set of household and farm characteristics that might affect the food security parameters.

The choice of the explanatory variables for the above empirical model is based on review of theoretical work and previous empirical technology adoption and food security interlinkage studies mentioned in Section 2. Table 1 presents the descriptions and expected signs of the variables used in the model. The age of the household head impacts on his or her ability to supply labour for food production (Babatunde et al., 2007). The square of age is included in the model as result of nonlinear relationship between age and food security (KM et al., 2013). The education level of the household head determines the number of opportunities available to enhance livelihood strategies, improve food security and reduced poverty levels (Amaza et al., 2009). In the case of gender, Kassie et al. (2012) have documented an increased food security of male headed households compared to female headed household stating that female headed households are mostly single parented and have limited access to productive resources. Household heads with many years of mango farming activities is expected to increase their ability to diversify production hence reduce the food shortage risk. Research findings by Feleke et al. (2005) and Oluyole et al. (2009) have shown a positive relationship between food security and farming experience.

Household size determines the amount of labor available for farm production, farm produce kept for own consumption, and agricultural marketable surplus of farm harvest (Amaza et al., 2009). Households with large family members are mostly associated with a high dependency ratio and more food requirements, depicting a negative effect on food security. However, an increase in a household size could translate to an increase in the number of income earning adults depicting a positive effect on food security (Iyangbe and Orewa, 2009). Therefore, the expected sign for household size can be either positive or negative. It is hypothesized that as the size of the farm increases, the level of food production increases as well. Studies by Jayne et al. (2005) and Deininger (2003) established a positive relationship between farm size and food security. Therefore, the expected effect of farm size on food security is positive. Credit availability includes the ability of a household to access credit either in cash or in kind for either consumption or production (KM et al., 2013). Mulugeta and Hundie (2012) have documented a positive relationship between credit availability and food security.

Group membership acts as a form of social capital which (Martin et al., 2004) found to have a positive association with food security. Sseguya (2009) found that households that had membership in one or more groups were more food secure. Field extension officers are important in dissemination of improved technology in food production. Lewin (2011) found that at least one visit to each household from an agricultural extension agent during each cropping season would reduce food insecurity by 5.2 percent. Households with a lot of resources (wealth) tend to diversify their diets (Arimond and Ruel, 2004).

Table 2: Variables Definition and Hypothesized Signs for Determinants of Food Security

Variable	Definition and Measurement	Expected sign
Age	Years of household head (Continuous)	+
Age Squared	Square of household head's age (Continuous)	+
Education	Household Head number of formal education (Continuous)	+
Gender	Gender of the household head (Dummy) 1=male 0=female	+/-
Household Size	Number of household members (Continuous)	+/-
Experience	Total number of years of experience in mango farming (Continuous)	+
Group Membership	Whether a farmer belongs to a farmer group (Dummy) 1=yes 0=No.	+
Farm Income	Total income from all farming enterprises (Continuous)	+
Extension	Whether a farmer had any contact with an extension worker over the last one year (Dummy) 1=Yes 0=No	+
Livestock Units	Livestock equivalent units owned by the household (Continuous)	+
Market Distance	Distance in to the nearest market (km) (Continuous)	-
Mango Farm size	Log of farm size (acres) under mango cultivation (Continuous)	+
Credit	Credit access for mango production (Dummy) 1=Yes 0=No	-
Wealth Category	Wealth category classification of the household (Categorical) 2=Wealthy 1=Moderate wealthy 0=Poor/not wealthy	+

The DiD estimator for per capita calorie intake (Y_i), a continuous covariate, was estimated with ordinary least squares (OLS) (Omilola, 2009). Ordinary Least Squares (OLS) produces best linear unbiased estimators (BLUE) of the coefficients given that sum errors have an expectation of zero and are uncorrelated and have equal variances. Eq. (4) below specifies the conditional model to be used in assessing the impact of fruit fly IPM on per capita calorie intake.

$$Per\ capita\ calorie\ intake\ = \alpha + \beta(HHTYPETi) + \gamma(BeforeAfterti) + \delta(InteractionTixti) + \lambda_1(AGE) + \lambda_2(EDUCATION) + \lambda_3(GENDER) + \lambda_4(HOUSEHOLDSIZE) + \lambda_5(EXPERIENCE) + \lambda_6(GROUPMEMBERSHIP) + \lambda_7(FARMINCOME) + \lambda_8(EXTENSION) + \lambda_9(LIVESTOCKUNITS) + \lambda_{10}(DISTANCE) + \lambda_{11}(FARMSIZE) + \lambda_{12}(CREDIT) + \lambda_{13}(WEALTH) + \varepsilon \quad (4)$$

On the hand, a poison regression was estimated to assess the impact of fruit fly IPM on HDDI. The poison model was chosen because the food security parameter HDDI is a count data variable that is used to measure diet quality. Following (Greene, 2007), let *Yi* denote the number of food groups consumed by the *i*th household. The empirical specification of this "count" variable is assumed to be random and, in a given time interval (24 hours), has a Poisson distribution with probability density, such that:

$$P(Y_i)=\frac{e^{-\mu}\mu^y}{y!} \quad (5)$$

where Y_i denotes the number of food groups consumed by the *i*th household i= 1, 2, 3…12 and μ = *E(Y)* expected index (and variance). The mean (μ) depends on a vector of explanatory variable (s) X. The Model log of μ as a function of X:

$$\mu=e^{\sum_{j=1}^{K}\beta T_i+\gamma t_i+\delta T_i * t_i+\lambda_i X_{ji}} \quad (6)$$

Eq. (6) can also be written as follows;

$$ln(\mu)= \sum_{j=1}^{K}\beta T_i+\gamma t_i+\delta T_i * t_i+\lambda_i X_{ji} \quad (7)$$

Or

$$ln(\mu)=\alpha+\beta T_i+\gamma t_i+\delta T_i * t_i+\lambda_i X_i+\ldots+\lambda_k X_k \quad (8)$$

where α is the constant, β ,γ, δ and λ_1…… λ_{13} are parameters to be estimated and X_{1}.….X_{13} are the explanatory variables. It should be noted that Y>0 as the number of food groups consumed by a household over the previous 24-hour period must be strictly positive. Eq. (9) below specifies the conditional model to be used in assessing the impact of fruit fly IPM on HDDI.

$$HDDI = \alpha + \beta(HHTYPETi) + \gamma(BeforeAfterti) + \delta(InteractionTixti) + \lambda_1(AGE) + \lambda_2(EDUCATION) + \lambda_3(GENDER) + \lambda_4(HOUSEHOLDSIZE) + \lambda_5(EXPERIENCE) + \lambda_6(GROUPMEMBERSHIP) + \lambda_7(FARMINCOME) + \lambda_8(EXTENSION) + \lambda_9(LIVESTOCKUNITS) + \lambda_{10}(DISTANCE) + \lambda_{11}(FARMSIZE) + \lambda_{12}(CREDIT) + \lambda_{13}(WEALTH) \quad (9)$$

Section 4: Results and Discussion

Descriptive statistics of participants and non-participants in the fruit fly IPM strategy

Descriptive statistics of variables used in modeling fruit fly IPM participation and food security outcomes from the baseline are presented in Table 1. With respect to demographic characteristics, independent sample *t*-test of mean differences showed that fruit fly IPM participants had household heads with lower age on average, lower level of education but large household sizes. The age of the household heads ranged from 26 to 95 years with an average of 57.51 and 60.50 years for fruit fly IPM participants and non-participants respectively. On average, heads of non-participating households had formal education of about 10.16 years while fruit fly IPM participants reported about 8.56 years. On the other hand, non-users of the fruit fly IPM strategy has lower farm size allocated to mango production (0.75 acres compared to 1.10 acres). Fewer households (11%) among those who were not using the fruit IPM reported to have received extension services on mango farming compared to the participants (24%). The average household size was 5 people among the sampled groups. The results indicated that on average, IPM non-participants traveled longer distance (10.48 km) to the market than participants (4.96 km). More IPM participants than non-participants belonged to a farmer group (31% and 24% respectively).

Table 3: Social-economic characteristics of sample households

VARIABLE	**IPM participants Mwala (n=299)**		**Non-IPM participants Kangundo (n=282**		**Test of difference in means t-stat**
	Mean	**SD**	**Mean**	**SD**	
Age	57.51	12.56	60.50	12.13	2.921***
Education	8.58	3.94	10.16	3.88	4.881***
Gender	85.62	35.15	88.65	31.77	1.089
Household size	4.92	2.10	4.63	1.88	-1.783*
Experience	11.26	9.40	8.52	6.97	-3.964***
Group membership	31.44	46.50	23.76	42.64	-2.071**

Farm income	89740.10	104426.80	104744.20	127365.30	1.557
Extension	24.08	42.83	11.35	31.77	-4.051***
Livestock units	2.53	2.21	2.64	3.84	.428
Farm size	1.10	1.48	0.75	1.22	-3.113***
Credit	4.68	21.16	1.42	11.85	-2.276**
Distance	4.96	5.11	10.48	7.56	10.37***

*Note:**significant at 10% **significant at 5% and *** significant at 1%; sd- Standard deviation
Source: Own survey

Food Security Outcomes

Table 4 presents the average per capita calorie intakes and the household dietary diversity indices for the two study areas across the two time periods. The result shows that the average per capita intake was higher among the non-fruit fly IPM users (Kangundo sub-County) of about 3007 Kcal and 2843 Kcal while the participants (Mwala Sub-County) reported about 2840 Kcal and 2731 Kcal during the baseline and follow-up survey respectively. This shows that on average both areas were above the required per capita calorie intakes of 2250 Kcal (Chege et al., 2015b) and thus food secure. In contrast, the HDDI results shows that fruit fly IPM participants had a higher average HDDI of 9.81 and 9.71 compared to non-participants' 9.80 and 9.70 during the baseline and follow-up survey respectively.

Table 4 Food security outcomes of the sample households Mwala and Kangundo

	Baseline survey			**Follow-up survey**			**Change (follow-up – Baseline)**		
	IPM participants (Mwala sub-County) n=299	IPM non-participants (Kangundo sub-County) n=282	t-tests	IPM participants (Mwala sub-County) n=299	IPM non-participants (Kangundo sub-County) n=282	t-tests	IPM participants (Mwala sub-County) n=289	IPM non-participants (Kangundo sub-County) n=277	t-tests
Per capita calorie intake (Kilocalories)	2839.52	3006.52	0.010**	2731.48	2843.22	0.098*	-97.56	-159.41	0.367
Household dietary diversity index (HDDI)	9.81	9.80	0.876	9.71	9.70	0.895	-.10	-.10	0.973

Source: Own survey

Figure 2 and 3 gives the graphical representations of the percentage of food secure and food insecure households in Mwala and Kangundo sub-counties based on food availability (percapita calorie intake). In Mwala, 72 percent and 67 percent of all farmers were food secure during the baseline and follow up respectively based on the recommended per capita calorie intake of 2250 kcal. On the other hand 81 percent and 75 percent of all farmers in Kangundo were food secure during the baseline and follow up respectively.

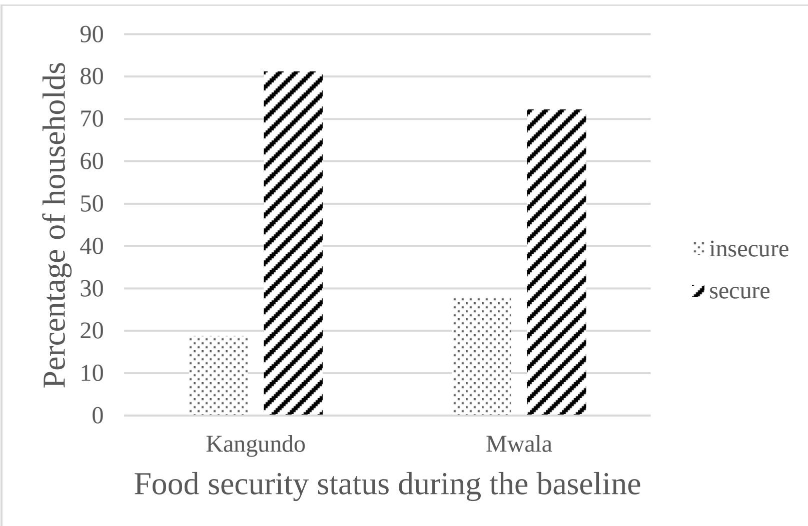

Figure 2: Food security status among fruit fly IPM participants (Mwala sub-county) and Non-participants (Kangundo sub-county) during baseline.

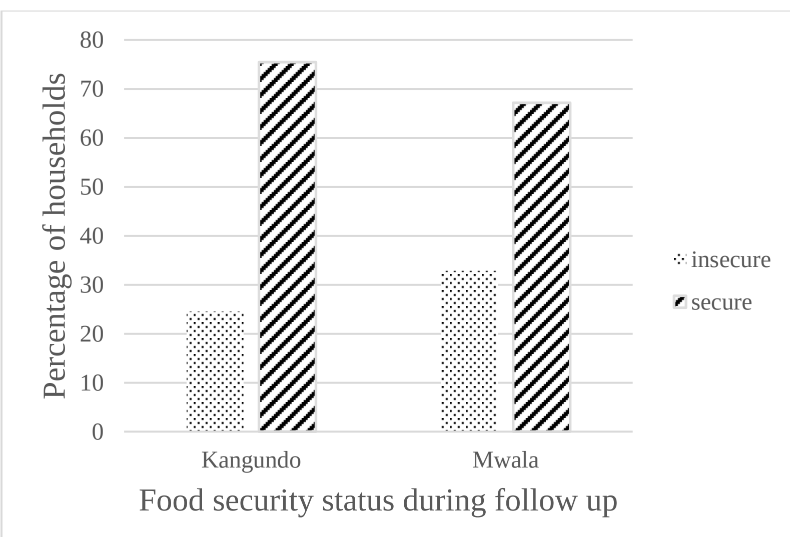

Figure 3: Food security status among fruit fly IPM participants (Mwala sub-county) and Non-participants (Kangundo sub-county) during follow up.

Impact of IPM technology on Per Capita Calorie Intake

Before estimating the DiD regression model, preliminary tests were carried out. To check for the presence of multicollinearity problem among the independent variables, the Variance Inflation Factor (VIF) was computed. The results of the VIF for the variables included in all the models were less than 10 and the pairwise correlations were less than 0.5 hence no independent variables were dropped from the estimated model. To adjust for autocorrelation, the Iterative Prais-winsten method was used. Robust standard errors were used to correct heteroscedasticity.

The results indicate that difference in calorie intake between the two groups was lower in post intervention period than baseline. The DiD estimate indicates that on average IPM participants received approximately 1.93 percent more per capita calorie intake than the non-participants. This implies that IPM intervention had a positive impact on calorie intake from mango production.

Table 5: Difference in Difference (DiD) estimate of average IPM technology effect on per capita calorie intake

Survey Period	**IPM participants (I)**	**IPM Non participants (C)**	**Difference across I&C**
Follow up (2015)	2731	2843	-112
Baseline (2014)	2840	3007	-167
Difference across time	-109	-164	55
Percentage change	55/2840*100= 1.93%		

Source: author's calculation using own survey data

Table 6 reports the estimates derived using the difference-in-difference estimator for the impact of IPM on food security parameters based on the unconditional treatment effect, Eq. (2). Although the coefficient of the unconditional treatment effect of IPM technology is statistically insignificant, the positive sign associated with this coefficient illustrates that participants had an increase in calorie intake than the non-participants. The results should be interpreted with care, however, as we assume that change in per calorie intake is only affected by the intervention, mango fruit fly IPM.

The analysis results presented in Table 6 present rests on a conditional treatment effect as outlined in Eq. (3). In this model, household and farm characteristics that may determine change in per capita calorie intake are included in the analysis. The inclusion of these explanatory variables also allows relaxation of the stringent parallelism assumption (Khandker et al., 2010). The coefficient of the conditional treatment effect of IPM (interaction Tixti) is positive and statistically significant after controlling for other exogenous factors that may influence the level of household food security. This implies that per capita calorie intake increased for those who used fruit fly IPM strategy in comparison with those who did not.

Table 6: DiD model estimates for the effect of Fruit fly IPM technology on Per Capita Calorie Intake

	Unconditional effect			**Conditional effect**		
Variable	**Coeff**	**Semi Robust Standard error**	**t-stat**	**Coeff**	**Semi Robust Standard error**	**t-stat**
Household Type Ti	-165.69	64.75	-2.56**	-162.86	62.04	-1.94*
Before_After ti	-157.82	46.76	-3.38***	-190.00	46.76	-4.22***
InteractionTixti	57.45	64.46	0.89	105.19	63.92	1.69*
Age				-11.97	16.89	-0.73
Age squared				0.12	0.14	0.85
Gender				13.95	81.75	0.16
Household size				-171.20	13.20	-12.87***
Experience				-1.92	2.28	-0.88
Farm income				0.00	0.00	1.71*
Group membership				-48.57	53.79	-0.90
Extension				164.16	59.52	2.30**
Livestock units				3.67	4.74	0.80
Farm size				24.13	32.94	0.74
Credit				-141.02	131.59	-1.08
Moderately wealth				166.34	75.29	2.24**
Wealthy				188.12	105.18	1.85*
Distance				14.23	0.57	2.95***
Constant	3005.21	45.64	65.85***	3864.89	506.46	7.78***
R^2	**52**			**57**		
F value	**0.00**			**0.00**		
Number of observations	**1147**					

Notes: *significant at 10 percent, ** at 5 percent and *** at 1 percent level

Source: Author's calculation using own survey data

With respect to the exogenous variables included in Table 6 that are likely to influence the per calorie intake, farm income, access to extension services, wealth category and distance to agricultural input market were positively and significant, while household size exhibited a negative and significant effect. One additional member of a household was associated with 171 Kcal decline in the household per capita intake. This is plausible, since households with large family members are mostly associated with a high dependency ratio and more food requirements, depicting a negative effect on food security (Olayemi, 2012). The results were consistent with findings by

(Goshu *et al*., 2013) who found that family size was negatively related to food security in rural Ethiopia.

Contrary to the *a priori* expectation, the results indicate that all else held constant an additional increase in agricultural market distance increases calorie intake by 14 Kcal. These results were inconsistent with most of the available literature (Feleke et al., 2005; Matchaya and Chilonda, 2012; Staal et al., 2002), which suggests that food security is negatively related to market distance. Households that accessed agricultural extension were found to be consuming 164 Kcal more other factors held constant. The results agree with earlier studies by Kassie *et al*., 2012 and Lewin, 2011, who found that government investment in agricultural extension has a significant impact in food security status. Households that belonged in the moderate wealthy category compared to those not wealthy, with all other variables held constant resulted to 166 Kcal increase in the household per capita calorie intake. Similarly, belonging to a wealthy category compared to moderate wealthy also resulted to an increase of 188 Kcal in the household's per capita calorie intake.

Impact of IPM technology on HDDI

Table 7 presents the results of average IPM technology effect on HDDI between IPM participants and non participants across the two time periods. The results showed that the two groups did not differ much in terms of HDDI both in the baseline and follow up. The Difference-in- Differences (DiD) estimate show a positive (0.001) which indicates a 0.01 percent increase in HDDI for the two group. Although not statistically significant, the coefficient presented in Table 7 tends to suggest that IPM technology led to an increase in HDDI levels of the participants.

Table 7: Difference in Difference (DiD) estimate of average IPM technology effect on HDDI

Survey Period	**IPM participants(I)**	**IPM Non participants (C)**	**Difference across I&C**
Follow up (2015)	9.709	9.700	+0.009
Baseline (2014)	9.806	9.798	+0.008
Difference across time	-0.097	-0.098	+0.001
Percentage change	0.001/9.806*100=0.01%		

Source: Author's calculation using own survey data

The marginal effects from the truncated Poisson regression show that the major factors influencing impact of IPM technology on HDDI include; Household head's years of formal education, years of farming experience, farm income, number of livestock owned, mango farm size and wealth category (Table 8). A higher education level is associated with 0.023 unit increase in the household's access to food all other variables held constant. Given that the average years of schooling is 9 years, with most farmers completing primary education, this finding implies that with this level of literacy most households are likely to diversify their food.

Table 8: DiD model estimates for the effect of Fruit fly IPM technology on HDDI

Variable	Marginal effects	Robust std errors	z-stat	Marginal effects	Robust std errors	z-stat
Household type Ti	0.008	0.005	0.16	-0.024	0.057	-0.40
Before_After ti	-0.098	0.006	-1.71	-0.100	0.057	-1.81*
Interaction Tixti	0.001	0.009	0.01	0.021	0.082	0.25
Age				0.014	0.014	1.04
Age squared				-0.000	0.000	-1.06
Education				0.023	0.007	3.35***
Gender				-0.035	0.070	-0.47
Experience				-0.006	0.003	-3.28***
Farm income				0.001	0.000	1.89*
Group membership				-0.013	0.048	-0.28
Livestock units				0.017	0.005	3.16***
Farm size				0.066	0.026	2.56**
Credit				-0.053	0.181	-0.29
Moderately wealth				0.049	0.053	0.71
Wealthy				0.150	0.070	1.86*
Distance				-0.004	0.003	-1.34
Constant	_	_	631.58	_	_	54.11***
Pseudo R^2 Prob > chi^2	0.01 0.00			0.12 0.00		

significant at 10 percent, ** at 5 percent and * at 1 percent level*

Source: Author's calculation using own survey data

The marginal effect of the total livestock owned has a positive sign and is significant at one percent level implying that an additional increase in livestock increases households' HDDI by 0.017 units. Livestock act as a source of food for instance, milk, eggs and meat hence households with more livestock units are likely to access more food. Farm income was found to positively influence a household's HDDI, where an addition increase in income increased HDDI by 0.001

units all other factors held constant. Increase in farm income improves the economic food access especially to households previously undernourished (Chege et al., 2015a). Also, higher incomes may result to better dietary quality and increased demand for more nutritious foods. Wealthy households compared to moderate wealth category to increase the HDDI by 0.150 units all else held constant. This can be explained that households with a lot of resources tend to have more diverse diets (Arimond and Ruel, 2004).

One additional acre of mango farm size, with all the other variables held constant was associated with an increase of 0.066 units of HDDI. According to Van Der Veen (2010), expansion of area under food production can increase food security. Households with large farm size can produce more food and also increase diversification. This outcome is consistent with the finding from a research conducted by Bogale (2009) and Aidoo et al. (2013) in Ethiopia and Ghana respectively. The results however contradict the findings by Sikwela (2008) who found a negative relationship between farm size and food security in Zimbabwe. Farming experience exhibited a different pattern of decrease of 0.006 units of HDDI with an additional year in farming.

Conclusions and recommendations

The empirical findings of this study suggest that promoting IPM technology is likely to benefit farmers, especially smallholder farmers to improve their food consumption levels. Findings from this study help to draw the conclusion that distance to nearest agricultural input market, household size, access to relevant information and the diverse financial status of farmers should be considered in the design and implementation of a workable dissemination and promotion strategy for IPM technology. Although the findings indicate that participation in IPM does not automatically lead to an increase in HDDI of the smallholder farmers, developing countries should invest more in such technologies to reduce food insecurity. There is need of using data for several years so as to include other aspects of food security which were not captured in this study that are recommended to evaluate the true effect of IPM technology on food security from mango production

Acknowledgements

The authors are extremely indebted to the African Fruit Fly Programme (AFFP) of the International Centre of Insect Physiology and Ecology (icipe) for financially supporting this research.

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