Health and environmental effects of adopting an integrated fruit fly management strategy among mango farmers in Kenya

Chris Miyinzi Mwungu
Department of Agricultural Economics and Resource Management, Moi University, Eldoret, Kenya. E-mail: miyinzic@gmail.com

Beatrice Muriithi*
International Centre of Insect Physiology and Ecology, Nairobi, Kenya. E-mail: bmuriithi@icipe.org

Vincent Ngeno
Department of Agricultural Economics and Resource Management, Moi University, Eldoret, Kenya. E-mail: vcngeno@gmail.com

Hippolyte Affognon
West and Central African Council for Agricultural Research and Development (CORAF/WECARD). E-mail: haffognon@yahoo.com

Caroline Githiomi
Department of Agricultural Economics, University of Nairobi, Nairobi, Kenya. E-mail: carolinegithiomi@gmail.com

Gracious Diiro
International Centre of Insect Physiology and Ecology, Nairobi, Kenya. E-mail: gdiiro@icipe.org

Sunday Ekesi
International Centre of Insect Physiology and Ecology, Nairobi, Kenya. E-mail: sekesi@icipe.org

* Corresponding author

Abstract

Integrated pest management (IPM) has been promoted globally as an alternative approach to the widespread broad-spectrum chemical insecticidal application for the control of pests and diseases in agricultural production to minimise the harmful effects of the chemicals on humans and the environment. This study examines the impact of an IPM strategy developed to control mango fruit flies on humans and the environment. Using a random sample of 371 mango farmers from Meru County in Kenya, health and environmental outcomes were measured using the environmental impact quotient (EIQ) field use and causal impacts, which were estimated using the endogenous switching regression (ESR) model. The results indicate that the adoption of the IPM strategy reduced pesticide use and pesticide toxicity. Policy efforts therefore should focus on promoting and disseminating fruit fly IPM to improve the livelihoods of rural mango farmers, but also reduce human health and environmental threats as a result of pesticide use.

Key words: integrated pest management; environmental impact quotient; mango fruit fly

1. Introduction

Agriculture has been a significant source of food for the human population across many generations. However, contemporary challenges, such as global warming, invasive species, land degradation and chronic diseases, among others, have presented new problems in the sector. Hawkes and Ruel (2006) developed a conceptual framework that shows a bidirectional relationship between health and agriculture. Good health and productive agriculture are two sides of a coin that are both imperative in the fight against poverty and malnutrition. Good agricultural practices promote health through the provision of safe food, medicine and fibre, while good health translates into productive labour in agriculture (Chang *et al*. 2015).

Although food crops are the most significant crops in Kenya, mango production contributes immensely to the horticultural sector of the country (Sennhenn *et al*. 2014; Horticultural Crops Development Authority [HCDA] 2016). Besides their well-known nutritional benefits (Septembre-Malaterre *et al*. 2016), mangoes provide income to farmers through local markets and also earn the country foreign exchange through exports (HCDA 2016; Ndlela *et al*. 2017). The crop provides employment opportunities to smallholder farmers, thereby presenting an excellent opportunity for rural development. Despite the seeming benefits of the mango enterprise, the productivity of the crop in Kenya is still below its potential due to various challenges, among them two main pests (fruit flies and mango seed weevil) and two primary diseases (powdery mildew and anthracnose) (Griesbach 2003). Fruit fly infestation is the most disastrous constraint to mango production, contributing a loss of up to 40% of annual mango production because of its numerous generations per season, which cause rapid multiplying and spread, along with resistance to existing chemical pesticides over time (Ekesi *et al*. 2014).

While pesticides are known to intensify agricultural production (Carvalho 2017), they are often over(mis)used (Bertrand 2019). The limited effectiveness of synthetic pesticides, due to the progressive loss of the pesticidal potency of the active ingredients and farmers' low levels of knowledge, could prompt delayed treatment or incorrect dosages (Fan *et al*. 2015). Mis(over)use of chemical pesticides contributes to adverse environmental effects such as loss of biodiversity, pollution of soils and water resources, alteration of soil and groundwater pH, and permanent changes to the ecosystem (Gill & Garg 2014). Besides, pesticides affect the health of domestic animals, mammals, fish, bees, soil microorganisms and other beneficial organisms (Maumbe & Swinton 2003; Donga & Eklo 2018). Synthetic chemicals might cause short-term health effects such as pain in the chest, and long-term consequences such as cancer (Macharia 2015).

Chemical-free protection strategies that are less harmful to the environment and humans offer safe and cost-friendly protection of crops against pests and diseases. One such approach is integrated pest management (IPM), which decreases the net quantity of pesticide used in pest control (Alam *et al*. 2016). The IPM approach combines different pest control methods (e.g. biological, chemical, mechanical and cultural) to develop the most effective and cost-friendly package of strategies to manage insects and diseases below their economic injury level (Fernandez-Cornejo 1998; Fernandez-Cornejo & Ferraioli 1999). In Africa, the International Centre of Insect Physiology and Ecology (ICIPE), under the Africa fruit fly programme (AFFP), in collaboration with its local and international partners, has developed and promoted an IPM package for the suppression of fruit flies (Ekesi & Billah 2007; Mohamed *et al*. 2008; Mohamed *et al*. 2010; Ekesi *et al*. 2014; Ekesi 2015). The package comprises: (1) spot application of food bait, (2) male annihilation technique, (3) *Metarhizium anisopliae*-based biopesticide application, (4) releases of parasitoids (*Fopius arisanus* (Sonan) and *Diachasmimorpha longicaudata* (Ashmead) (both Hymenoptera: Braconidae), and (5) the use of orchard sanitation. AFFP aims at stimulating mango productivity and enhancing the marketing of mangoes and to increase the income and food security of mango farmers and other value chain actors in the region.

While socioeconomic-related literature exists on the effectiveness of IPM in reducing pest damage in horticultural enterprises in developing countries (see, for example, Kibira *et al*. 2015; Muriithi *et al*. 2016; Githiomi *et al*. 2019; Midingoyi *et al*. 2019), rigorous empirical literature, particularly on the health and environmental impacts of IPM practices and especially on Sub-Saharan Africa, is limited. The few existing farm-level IPM impact studies (Isoto *et al*. 2014; Kibira *et al*. 2015; Muriithi *et al*.

2016; Githiomi *et al*. 2019) focused mainly on the direct economic benefits of IPM adoption. Understanding the environment and health benefits of IPM is essential because continuous chemical inputs pose a considerable risk to human health and the environment (Macharia 2015).

Our study contributes to the existing literature by quantifying the health and environmental benefits of IPM adoption, utilising the environmental impact quotient (EIQ) model (Kovach *et al*. 1992). Unlike previous studies that relied on descriptive results based on EIQ field-use rating (e.g. Mujica & Kroschel, 2019), we empirically evaluated the health and environmental impact of IPM adoption using the endogenous switching regression model, a more rigorous approach for estimating treatment effects. Although Midingoyi *et al*. (2019) used similar methods, the literature on the health and environmental impacts of IPM technologies is limited.

2. Methodology

2.1 Study area and sampling technique

This study was conducted in Meru County, Kenya. The county represents one of the significant mango-growing regions in the country and it is one of the counties in which ICIPE previously disseminated the IPM strategy for the suppression of fruit flies. The study utilised a sampling frame developed by an earlier survey done by ICIPE to evaluate the direct effects of the approach on mango production. An elaborate description of the study area, sample size, target population and sampling procedure is provided by Muriithi *et al*. (2016).

Out of the 828 mango producers successfully interviewed previously, a sample of 371 households was randomly selected for this study. Similarly to the case in the earlier survey, we followed the probability proportional-to-size (PPS) sampling technique to select 206 IPM farmers from Central Imenti, North Imenti and South Imenti sub-counties, and 165 non-IPM farmers from Tigania West sub-county. The data were collected using face-to-face interviews to capture mango-related variables (production, pest management and sales, among others) referring to the mango season from July 2014 to April 2015. Farm and household characteristics and contextual information were also captured.

2.2 Environmental impact quotient (EIQ)

This paper utilised the environmental impact quotient (EIQ) model to quantify the health and environmental effects of IPM technologies. The EIQ model was developed by Kovach *et al*. (1992) to quantify the effects of various crop pests and disease-control strategies on humans and the environment. The model aggregates the pesticide risks posed to farm workers, consumers of farm products and the environment into a single numerical value (Macharia *et al*. 2009). The model estimates pesticide risks on a three-point scale, following the hazard of the various pesticides, with 1 representing the lowest, 3 intermediate and 5 the highest. The potential risks of pesticide toxicity can also be determined by other proxies, such as LD50 (dose at which 50% of the treatment group dies within a specified period) or LC50 (concentration at which 50% of the treatment group dies within a specified time), and the potential exposure such as the half-life, runoff or leaching potential (Swinton & Williams 1998). The EIQ formula is defined as stated below:

$$EIQ = \{C[(DT*5)+(DT*P)]+[C*((S+P)/2)*SY)+(L)]+[(F*R)+(D*((S+P)/2)*3)+(Z*P*3)+(B*P*5)]\}/3 \quad (1)$$

where:

C = chronic toxicity, DT = dermal toxicity, P = plant surface residue half-life, S = soil residue half-life, SY = systematicity, L = leaching potential, F = fish toxicity, R = surface loss, D = bird toxicity, Z = bee toxicity, and B = beneficial arthropod activity.

The values of the parameters in the equation are determined by toxicity information from several sources, including the extension toxicology network, published journals and individual chemical manufacturers. However, EIQ is not a convincing measure of pesticide health and environmental health impacts. There are pesticides of different formulations that have the same active ingredient and are applied in various dosages and frequencies by farmers. To account for this discrepancy, we adopted the EIQ field use component to compare the health and environmental impacts of IPM technologies and conventional methods. We computed the EIQ field use by finding the product of EIQ, the pesticide dose, the percentage active ingredient and the frequency of pesticide application, as shown in the formulae below (Donga & Eklo 2018).

$$EIQ \text{ field use rating} = \text{EIQ} * \% \text{ active} * \text{frequency of application} * \text{dose} \tag{2}$$

EIQ field use helps in comparing the health and environmental impacts of different pest control strategies. The weights used were based on the area sprayed with pesticides, the dose, and the frequency of application.

2.3 Endogenous switching regression (ESR) model

The endogenous switching regression (ESR) model was estimated to determine the counterfactual health and environmental effects between the control and treatment groups. This is a two-stage model according to which a probit model is used in the first stage to evaluate the adoption determinants of IPM technologies. We specified the probit model, as shown below:

$$Z_i^* = \beta X_i + u_i \text{ where } Z_i = 1, \text{when } Z_i^* > 1 \text{ and 0 otherwise,} \tag{3}$$

where Z_i^* is the unobserved variable of IPM adoption, Z_i is the observed adoption variable in terms of which 1 represents adoption and 0 otherwise, X_i are noted variables that influence IPM adoption, and u_i is the unobserved variable related to IPM adoption.

We assume farmers are rational and that they will make decisions based on the expected benefits of the new technology. However, technology adoption is potentially endogenous (Adego *et al.* 2019). Thus, we adopt an ESR model that treats the control and treatment farmers in two separate regimes, expressed as:

$$Y_{1i} = \alpha J_{1i} + e_{1i} \text{ if } \mathrm{Z}_i = 1 \tag{4}$$

$$Y_{2i} = \alpha_2 J_{2i} + e_{2i} \text{ if } \mathrm{Z}_i = 0 \tag{5}$$

where Y_i refers to the computed EIQ field use of the control and treatment, J_i is a vector of covariates that influence the magnitude of EIQ field use, and e_i is white noise.

The error terms in Equations 3 to 5 are assumed to have a trivariate normal distribution with a zero mean and a non-zero determinant matrix, as follows:

$$cov(e_{1i}, e_{2i}, u_i) = \begin{bmatrix} \sigma_{e2}^2 & . & \sigma_{e2\mu} \\ . & \sigma_{e1}^2 & \sigma_{e1\mu} \\ . & . & \sigma_\mu^2 \end{bmatrix}, \tag{6}$$

where $\boldsymbol{\sigma_{\mu}^2}$ refers to the variance of the random disturbance term in the probit model, while $\boldsymbol{\sigma_{e1}^2}$ and $\boldsymbol{\sigma_{e2}^2}$ are variances of Equations 4 and 5 respectively. The covariance of the error terms in equations 3,4 and 5 are represented by $\boldsymbol{\sigma_{e1\mu}}$ and $\boldsymbol{\sigma_{e2\mu}}$. According to Maddala (1983), since $\boldsymbol{u_i}$ is correlated with $\boldsymbol{e_{1i}}$ and $\boldsymbol{e_{2i}}$, the expected values of $\boldsymbol{e_{1i}}$ and $\boldsymbol{e_{2i}}$ conditional on the selected sample of 371 are not equal to zero. While analysing the model in STATA, we followed a full information maximum likelihood (FIML), as discussed by Lokshin and Sajaia (2004). The advantage of FIML is that the first and second stages of the ESR model are estimated concurrently to yield consistent standard errors (Hensher 1986). The model was further identified by the use of distance to the hospital as an instrument that was obtained using the falsification process (Di Falco & Veronesi 2013).

2.4 Counterfactual analysis and treatment effects

The ESR model has the capability to conduct a counterfactual analysis. In other words, the model helps us to compute hypothetical values of EIQ field use if the farmers in the treatment region had not adopted IPM technologies. Similarly, we can calculate EIQ field use for control farmers had they adopted IPM technologies. The difference between the observed EIQ field use and the respective hypothetical values for the treatment and control farmers gives the treatment effects. The average EIQ field use for IPM adopters is calculated as shown in Equation 7. If they had not adopted IPM technologies, the average EIQ field use would be computed using Equation 8.

$$E(Y_{1i}/Z_i = 1) = \alpha_1 J_{1i} + \sigma_{e1u}\lambda_{1i} \tag{7}$$

$$E(Y_{2i}/Z_i = 1) = \alpha_1 J_{1i} + \sigma_{e2u}\lambda_{1i} \tag{8}$$

Similarly, the average EIQ field use for non-adopters is computed as shown in Equation 9. Had they adopted IPM technologies, the new EIQ field use for non-adopters would be arrived at as shown in Equation 10.

$$E(Y_{2i}/Z_i = 0) = \alpha_2 J_{2i} + \sigma_{e2u}\lambda_{2i} \tag{9}$$

$$E(Y_{1i}/Z_i = 0) = \alpha_2 J_{1i} + \sigma_{e1u}\lambda_{2i} \tag{10}$$

Treatment effects are obtained by obtaining the difference between the observed and counterfactual expected values of EIQ field use (Adego *et al.* 2019). The average treatment of the treated (ATT) is the difference between Equations 7 and 8, as illustrated below:

$$ATT = E(Y_{1i}/Z_i = 1) - E(Y_{2i}/Z_i = 1) = J_{1i}(\alpha_1 - \alpha_2) + \lambda_{1i}(\sigma_{e1u} - \sigma_{e2u}) \tag{11}$$

In the same way, the average treatment on the untreated (ATU) is the difference between Equations 9 and 10. This is expressed below:

$$ATU = E(Y_{1i}/Z_i = 0) - E(Y_{2i}/Z_i = 0) = J_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\sigma_{e1u} - \sigma_{e2u}) \tag{12}$$

3. Results and discussion

3.1 Descriptive estimation of health and environmental effects of IPM technologies and pesticides

Table 1 presents the field use environmental impact quotient (EIQ) for pesticide use in mango production for the control and treatment regions in Meru County. The results from the table show that Bayleton and Bulldock are the most used pesticides in mango production in the study area, representing 34.50% and 33.96% of the total pesticide used respectively. The two pesticides recorded 15.43% and 24.47% of the total pesticide usage by the IPM farmers and 22.78% and 22.42% among non-IPM farmers respectively. Mean EIQ values for farmworkers, consumers and environmental components among the non-IPM users were 24, 10 and 75 respectively, while among IPM farmers the mean components were 25, 10 and 73 respectively.

To obtain the volume of individual pesticides applied per acre, we first computed the treated area by multiplying the percentage of farmers using pesticides in mango production by the total area under mango trees. The obtained treated area was then multiplied by the rate of pesticide applied per acre to find the estimated amount of chemicals used. From the literature, we listed all pesticides applied to mangoes and their recommended application rates. We also interviewed pivotal agricultural experts and pesticide vendors to obtain information on recommended pesticide dosages, which were counterchecked with the report on the Pest Control Products Board (PCPB) Kenya website and the product labels. With the aid of the procedure proposed by Kovach *et al*. (1992), EIQ values for each active ingredient of a pesticide used were calculated based on the active pesticide ingredient and physical properties, while others were obtained from internet sources and published journals (Macharia *et al*. 2009).

Based on the EIQ classification rule of Mazlan and Mumford (2005), values for all the pesticides used in mango production showed that 30%, 25% and 45% of those pesticides were rated as low (EIQ = 0 to 20), moderate (EIQ = 21 to 40) and high (EIQ ≥ 41) respectively. Pesticide active ingredients that had EIQ field use below 40 were deltamethrin (II), acephate (III), thiamethoxam (U), lambda cyhalothrin (II), carbendazim (U), cypermethrin (II), imidacloprid (II), propineb (1II), thiophanate-methyl (U) and sulphur (U). Methomyl (IB), dimethoate (II), triadimefon (III), acephate (III), copper oxychloride (III) and beta-cyfluthrin (II) had an EIQ field use of greater than 40. Generally, the results show that the environmental component of the EIQ was high among both the IPM and non-IPM farmers, but there was a significant difference in the EIQ field use between the two categories of farmers. Continued use of pesticides in mango production among the IPM farmers is puzzling, since the strategy is expected to reduce pesticide use. Muriithi *et al*. (2016) made a similar observation in this region, where they found no significant difference in pesticide expenditure between the IPM and non-IPM farmers.

Amongst the total pesticides used for mango production in Meru County, none were classified in category 1a (extremely hazardous), 10% were in category 1b (highly hazardous), 40% were in category II (moderately hazardous), 25% in category III (slightly hazardous), and 25% were in category U (unlikely to present acute hazard when in regular use). The remaining two categories – FM (fumigant, not classified) and O (obsolete as a pesticide, not ranked) – were not used in mango production. The total EIQ field use in Meru County was 4 049.67, with 84% found among the non-IPM farmers. The overall field-use EIQ rating per individual pesticide ranged from 0.58 to 946.16, being lowest for deltamethrin (0.58) and highest for dimethoate (946.16).

There is a need to encourage farmers to use more moderate hazardous pesticides, since only 25% of pesticides in this category are used in mango production. The use of less hazardous pesticides and IPM technologies by mango farmers will promote environmental and economically sustainable agriculture that is consistent with the sustainable development goals. Although this study was done for mango production, increasing awareness of the use of less hazardous chemicals in combination with IPM will help in safeguarding the environment and human health.

Table 1: EIQ component values related to health and environmental effects of pesticides used by mango farmers in Meru County

Active ingredient	Trade name	EIQ F	EIQ C	EIQ E	EIQ T	Rate (kg/acre)	EIQ field use overall	EIQ field use IPM non-participants	EIQ field use IPM participants	T value	P value	% of farmers using	Vol.kg
Thiamethoxam (U)	Actara	10.35	12.03	77.52	33.3	0.12	5.75	3.55	2.19	0.7891	0.2341	0.81	1.14
Methomyl (IB)	Agrinate	6	11	75	31	0.28	277.38	221.12	56.27	0.2389	0.8805	6.20	452.31
Propineb (1II)	Antracol	6	5.78	14	18.34	0.27	30.93	0.10	30.82	1.2615	0.5807	6.20	534.42
Triadimefon (III)	Bayleton	12.15	15.15	53.57	33.3	0.25	277.31	105.04	172.27	-2.9994***	0.0033	34.50	134 040.8
Beta-cyfluthrin (II)	Bulldock	9	4	69	27	0.21	634.28	550.42	83.86	2.6674***	0.0087	33.96	69 418.38
Copper oxychloride (III)	Copper	108	19	76	67.7	0.20	557.61	512.49	45.12	3.0990***	0.0035	12.12	9 444.32
Cypermethrin (II)	Cyclone	9	4	69	27	0.14	22.75	12.14	10.61	-1.5302	0.1482	4.58	173.3091
Dimethoate (II)	Danadim	72	9	141	74	0.22	76.91	46.79	30.11	-0.5301	0.6104	2.67	35.25
Deltamethrin (II)	Decis	6	3	68	26	0.26	0.58	0.21	0.37	0.2350	0.4325	2.43	101.10
Dimethoate (II)	Twigathoate	72	9	141	74	0.21	946.16	794.15	152.01	1.3425	0.7856	8.63	2 855.765
Mancozeb (U)	Dithane	12	3	29	44	0.40	532.53	515.95	16.56	0.0955	0.92566	2.43	90.54
Lambda cyhalothrin (II)	Karate	21	3	106	44.17	0.09	7.96	7.12	0.84	0.1144	0.9100	6.20	84.38
Methomyl (IB)	Weiling	6	11	75	31	0.31	56.45	38.27	18.18	-1.9925*	0.0866	2.42	69.92
Propineb (III)	Milraz	6	6	14	9	0.17	1.54	0.00	1.54	0.8745*	0.0534	1.35	5.07
Acephate (III)	Orthene	15	12.5	47.15	24.88	0.19	16.81	12.59	4.22	0.7131	0.4875	4.58	230.25
Carbendazim (U)	Rodazim	25	40.5	86	50.5	0.26	490.33	485.54	4.79	-0.7419	0.4752	3.23	28.57
Alpha-cypermethrin (II)	Tata alpha	21	3	106	44	0.30	39.62	39.62	0.00	0.1451	0.8862	5.39	34.38
Sulphur (U)	Thiovit	10	6	120	45.5	0.32	24.09	14.12	9.97	0.7117	0.4835	7.00	1 427.01
Imidacloprid (II)	Thunder	6.9	10.35	92.88	36.71	0.21	36.36	35.51	0.85	-1.1227	0.2722	7.27	435.39
Thiophanate-methyl (U)	Topsin	16.2	15.3	39.95	23.83	0.10	14.32	11.30	3.02	-0.58546	0.5796	2.16	2.87
	Total						**4 049.67**	**3410.27**	**639.40**	**-7.7660*** **	**0.000**	**100**	**219 465.20**

NB: Statistical significance at 0.01 (***), 0.05 (**) and 0.1 (*)
EIQ F refers to the EIQ component for the farmer
EIQ C refers to the EIQ component for the consumer
EIQ E refers to the EIQ component for the environment
EIQ T refers to the EIQ total

3.2 Determinants of IPM adoption

A probit model was estimated in the first stage of the ESR model to evaluate determinants of IPM adoption. Post-estimation tests were also determined to test the validity of the model. First, the variance inflation factor (VIF) was applied among the independent variables. The results show that there was no strong correlation between the variables, since the values of VIF were far below 10. The Hosmer-Lemeshow test was also conducted to test the goodness of fit of the model. With a p-value of 0.29, we can say that Hosmer and Lemeshow's goodness-of-fit test justified our choice of model.

Exclusion restriction is required for the identification of the ESR model. This is because at least one variable that affects farmers' adoption of IPM but does not directly affect the EIQ field use is needed. Based on the existing literature and our study context, we use households' access to a health centre proxied as the distance to the nearest health centre as our identification strategy. Households' access to a health facility has been used for identification purposes in previous, related studies (Baiocchi *et al*. 2010). We hypothesised that households that are near a health centre are likely to be more informed about the adverse effects of chemicals and consequently will adopt alternative methods of pest control, such as IPM. However, distance to a health centre may not relate directly to the EIQ field use. The suitability of this variable as a valid instrument is established by performing a falsification test, following Di Falco and Veronesi (2013). The variable exhibited a significant effect on IPM adoption decisions, but did not affect EIQ field use among the non-IPM households.

The parameter estimates of the probit model are presented in Table 2. The likelihood to adopt IPM technologies was influenced by the size of agricultural land, the number of mature mango trees, access to irrigation water, IPM training, distance to the nearest health facility, group membership, and age of the household head. The probability of IPM adoption increased with the number of mature mango trees. This is reasonable, because more productive trees imply high production, and thus higher revenue from mango production may provide the necessary capital for investing in new technologies. This finding is consistent with Korir *et al*. (2015), who found that farmers with more mango trees are likely to adopt more IPM components.

Table 2: Probit model for determinants of IPM adoption

Variables	**Coefficient**	**SE**	**ME**
Wealth variables			
Agricultural land owned	0.3031**	0.1329	0.1183**
Number of mango-producing trees	0.0034***	0.0010	0.0013***
Human and productive capital variables			
Years is school	0.0057	0.0184	0.0022
Years in mango farming	0.0121	0.0094	0.0047
Household head age	-0.0126*	0.0071	-0.0049*
Household size	-0.0152	0.0370	-0.0059
Gender of the household head	0.2457	0.2027	0.0959
Labour management	0.1357	0.1046	0.0529
Institutional and finance variables			
Access to extension officers	0.0696	0.1783	0.0272
Attended IPM training	0.8281***	0.1726	0.3232***
Access to irrigation water	0.2826*	0.1536	0.1103*
Access to credit facilities	-0.0447	0.1756	-0.0175
Member of an agricultural group	-0.5360***	0.1694	-0.2092***
Distance to the nearest health facility	0.1718***	0.0429	0.3232***
Farm management variables			
Protective clothes usage	0.1919	0.1557	0.0749
Number of observations	371		

NB: Statistical significance at 0.01 (***), 0.05 (**), 0.1 (*)

The positive correlation between farm size and IPM adoption is consistent with the findings of Uaiene *et al*. (2009). A possible reason is that the collateral value of land could be used to access credit, which enhances the adoption of IPM. Farm size affects adoption costs, risk perceptions, human capital, credit constraints, and labour requirements. Households with small farms face enormously high fixed costs involved in the adoption of new technologies.

Access to water for irrigation is significantly correlated with the decision to adopt IPM technologies. Qualitative information from our study area revealed that access to water was a significant challenge, with only a few farmers having access to irrigation. Although Meru County receives adequate rainfall throughout the year, recent threats posed by climate change have induced farmers to supplement farm production with irrigation. Thus, farmers who access irrigation water can diversify production and produce different farm products throughout the year, which increases their yields and revenue (Bruinsma 2009), enabling farmers to adopt IPM technologies.

In contrast to our expectation, social capital in terms of membership of a farming group negatively affected the probability of adopting IPM technologies. This is unexpected, as participation in social networks is considered a channel for accessing new information and thus increasing the likelihood of being exposed to new farming ideas (Uaiene *et al*. 2009). It is possible that farmers in a group are limited by group dynamics, while individual farmers have the freedom to make their decisions independently. In a large group of farmers, for instance, learning externalities can lead to opposite effects because of free-riding behaviours (Bandiera & Rasul 2006).

The age of household heads is negatively related to the adoption of IPM. Adesina and Zinnah (1993) note that the rate of risk aversion and reluctance to invest in long-term technologies increases with age. Farmers who had attended IPM training were 32.32% more likely to adopt IPM technologies than those who had not. Trained farmers have prior knowledge of the potential benefits associated with technology, and thus they are likely to adopt the technology (Miheretu & Yimer 2017). Interestingly, farmers who reside further from health centres were more likely to adopt IPM technologies. A possible explanation could be that farmers far from health centres incur high transportation costs to these centres, thus increasing their health costs (Maumbe & Swinton 2003), and therefore are more likely to adopt technologies that are more health friendly.

3.3 Health and environmental effects of adopting IPM technologies

Table 3 reports the causal impacts of adopting IPM technologies. The descriptive statistics in the previous section comparing the mean of EIQ field use for the intervention and farmers' practices revealed that adoption of the fruit fly IPM has aggregate positive benefits of a lower EIQ field use value (639.40). However, the approach is not enough to justify the positive effects of IPM technologies. The adoption of IPM technologies potentially is endogenous. The difference in EIQ field use may be influenced by other, unobservable characteristics of the farm households, such as their education level, farming experience, skills or income level. For instance, the most successful farm households could also be the most able ones, hence they would have done better than others even without adopting IPM technologies. We address this issue by estimating an endogenous switching regression model, which enables us to construct a valid counterfactual.

Table 3: Treatment effects of IPM technologies

	Mean	Std dev.	T-test	P-value
IPM farmers with IPM (observed)	7.1231	1.7415	-9.4207***	0.0000
IPM farmers had they not adopted IPM (counterfactual)	7.8053	1.4993	-9.4207***	0.0000
Net change (ATT)	-8.74%***			
Non-IPM farmers without IPM (Observed)	6.5240	1.8916	13.2567***	0.0000
Non-IPM farmers had they adopted IPM (counterfactual)	5.2903	1.1881	13.2567***	0.0000
Net change (ATU)	23.32%***			

*** mean values are significant at the 1% level

The results indicate that fruit fly IPM plays an essential role in reducing the harmful effects of pesticide use among IPM farmers. The adoption of IPM helps reduces the EIQ field. Specifically, farmers who used fruit fly IPM reduced the EIQ field use by 8.74%. The finding corroborates other studies that utilise different methodologies, and finds definite evidence of the impact of IPM on health and the environment (e.g. Fernandez-Cornejo 1998; Fernandez-Cornejo & Ferraioli 1999; De Bon *et al*. 2014). The ATU results in the lower part of Table 2 would show heterogeneous health and environmental effects of fruit fly IPM for non-IPM farmers if they adopted. The results suggest that non-IPM farmers would have reduced the value of EIQ field use by 23.32% if they had adopted the strategy.

4. Conclusion and policy implications

This study utilised household-level survey data collected from 371 mango growers in Meru County, Kenya to evaluate the health and environmental benefits of using IPM technologies for controlling fruit flies in mango production. While substantial literature exists on the effectiveness of IPM in reducing insect pests of horticultural output in developing countries, the empirical literature, particularly on the health and environmental impacts of IPM practices, especially in Sub-Saharan Africa, is limited. We contribute to the limited studies by utilising the environmental impact quotient (EIQ) model to quantify the health and environment effects of an IPM strategy developed and disseminated by ICIPE and partners to suppress fruit flies in Sub-Saharan Africa. Furthermore, in contrast to the previous studies, which relied on detailed results based on EIQ values or EIQ field-use ratings, we empirically evaluated the treatment effects using the endogenous switching regression (ESR) model.

We find that the adoption of IPM technologies reduces the negative impacts of pesticides, as demonstrated by a lower EIQ field-use rating among the IPM farmers and the significant average treatment effect. The first stage of the ESR model revealed that IPM adoption also depends on the size of agricultural land and the number of mango-producing trees owned, the age of the household head, IPM training, access to irrigation water, membership of a farming group, and distance to the nearest health facility. The findings recommend policy efforts that focus on promoting and disseminating fruit fly IPM to improve yields and income from horticultural production, and to reduce human health and environmental threats from pesticide use among the rural communities. Providing IPM training and access to irrigation water should be considered to enhance the adoption of fruit fly IPM. While this study provides useful insights regarding the health and environmental benefits of using IPM, our findings have limited generalisation, since the study is based on cross-sectional data. Besides, the effectiveness of IPM technologies is specific to each site. The benefits of these technologies vary geographically and depend on the level/intensity of adoption on the farm. We recommend that future studies should evaluate the long-term adoption and impact of the fruit fly IPM strategy on health and the environment, utilising panel datasets and focusing on different contexts in which the approach is being promoted. Further, we believe that collaboration by various disciplines, such as biologists, agronomists, environmentalists, soil scientists and economists, will be a great addition to future literature assessing the health and environmental benefits of IPM.

Acknowledgements

The authors would like to acknowledge financial support from the UK Government through UK Aid. ICIPE also receives core funding from the Swedish International Development Cooperation Agency (SIDA), the Swiss Agency for Development and Cooperation (SDC), the Federal Ministry for Economic Cooperation and Development (BMZ) in Germany, and the Kenyan Government. The authors are also grateful to the African Fruit Fly Programme (AFFP) of ICIPE, for their field support, to the farmers, who dedicated their time to participate in the focus group discussion and household surveys, and to the enumerators, for their hard work in data collection. A previous version of this paper was presented at the 2nd Biennial International Conference on Enhancing Sustainable Agricultural Production and Marketing Systems, hosted by the School of Agriculture and Enterprise Development at Kenyatta University, Nairobi, Kenya. The authors are indebted to the conference organisers and participants for their insightful comments.

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