

## **Contribution of Mango IPM Strategy for Fruit fly Control on Household Welfare in Kenya.**

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### **Abstract**

The objective of this study was to assess the contribution of mango IPM strategy for fruit fly control on household welfare in Kenya. Data was collected using a semi-structured questionnaire on a sample of 660 mango farmers from Embu, Meru, Machakos and Makueni Counties. The study employed a multi-stage sampling procedure technique. STATA software was used for data analysis. Descriptive statistics, multivariate Probit model, Endogenous switching regression method were used for data analysis. This study found that having a good combination of 2-3 IPM strategies gives the best returns to the farmer. A combination of fruit fly traps, bio-pesticides and orchard sanitation resulted to the highest returns. Education level was positively associated with the use of all IPM strategies available to the small-scale mango farmer. This study recommends that the government and other development partners should invest in the provision of formal education and extension services. Empowerment of farmers with formal education would help them understand faster the need to shift to new technology and the effect chemicals when used to control pests to the environment, farm and to the farmer. Farmers should also be sensitised to seek for extension services from both government extension agents and private extension service providers to get service regarding the use of IPM strategies. To enhance farmer education, frequent trainings on new technologies and innovation, seminars, field demonstrations and field days should be organised for mango farmers to participate fully so that the adoption of the IPM strategies is achieved uniformly.

**Key Terms:** Mango, IPM, strategy, fruit fly, control, household, welfare, Kenya

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## Introduction

Mango is an economically essential fruit crop in Kenya as it is traded on domestic and international markets. It has emerged as Kenya's third most important fruit crop in terms of acreage and total production volumes after bananas and pineapples according to value chain analysis conducted in 2009 (FAO, 2009). Its potential yields are about 15-20 tons per hectare, which are not achieved by many farmers due to poor control of pests and disease attacks. It provides many small-scale farmers with employment opportunities and improved livelihood, while helping the country generate foreign exchange earnings (Midingoyi et al., 2019). However, Kenya's mango production, quality and marketability are constrained by many problems, with fruit flies being a major threat to food security, poverty alleviation and agricultural livelihoods. Fruit flies are estimated to cause huge annual losses of approximately US\$2 billion in fruit and vegetable production in Kenya (Ekesi et al., 2016).

The International Centre of Insect Physiology and Ecology (ICIPE)-African Fruit Fly Program (AFFP) has over the last decades developed and disseminated an Integrated Pest Management (IPM) package for suppression of mango fruit flies in Africa and particularly in Kenya (Ekesi, Mohamed, & Hanna, 2010; Muriithi et al., 2016). IPM is one of the methods used for suppression of pests and diseases in Kenya. It selects the most appropriate, cost-effective, compatible method of managing pests. Thus, minimises pest damage with minimal disturbance to the natural balance of the agro-ecosystem and minimal risk to human health. It decreases the net chemical pesticide inputs to agriculture. Thus minimises dependence on chemical pest control.

However, the adoption of new technology still remains low despite the potential to improve mango productivity in Kenya given that time plays a vital role as circumstances are likely to change during the observation period (Läpple,

2010; Muriithi et al., 2016). New technology studies are increasing and their significance has been abundantly documented in econometric literature (Feder, & Slade, 2004; Beyene, & Kassie, 2015; Lemesa et al., 2017). Despite this, many studies on the adoption of new technologies, and the existing empirical and theoretical frameworks, tend to provide only a limited explanation on the adoption durations-commonly known as adoption spell-the time that farmers should wait before adopting a given technology once they have heard about the existence of the technology.

Previous adoption studies in developing countries failed to consider the timing of the adoption event and do not clearly address the effect of explanatory variables on the time path of adoption (Munasib, & Jordan, 2011; Teklewold et al., 2013). Having the scarcity of literature on adoption spells of IPM strategies, this study aims to thoroughly analyse the adoption duration of IPM strategies for control of mango fruit flies in selected counties in Kenya, using the duration model. Given that duration model focuses on the time of adoption, they have advantages in the study of the take-up of new technologies by providing better-informed policy intervention in the sector (Burton, & Turner, 2003). This analysis also helps to understand factors that explain the length of a spell, where the spell starts or ends (Qain et al., 2008).

Additionally, the standing aspect of technology adoption explains why, at a point in time some farmers adopt when others are late or slow adopters and others are non-adopters. Several factors such as socioeconomic, institutional, cultural and social networks affect the ability of farmers to adopt technologies. A better understanding of the constraints that condition farmers' adoption behaviour is important for designing and implementing policies that could stimulate the adoption of mango IPM strategies (Kassie et al., 2020).

Using duration analysis to explore the factors that affect the length of time required for mango farmers to adopt IPM strategies, the paper contributes to the existing literature in the following ways; firstly, given that there is scarcity of literature on the application of duration models to analyse the adoption time of IPM strategies for control of mango fruit flies. This study thoroughly analyses the adoption spell of mango IPM strategies that were introduced by ICIPE research centre in selected counties in Kenya. Secondly, the empirical knowledge and information obtained from this study on factors that affect the adoption spell may be useful in designing relevant agricultural policies to strengthen and speed up technology dissemination of mango IPM strategies for control of fruit flies. Thirdly, IPM is a sustainable production intensification approach, which does not rely on the enlarged use of insecticide. As a result, its adoption could potentially allow farmers to increase their mango productivity and incomes, without increasing dependence on insecticides.

## MATERIALS AND METHODS

This study used data collected from 660 farm households across four selected counties in Kenya where awareness on IPM strategies was done by ICIPE, namely; Embu, Meru, Machakos and Makueni. Data was collected in between November and December 2016 in collaboration with ICIPE. Well-trained and experienced enumerators who had the knowledge of the local language administered structured survey questionnaires. The survey targeted the mango farmers who were supplied with the IPM strategies for control of mango fruit flies. The study employed multistage sampling procedure was. In the first stage, four mango-growing Counties (Embu, Meru, Machakos and Makueni) were purposively selected based on their production and high incidences of mango fruit flies. Each of the four counties was assigned an equal number of sample households (165). Sub-counties where IPM strategies had been distributed, in which the survey could be conducted were selected. In Embu County, Runyenjes Sub-county was

picked. In Meru County, Central Imenti, North Imenti, South Imenti, and Tigania West Sub-counties were selected. In Machakos County, Mwala and Kangundo were covered, while in Makueni County, Makueni sub-county was chosen. Agricultural information was obtained from the County Integrated Development Plans in every County in Kenya. Trained enumerators collected information on socioeconomic characteristics, agricultural assets, farmers income sources, mango production practices and related constraints, mango yields, number of years the farmer was aware of mango IPM strategies, damage levels and marketing, IPM knowledge and adoption or non-adoption, health effects of pesticides, social capital, networking and infrastructure and institutional factors.

## Econometric specification of duration model

The Duration Analysis (DA) is a statistical method from biometrics and statistical engineering that studies the probable time an individual spends in one state before transitioning to another. DA is a dichotomous choice method, in which individual adoption decision methods are modelled using cross sectional data and measurements of aggregate diffusion in a dynamic framework (Murage et al., 2011). Originally, as it dealt with the transition process of the death of a patient, or mechanical failure of a piece of equipment, it has acquired the name “survival analysis” (Alcon et al., 2011). In recent times, duration analysis has been used to capture the dynamic aspects of new technology adoption processes (Beyene, & Kassie, 2015; Lamessa, 2017). To mention particular cases where duration analysis has been applied is in adoption of agricultural technologies for improved potato, maize and common bean varieties.

In duration analysis, the idea of probability plays an elementary role (Kassie et al., 2015). It means that instead of focusing on the time length of a spell, one can consider the probability of its end, or on the likelihood of transition to a new state. The important question would be

therefore; what is the probability of a farmer adopting a certain technology at a time  $t$ , given that it has not been adopted at that time (Beyene, & Kassie, 2015). The length of 'time' or 'duration' a farmer waits before adopting a new technology is expected to depend on several variables. Some of these variables vary with time (age of the farmer, input prices, output prices) and some are constant (gender of the farmer, geographical location, education level). To adopt the new technology requires that the farmer has the technology available, and is able to earn a profit ( $V_1$ ) from the adoption that is more than the profit ( $V_0$ ) from non-adoption. For a given farmer, the non-adoption exit (to adoption) hazard rate  $\varphi(t)$  can be written as the product of the exposure to adoption (availability of innovation)  $\xi(t)$  and the technology adoption hazard  $A(t)$ :

$$\varphi(t) = \xi(t)A(t)$$

In making the technology adoption choice, the non-adopter makes the decision based on the distribution of profits from adoption  $V_1$ . The optional decision is to adopt if  $V_1$  is greater than the profit from the existing technology  $V_0$ .  $V_1 > V_0$  therefore,

$$\varphi(t) = \xi(t)[1 - V(t)]$$

(2)

Where,  $V(t)$  is the cumulative distribution function (cdf) of the profit distribution from adoption. How the hazard of adoption varies with the duration depends on; (1) the profit with the duration of non-adoption, and (2) how the hazard information about the new technology varies with duration. With the negligible influence via  $\xi$ , the structural model provides strong restriction on the hazard rate, but the hazard rate in reduced form can be written as;

$$\varphi(t) = \varphi(X(t, s), t)$$

(3)

Where;  $X$  is a vector of personal characteristics that may vary with non-adoption duration  $t$ , or with time  $s$ . Some of the factors in  $X$  increase hazard duration; others reduce it.

The most popular specification of duration models is the proportional hazard (PH) model, which is suitable in cases of exponential, Weibull, and Gompertz distribution (Addison and Portugal, 1998; Jenkins, 2005; Laple, 2010). In the PH specification, covariates are related multiplicatively with the baseline hazard and the hazards are independent of time;

$$h(t / X, \beta) = h_0(t)\varphi(X, \beta)$$

(4)

Where;

$h_0(t)$  is the baseline hazard and depends on time  $t$ , while  $h$  is the household in reference  $\varphi(X, \beta)$  is the hazard that depends on covariates determined by econometric theory, and  $\beta$  is the vector of parameters to be estimated.

Equation (3) above can be estimated using two approaches: semi-parametric and full parametric. The Cox PH specification estimates (3) above without any parametric specification of the baseline hazard,  $h_0(t)$ .

The specification of the scale parameter;

$\lambda = \exp(X, \beta) = \varphi(X\beta)$  is widely used to estimate the exponential, Weibull, and Gompertz models as no assumption/restriction are made on  $\beta$  to get a positive hazard (Prentice et al., 2002).

## RESULTS AND DISCUSSION

### Descriptive and Inferential Statistics

Table 1 below presents inferential results for farm, farmer, and institutional characteristics.

**Table 1: Inferential results for farm, farmer, and institutional characteristics**

County		Embu	Meru	Machakos	Makueni	Pooled Mean	F-stat	
<b>socio-economic variables</b>								
Age of household head		59.31	57.92	59.6	52.77	57.72	10.50***	
Household size		4.02	4.74	4.65	5.71	4.71	20.58** *	
Farm size (acres)		2.71	4.48	4.36	4.26	3.9	7.62***	
Education (yrs.)		9.39	8.96	9.86	9.6	9.46	1.66	
Number of Trees		66	62	52	19	52	1.8	
Income (KES)		264899	204061	223830.9	267864.7	240052.1	0.43	
Assets (KES)		5520956	554508	4563020	4744044	5103934	0.65	
<b>Institutional variables</b>								
Market dist. (minutes)		59.63	96.49	53.05	34.34	60.87	6.88***	
		(71.67)	(197.3)	(106.78)	(68.99)	122.68		
Credit dist. (minutes)		101.32	86.83	116.42	90.32	99.81	3.38**	
		(77.99)	(85.87)	(107.74)	(67.68)	(87.69)		
Extension dist (minutes)		90.18	72.29	74.61	84.91	80.65	4.41***	
		(56.03)	(61.41)	(58.75)	(48.08)	(56.95)		
<b>Institutional &amp; farm characteristics</b>							<b>chi2</b>	
Intercropping	Never intercropped	22.75	16.23	17.68	23.53	20	3.93***	
	Intercropped	77.25	83.77	82.32	76.47	80		
Group membership	Non-group members	88.36	66.88	80.11	92.65	81.97	39.85** *	
	group members	11.64	33.12	19.89	7.35	18.03		
Training mango farmers	Never received training	14.81	17.53	30.39	42.65	25.45	39.87** *	
	received training	85.19	82.47	69.61	57.35	74.55		

Note: \*\*, \*\*\* represents (p<0.05) and (p<0.01) respectively.

: Figures in brackets represent standard deviations.

Machakos County had the highest mean age of 59.0 years of mango farmers as compared to other counties besides having the highest mean distance of 116.42, in walking minutes, to the nearest credit institutions. The highest household size of 6 members was witnessed in Makueni County. Meru County had the highest mean size of land of 4.48 acres owned by mango farmers. The same county also witnessed the highest mean distance to the nearest market for input and output dealers of 96.49, in walking minutes, with the highest percentage of 83.77 for intercropping mango plants with other crops. Findings still showed that Meru County had the highest percentage of 33.12 of mango farmers who had formed mango farming groups. Further analysis revealed that Embu County had the highest distance of 90.18, in walking minutes, to the nearest extension services as compared to other Counties. Makueni County had offered the highest percentage of training of 42.65 of mango farmers.

### Duration model of technology adoption

The econometric model specification for duration analysis is often based on exponential or *Weibull* distribution (Chao, & White, 2010). The speed of adoption of IPM strategy for control of mango fruit flies in the selected counties in Kenya was analysed using the *Weibull* and Log-logistic models. Alternative models such as the *Compertz* and Log-normal could have been used. However, after *Akaike* Information Criterion (AIC) and *Schwartz* Information Criterion (BIC) tests were performed, they gave lower log-likelihood ratios and higher AIC and BIC values. For instance, regressing time against fruit fly traps as an IPM strategy gave the following results using *Weibull* model; -901.5924 for AIC and -839.4941 for BIC values. Regression results for *Compertz* model gave -563.3877 for AIC and -501.2895 for BIC values. Modelled results of the remaining mango IPM strategies in the *Compertz* model gave lower log-likelihood ratios and higher AIC and BIC values as compared to *Weibull*. On the other hand, *Weibull* and Log-

logistic models fitted the data well as they gave higher log-likelihood ratios in the *Weibull* and least AIC and BIC values in both. Therefore, the *Weibull* and Log-logistic were found appropriate.

Table 2 presents results for likelihood ratio tests based on the log-likelihood values indicate  $\text{prob} > \chi^2 = 0.0000$  justifying that the explanatory power of the duration analysis model had a strong effect. This further shows that the explanatory variables taken together jointly influence the conditional probability of adopting IPM strategies for suppression of mango fruit flies in the selected counties of Kenya. The shape parameter,  $p$ , in the table for the *Weibull* is 2.0401.

Given that this parameter,  $p$ , in the *Weibull* model is greater than unit, indicates the positive duration dependence. That is, the probability of IPM adoption increases with time. Hazard ratios are reported for the Proportional hazard models signifying that a hazard ratio greater than one in the PH models, denotes that the variable has a positive impact and experiences increased hazard (risk) of failure (adoption) (Gutierrez, 2002). A unit hazard ratio implies no impact of the variable on adoption. Results for *Weibull* hazard ratios and Loglogistic coefficients were presented in table 2. Household size had hazard ratios less than one ( $p < 0.01$ ). The coefficient of After Failure Time (AFT) model is positive implying that an increase in the household size by one member increases the time taken to adopt an IPM strategy by 0.032. This means that increasing the number of household size by one member experiences less influence on the adoption of IPM strategies. The result could attribute to the difficulty of decision making among many household members. Thapa and Rattanasuteerakul (2011) noted that farmers with larger household size were not interested in adopting new farming technologies due to difficulties in reaching consensus over a new idea.

**Table 2: Weibull hazard ratios and Log-logistic Coefficients.**

Variable	PH model(Weibull)		AFT model (Loglogistic)	
	Haz.Ratio	Std.Err.	Coef.	Std. Err.
Gender of household head	1.0494	0.1470	-0.0380	0.0856
Age of household head (Yrs.)	0.9999	0.0036	0.0005	0.0021
Household head's educ (Yrs.)	0.9956	0.0106	0.0031	0.0067
Household size (No)	0.9644*	0.0209	0.0321*	0.0128
Participation in off-farm activity	0.8644	0.0855	0.0941	0.0613
Farm assets	1.0086	0.0378	0.0136	0.0233
Number of mango trees	1.0024**	0.0001	-0.0021**	0.0006
Market distance	2.9736***	0.4889	-0.5321***	0.0792
Credit access	0.9436	0.0849	0.0707	0.0566
Extension distance	0.7872**	0.0883	0.1106	0.0686
Group membership	0.4292***	0.0749	0.3167***	0.0891
Social network	1.2520**	0.1105	-0.2700***	0.0550
Constant	0.029***	0.0197	1.2715***	0.4060
Ancillary	p=2.0402	0.0639	$\gamma=0.3515$	0.0111
Loglikelihood	-571.8		-608.70	
AIC	1200.9		1280.7	
BIC	1260.7		1343.6	
N	660			

Note: \*\*\*, \*\*, and \* indicate statistically significant levels at ( $p < 0.01$ ), ( $p < 0.05$ ) and ( $p < 0.1$ ) level, respectively.

A farmer with 52 or more number of mango trees has 1.01 times higher hazard rate of adopting an IPM strategy than the farmer with fewer mango trees ( $p < 0.05$ ). The AFT model results reveals that increasing the number of mango trees by one, decreases the log of time to failure (time to adopt) by 0.0021. That is, increasing the number of mango trees by one decreases the waiting time to adoption ( $p < 0.05$ ). A mango farmer with 50 or more number of mango trees could be practicing it for commercial

purposes. Therefore, for the farmer to meet the quality of produced mangoes for international markets, adoption of new IPM strategy becomes mandatory to such a farmer in order to improve on its quality and quantity produced. Findings by Kibira (2014), noted that the number of mango trees the farmer has is related to the quality of mangoes because of using the new IPM technologies available to the farmer.

Distance to the nearest market increases hazard ratio of adoption of IPM strategy by over 100% of its starting value. That is, decreasing the distance to the nearest market by one kilometre increases the likelihood of adopting an IPM strategy. The AFT model has a negative coefficient (-0.53) ( $p < 0.01$ ), indicating that one-kilometre decrease to the nearest market for a mango farmer reduces the time taken in walking minutes when a farmer wants to access IPM strategies. It could be argued that the decreased time to adoption of IPM strategies due to living closer to the market is linked to acquiring information with ease about the innovation. Similar findings arrived at by Ahsanuzzaman (2015), noted that increased time to adoption is closely related to obtaining information about the innovation than to increased transportation costs.

Distance to the nearest extension agents had a hazard ratio less than one ( $p < 0.05$ ). This means that the farther the distance to the extension agents, farmers will be 78% less likely to influence the adoption of IPM strategies. The AFT model results had positive coefficient of 0.11, denoting that a one kilometre increase in the distance walking to the extension service providers increases the time taken to adopt an IPM strategy by 11%. This suggests that extension agents pass information to farmers on the use of new skills and knowledge relevant to them but when farmers are far away, it becomes difficult for information to reach them earlier. Farmers' assurance in the skills of extension workers increases the speed of adoption. Findings by Kassie et al. (2015) noted that improving the quality of the extension workers through upgrading their skills helps increase their acceptance by their farmers, which later enhances the speed of adoption. Kibira (2014) in Embu County in Kenya noted that effort by mango farmers in seeking agricultural extension services prepared them with knowledge of fruit fly control and that they were well updated on new pest management techniques.

Group membership reduces the hazard ratio of adoption of IPM strategies ( $p < 0.01$ ). The AFT model results indicate that membership to more than one group increases the time taken to adopt an IPM technology by 32%. This means that being a member to more than one group requires that a member has to spend more time in several separate groups than in farming. Participation in many groups could limit time taken in farming hindering the adoption of new technology. Contrary findings by Ahsanuzzaman (2015), noted that being a member in any association in the village increases the likelihood of early adoption of IPM technologies. Findings by Beyene and Kassie (2015) noted that group membership effectively assist farmers in increasing the speed of adoption of IPM technologies.

Social networks increases the hazard rate of IPM adoption ( $p < 0.05$ ). This means that social capital increases the likelihood of IPM adoption by 125%. The AFT model results reveals that social networks reduces the time of adoption of new technology by 27% ( $p < 0.01$ ). Personal contact associated with the proximity of small-scale farmer, besides being part of the social network enables farmers to closely relate with fellow farmers that influences adoption of IPM strategies. A study by Levine et al. (2016) noted that the spread of information about the benefits of the adoption of technological innovations is significantly facilitated by the participation of individuals within their social networks.

## CONCLUSION AND POLICY RECOMMENDATIONS

This study analysed the adoption spell of IPM strategies for suppression of mango fruit flies in the selected counties in Kenya using duration models. The results based on a survey data collected in selected mango growing counties in Kenya namely; Embu, Meru, Machakos and Makueni show that the reduced time of adoption is positively influenced by size of the household, number of mango trees, market access, extension access, group membership and social networks. It is important to note that the duration of

adoption of IPM strategies is influenced by the process of decision-making, priority crop, information flow, knowledge sources and linkage to other institutions. It is assumed that farmers who take a longer time to adopt any IPM strategy, do so when mango destruction by fruit flies is alarming that they eventually do not achieve better output whose impact is negative.

The information acquired through government extension officers and other development partners was found to be an important factor in speeding up technology adoption. This highlights the importance of strengthening extension services and improving the skill of extension officers in supplying quality information that maximises the risk of adoption of IPM technologies. The speed of adoption

increases with the participation in farmer's group membership and the number of mango farmers known to each other in the locality whose information flow could be achieved uniformly.

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