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Health Effects of Pesticide Use among Vegetable farmer in Kenya

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Abstract

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Paper investigates the determinants of pesticide related Cost of Illness (COI), and acute symptoms, using a balanced panel of 363 farmers interviewed in 2005 and 2008. Finding shows that the incidences of pesticide-related health impairments have increased. Variation in number of symptoms and symptom severity significantly explained COI. The Personal Protective Equipment (PPE), education level, record keeping and geographical location considerably determined health impairments. Encouraging the proper use of PPE and record keeping of pesticide use could great reduce poisoning cases and COI.

Key words: agriculture; cost-of-illness; farmer health; Kenya; personal protective equipment; pesticides; vegetables

1. Introduction

The health effects of pesticide use have become one of the major public health problems worldwide. In developing countries, frequent exposure to pesticides by farmers and farm workers is very common (Antle *et al.*, 1998; Maumbe and Swinton, 2003; Garming and Waibel, 2009). The frequent exposure to pesticides results in both short-term (acute) and long-term (chronic) illnesses. Scientific confirmed pesticide related acute illnesses include: headaches, stomach pains, vomiting, skin rashes, respiratory problems, eye irritations, sneezing, seizures, and coma (Antle and Pingali, 1994). The chronic illnesses include: cancer, asthma, dermatitis, endocrine disruption, reproductive dysfunctions, immunotoxicity, neuro behavioral disorders and birth defects (Raschke and Burger, 1997; Horrigan *et al.*, 2002; Alvanja *et al.*, 2004; Kamel and Hoppin, 2004; Kishi, 2005; Dick, *et al.*, 2007; Nasterlack, 2007; Kamel *et al.*, 2007; Hancock *et al.*, 2008). Furthermore, deaths resulting from direct exposure to pesticides are also common (Dasgupta and Meisner, 2005).

The World Health Organization (WHO) and the United Nations Environment Program (UNEP) estimates pesticide-poisoning rates of 2-3 per minute, with approximately 20,000 workers dying from exposure every year (Dasgupta and Meisner, 2005). The largest number of poisonings and deaths are said to occur in developing countries (Wilson, 2005). It has been argued that pesticide related health issues constitute a serious threat to development and can easily reverse or undermine the gains made in agricultural growth (Binswanger and Townsend, 2000). Poor access to health services and medical profession that lacks the ability to recognize pesticide-related morbidity raises further concerns (Pesticide Trust, 1993). Although pesticide related poisoning is still not as high or more pronounced in Africa as in Asia, it is a growing problem as the increasing intensification of agricultural production with more widespread use of pesticides will result in possible increased in pesticide poisoning (London *et al.*, 2005)

In Kenya, by some empirical studies the link between pesticide use and farmers health have been documented (Asfaw, 2008; Okello, 2005; Ohayo-Mitoko *et al.*, 2000). However, these studies were based on a snap short cross sectional surveys and a clear trend of poisoning is not well understood. In addition, the only two studies that looked at the determinants of pesticide related acute poisoning symptoms among farmers are the studies by Asfaw (2008) and Okello (2005). However, the problem is that pesticide poisoning effects on human are not random but rather depend on other unobserved characteristics such as genetic characteristic. Such effects cannot be captured with cross sectional data as utilized in the above studies. Thus the true underlying causal relations may be very different-either larger or smaller-than those noted in those research.

The objective of this article therefore is to examine the incidences and the determinants of acute pesticide poisoning among vegetable farmers in Kenya controlling for unobserved heterogeneity.

2. Methods

2.1. Surveys and data

The study was conducted in seven major vegetable producing districts of Central and Eastern provinces of Kenya (namely Nyeri North, Kirinyaga, Kiambu, Nyandarua, Meru Central Makueni and Muranga districts, Figure 1) in the year 2005 with follow-up visits in 2008.

Figure 1 here

The 2005 survey comprised of 839 interviews from the Diamondback moth biological control impact assessment survey ('DBM' with 295 farmers) and the Global Good Agricultural Practices ('GLOBALGAP' with 544 farmers) assessment survey. GLOBALGAP (formerly known as EUREPGAP) is a private sector body that sets voluntary standards for the certification of agricultural products around the globe. The aim is to establish one standard for Good Agricultural Practice (GAP) by translating consumer requirements into agricultural production.

In both surveys, a multi-stage sampling procedure was used to select districts, sub-locations, and farmers respectively. First, districts were purposely sampled according to intensity of vegetable production and agro-ecological zones. Lists of farmers that were compiled by extension workers at sub location level, served as sampling frame from which, 839 farmers were randomly sampled by probability proportional to size (PPS) procedure. Sampled farmers were then, monitored in one cropping season and were trained in record keeping of their production activities by trained enumerators¹. The trained enumerators

¹Enumerators were trained for 4 days. One day was used for pre-testing the questionnaire. The pre-testing aimed at improving the skills of the enumerators and also testing the applicability of the questionnaire to the study area. During the first pre-testing, random selected enumerators did the interview, while the others listened and observed. A discussion of

under direct supervision of the researcher visited the farmers to check the records and transferred the information to the survey questionnaire. Due to budget constraints, the 2008 survey was a recall survey of a random sub-sample of 425 farmers among the 839 farmers. Table 1 displays the distribution of farmers in the sampled districts.

(Table 1 here)

The semi-structured questionnaires employed, covered a wide range of topics, such as cropping systems, demographics, common farming practices, pesticide use and handling practices, type and quantities of pesticides sprayed. Health symptoms investigated were specified as those that only began during the spraying operation or within 24 hours after spraying. Additional information collected included: number of times the symptom occurred, workdays lost partially or completely due to the health impairment, medication taken by victims and direct costs due to the symptoms i.e. pharmacy cost, consulting fees and indirect costs such as travel expenses to and from health centre and dietary expenses resulting from illness like drinking milk or taking honey.

It was decided to exclude from the sample the entire sampled farmers that did not have a balance data² set for the 2005 and 2008. The sample size, thus after dropping those observations, reduces to a balanced panel of 363 farmers.

2.2. Analytical framework

As discussed earlier panel data setup was used to control for the unobserved heterogeneity. In general, panel data model offers some distinct advantages over the cross sectional data analysis. Greene (2008) concluded that the main advantage of panel data is that one can formally model the heterogeneity across groups that are typically present in panel data. Baltagi (2005) confirms this in his statement that the first benefit of panel data is “controlling for individual heterogeneity.” Additional benefits of using panel data include: panel data model is able to capture both cross-section and time-series variation in the dependent variable, panel data model is able to measure not only the effects that observable variables have on the dependent variable, but also the effects of relevant unobservable or non-measurable influences.

A general panel regression model is presented as:

the experience under the guidance of the researcher was then conducted in a plenary every enumerator contributing to what he/she observed as an improvement or a mistake. The enumerators were then divided into groups of two and interviewed the respondents in turns.

² Unbalanced panel have a possibility that the causes of missing observations are endogenous to the model. Equally, if a balanced panel has been created artificially by eliminating all units of observation with missing observations, the resulting dataset may not be representative of its population. We compared the responses from unmatched farmers based on several characteristics and the two groups differ only marginally.

$$\begin{aligned}
y_{it} &= \alpha_0 + \beta X_{it} + \gamma Z_i + V_{it} \\
V_{it} &= \varepsilon_i + \mu_{it}
\end{aligned}
\tag{1}$$

Where y_{it} is the response of the dependent variable (in our case this is the COI, number of acute symptoms, and health impairment) for the i th farmer in the sample at the t th year. α_0 is an intercept that may be different for each point in time, and β and γ are vectors of coefficients. X_{it} is the set of K -vector of time-variant covariates for the i th farmer at the t th year and Z_i is another set of predictor variables that do not vary over-time (time-invariant) e.g. gender and location. V_{it} is the error term, which is decomposed into ε_i , and μ_{it} . ε_i is regarded as the combined effect on y of all unobserved variables that are constant over-time (time-constant unobserved heterogeneity such as cognitive ability, motivation e.t.c.), and μ_{it} representing the idiosyncratic error term (what is unaccounted for in the model) and varies over individual farmers and over-time.

The two main methods of dealing with ε_i are to make the random effects (RE) or fixed effects (FE) assumption. Random effects, assumes that the ε_i are random variables (ε_i is i.i.d. $(0, \sigma_\varepsilon^2)$) and that $Cov(x_{it}, \varepsilon_i) = 0$, while with fixed effects, ε_i are assumed to be potentially correlated with X_{it} . In fixed effect regressions we cannot estimate the effects of time constant covariates as these are normally cancelled out by the within transformation. Thus, classic fixed effects approaches do not produce any estimates of the effects of variables that do not change over-time. Moreover, in some cases fixed effects estimates may have substantially larger standard errors than random-effects estimates, leading to higher p -values and wider confidence intervals. In addition, fixed effects estimate use only within-individual differences, essentially discarding any information about differences between individuals unlike random effects that uses information both within and between individuals. Thus, if predictor variables vary greatly across individuals but have little variation over-time for each individual, then fixed effects estimates will be rather imprecise. When neither the cross-sectional unit nor times have significant effects, all of the data can be pooled and one can have the constant coefficients model.

The analysis was implemented in two steps. First, the COI³ model was estimated to evaluate the determinants of health costs among the vegetable farmers. In the second stage, the principal factors associated with the pesticide poisoning symptoms were examined seeking ones that are relevant at policy recommendation.

2.3. The Models

2.3.1. Cost-of-Illness Model

³ Computed as the sum of farmer-reported medical treatment costs to clinics and private physicians, the opportunity cost of workdays lost to illness, travel costs to and from health facility, time spent in traveling and the cost of home-based health care.

In previous studies, the health costs of pesticides were modeled using a Logarithmic regression model (Asfaw, 2008). In this study the estimations of the determinants of health costs was modeled using a censored⁴ random effects Tobit model (Xttobit), since zero costs from respondents who had suffered pesticide related illnesses but incurred no costs were considered. Using a Logarithmic model would have required adding a small unity value as log of zero is undefined. Estimation of dependent variables result into biased estimators in linear models (Tobin, 1958). The structural equation in the Tobit model is represented as:

$$y^*_{it} = x_{it}\beta + \varepsilon_i + u_{it} \quad (2)$$

where $\varepsilon_i \sim N(0, \sigma_\mu^2)$, y^* is a latent variable that is observed for values greater than T and censored otherwise. The observed y is defined by the following measurement equation:

$$y_{it} = \begin{cases} y^* & \text{if } y^* > T \\ T_y & \text{if } y^* \leq T \end{cases} \quad (3)$$

In the typical Tobit model, we assume that $T=0$, *i.e.* the data are censored at 0. For the empirical model, the explanatory factors for the model explaining health costs incorporate four broad classes of variables namely those related to health (number of acute symptoms and symptoms severity), farmer characteristics variables (age, education, gender), farm management variables (farm size⁵, GLOBALGAP certification, and record keeping), and location control (district dummies) (see equation 4). Variable definitions and descriptive statistics are presented in Table 2.

It is hypothesized that the number of acute symptoms, symptom severity, age, and farm size are positively associated with the health costs, while a negative association is expected for level of education, GLOBALGAP certification, and record keeping. The direction of the effect of gender on health costs is not clear a priori.

It is anticipated that young farmers may have a higher tendency to protect against pesticides exposure and consequently reduce the pesticide-related acute symptoms and associated health costs. Increased education is also expected to reduce health costs because farmers are more likely to read pesticide labels and follow the recommendation, again reducing the exposure and the acute symptoms. Likewise, GLOBALGAP certification, and record keeping can result in a more judicious use of pesticide use and higher tendency to protect against pesticide intoxication resulting in reduced acute symptoms.

⁴ Only farmers that reported health impairment were considered.

⁵ Proxy for wealth.

$$\text{HealthCost} = f(\text{TACUTE}, \text{SEVERE}, \text{AGE}, \text{AGESQ}, \text{EDUCATION}, \text{GENDER}, \text{FARMSIZE}, \text{GLOBALGAP}, \text{RECORD}, \text{District Dummies}, \text{YEAR2008 Dummy}) \quad (4)$$

Acute symptoms Model

The determinants of the number of acute symptoms were modeled as random effects. A Negative Binomial Regression model (Xtnbreg) was chosen to account for over-dispersion, since the equi-dispersion assumption that has to be met with the Poisson model was violated, *i.e.* the variance was larger than the mean and just over two third of the counts were zero. When there is over-dispersion, the Poisson regression is not appropriate because the standard errors estimated are biased downward and the *p*-values are small and spurious (Long, 1997).

A Negative Binomial Regression model is a count data model and a good facet of the model is that the Poisson model is nested within it (Long, 1997). However, the assumption of the standard Poisson model that the variance of the dependent variable is equal to the mean is not binding for the negative binomial model (Cameron and Trivedi, 1998). Negative Binomial Regression model deal with the problem of over-dispersion by assuming that y_{it} has a negative binomial distribution, which can be regarded as a generalization of the Poisson distribution with an additional parameter allowing the variance to exceed the mean. The negative binomial function can be presented as equation (5):

$$f(y_{it} | \mu_{it}, \varepsilon_i) = \frac{\Gamma(\mu_{it} + y_{it})}{\Gamma(\mu_{it})\Gamma(y_{it} + 1)} \left(\frac{\varepsilon_i}{1 + \varepsilon_i} \right)^{y_{it}} \left(\frac{\varepsilon_i}{1 + \varepsilon_i} \right)^{\varepsilon_i} \quad (5)$$

Where Γ is the gamma function, parameter μ_{it} is assumed both the mean and the variance and parameter ε_i is assumed constant over time for each individual, while the mean and variance of y_{it} are given by:

$$E(y_{it}) = \mu_{it}, \quad \text{var}(y_{it}) = (1 + \varepsilon_i)\varepsilon_i\mu_{it} \quad (6)$$

Under this model, the ratio of the variance to the mean is $1 + \varepsilon_i$ that can vary across individuals but is constant over time. The basic idea for this model is that the predictor information is related to the rate of the response to increase or decrease in counts.

For the empirical model, the acute symptom model aggregates skin irritation, diarrhea, sneezing, headache, dizziness, vomiting, stomach poisoning, blurred vision, eye irritation, and backache episodes incurred by the farmer during and/or soon after spraying pesticide as the dependent variable. For the explanatory variables, the medical literature indicates that the type and severity of pesticide poisoning depends on the toxicity of the pesticides,

amount of pesticides involved in the exposure and route of exposure (Extension Toxicology Network, 2004). The specification accounted for these factors. In addition, in order to understand farm management variables that can affect pesticide poisoning, GLOBALGAP certification and record keeping were included. Furthermore, following Antle and Pingali (1994), Wilson and Tisdell (2001) and Asfaw (2008), other control variables under farmer characteristics, *i.e.* age, gender, education and geographical location were also included (equation 7).

A priori, it is anticipated that WHO class Ia, Ib and II pesticides are positively correlated with incidences of acute poisoning whereas negative correlation can be expected with category III and U pesticide⁶. Age could increase acute symptoms, as older farmers may be less concerned about health effects of pesticides. As already mentioned in cost of illness model it is expected that pesticide-related acute symptoms decrease with the increase in level of education, GLOBALGAP certification, record keeping of production activities and appropriate use of personal protective equipments.

$$TACUTE = f(AGE, AGESQ, EDUCATION, GENDER, GLOBALGAP, RECORD, NPEST, PWHOIab, PWHOII, PWHOIII, PWHOU, COAT, GLOVE, GUMBOOT, MASK, District Dummies, YEAR2008 Dummy) \quad (7)$$

The models were estimated using the random effect estimator as the Hausman test showed the fixed effects were not correlated with the regressors. All variables were cross-checked for the problem of multicollinearity, through the simple correlation matrix and variance inflation factor (VIF). The highest correlation coefficient was 0.32 and VIF were by far less than three, indicating that correlation between explaining variables could not affect the estimation of coefficients. Likewise, for endogeneity none of the independent variables was suspected to be explained within the equation in which it appeared. Misspecifications of the models were also checked using a regression specification error test (Ramsey, 1969). In respect to the robustness of the Negative Binomial Regression model, a Poisson model was first fitted and the likelihood ratio test together with the statistical evidence of over-dispersion indicated that the Negative Binomial Regression model was preferred to the Poisson model. In addition, to check the robustness of all the models other restricted models were estimated in which, subsequently insignificant variables were dropped. The statistical quality of the models, and the direction of the signs did not change, and the coefficients deviated only marginally.

3. Empirical results and discussion

⁶ Pesticides in WHO Iab and WHO II are very toxic, while class III and U are relatively low in toxicity.

3.1. Descriptive statistics of variables used in empirical estimations

Table 2 summarizes the main descriptive statistics comparing 2005 and 2008 with t and z tests for the main variables investigated. The results showed that the incidences of pesticide-related acute illness had increased by over 70%. By cross check, although not indicated in the tables the analysis showed that only 45% of the farmers consequently reported the effect once more in 2008 showing a high rate of new episodes cases. However, the number of symptoms per farmer dropped by almost half in 2008. In terms of frequency of symptom occurrence, headache and sneezing were reported as the main symptoms in both surveys. Dizziness as one of the major neurological effects of pesticide exposure was also found to have doubled in 2008. These symptoms have been associated with pesticides acute poisoning (Extension Toxicology Network, 2004). They are also consistent with other studies of pesticides exposure on farmers' health elsewhere (Alavanja *et al.*, 2001; Martin *et al.*, 2002; Atreya, 2005).

Table 2 here

For minor poisoning, many farmers used home remedies such as milk, lemon juices, honey, and herbs. The medicines from the local pharmacy shops which were sometimes painkillers were bought in cases where the symptoms of illness were mild and farmers visited the health clinic if the symptoms either persisted or became serious, *i.e.* the victim was unable to talk, walk, see, or vomited continuously. This evidence seems to suggest that many farmers treat acute pesticide effects as minor problems that do not warrant medical attention. Although in only about a quarter of the cases, a physician was consulted, this cost component accounts for the largest share of the total.

The health cost almost doubled in 2008 as compared to 2005. On average, health cost was estimated at US\$ 6.55/farmer/season for 28% of the farmers who reported pesticide-related illnesses. These costs equal 47% of mean household chemical expenditures in 2008. Considering all the farmers this translates to a mean of US\$ 1.77/farmer/season and assuming two crop seasons per year the costs amount to US\$ 3.54/farmer/year. However, the true health costs are likely to be much higher because the costs arising from chronic diseases resulting from long-term pesticides exposure were not considered, as this would have required more detailed medical assessments. Moreover, only costs directly involving family members were reported, costs occurring to hired farm laborers were not included. Furthermore, other 'costs' to restore health status completely and non-monetary costs like suffering and income lost by family members assisting in seeking treatment were not captured (Rola and Pingali, 1993; Freeman, 1993). In addition, preventive costs associated with precautions taken to reduce exposure such as wearing protective equipments were not considered because they were mainly improvised from old clothing or pieces of cloth wrapped around the nose and mouth to reduce inhalation exposure. The cloths were also used for other purposes like spraying on coffee, other farm work and it was difficult to

desegregate specifically for spraying pesticides on vegetable crops. However, the combined mean of personal protective equipments used increased by 43%, with the largest increment noted for gumboots. Over 20% of farmers also paid wage premiums of up to 32% above the normal wage to hired labour for spraying pesticides, which were normally paid in cash. Comparison with other studies conducted in developing countries like Indonesia, Philippines and Vietnam shows that 58%-99% of the farmers exposed to pesticides had at least one health effect symptom (Pingali *et al.*, 1994). In Tanzania farmer spending on health due to pesticide, exposure ranges between US\$ 0.018 and 116 in a year (Ngowi *et al.*, 2007). In West Africa, the economic value of pesticide-related health costs equals to US\$ 3.92/household/season in the case of cotton–rice systems (Ajayi *et al.*, 2002). Zimbabwe Cotton growers incur a mean of US\$ 4.73 in Sanyati and US\$ 8.31 in Chipinge on pesticide-related direct and indirect acute health effects (Maumbe and Swinton, 2003). In Sri Lanka, cost to farmers from pesticide exposure equals 10 weeks' income (Wilson, 1998), while in India the average annual welfare loss to an applicator from pesticide exposure amounts to US\$ 36 (Devi, 2007). The immediate costs of a typical intoxication (medical attention, medicines, days of recuperation, *e.t.c.*) equaled the value of 11 days of lost wages in Ecuador (Yanggen *et al.*, 2003).

Pesticide application rate/hectare/season also increased by 47%. Comparison between the years for the specific farmers who participated in the DBM survey showed that many farmers had reduced the pesticides application rate by 8%, while the GLOBALGAP surveyed farmer had increased by 40%. Similar findings in support of the reduction of pesticide use were reported by Jankowski (2007) and Löhr *et al.* (2007) where farmers in the study areas with DBM bio-control (*Diadegma semiclausum*) reduced pesticide applications with others even stopping spraying altogether. The increase in application rate by GLOBALGAP farmers can partially be explained by the low number of farmers who were certified at the time of survey and the failure of the farmer certified in 2005, to maintain their certification status, *i.e.* certified farmers dropped from 18% to 7%, with only 31% of the farmers maintaining their certification for 2008.

3.2. Model estimations

3.2.1. Cost-of-Illness Estimation

The estimation results of the Tobit models with the health costs as dependent variable are reported in Table 3. Result shows that health costs are positively associated with number of symptoms and symptoms severity, which implies that an increase in any of these variables spontaneously influences positively the health costs, holding other factors constant.

The finding that the GLOBALGAP certification tends to decrease the health cost could indicate that the certified farmers use adequate safety precautions, or use low toxic pesticides, which generally reduce the health impairments and thus decrease costs. It could also be that these farmers are able to use the minimum treatment possibilities.

Among the farmers' characteristics variables, *i.e.* age, education and gender none had any discernible effect on health costs. In addition, farm size, does not have a direct effect on health costs, though it has the correct sign. In addition, no direct association was found between record keeping and the health costs.

District controls are insignificant, so location does not directly affect the health costs. When the model was re-estimated (restricted) by dropping insignificant variables, the estimates of the coefficients were robust.

Table 3 here

3.2.2. Acute Symptoms Estimation

Given the critical contribution of pesticide-related acute symptoms to the health costs as indicated in Table 3, the principal determinants of these symptoms are reported in Table 4.

The model shows that pesticide-related acute symptoms increase significantly with the number of pesticide products handled. This is not surprising, given that different pesticide products require different application rates and have different levels of toxicity. In addition, handling different pesticide products can increase incidences of symptoms since an interaction between pesticides can lead to unknown toxic chemical reactions (Yáñez *et al.*, 2002). Likewise, although, the coefficients for pesticides in WHO Iab and II are insignificant, they are positively correlated with acute symptoms whereas negative correlation is observed with WHO III and WHO U pesticides. Pesticides in WHO Iab and WHO II are very harmful, while WHO III and WHO U are less harmful⁷. The significant negative sign of the variable “record keeping” suggests that the probability of pesticide-related illnesses is less for farmers who keep records.

The level of education reduces the probability of reported symptoms, which implies that farmers with a higher education level are more knowledgeable and therefore have a better understanding of the dangers posed by pesticides. In previous studies however, the contrary effect was found because respondents with higher knowledge were more likely to report more health symptoms (Maumbe and Swinton, 2003).

The use of personal protective equipments particularly the use of a coat/apron and facemask significantly reduce the number of symptoms. Exposure to pesticides is often attributed to a failure to use protective equipments (Rola and Pingali, 1993). The positive sign of the use of boots although insignificant seems perverse and alarming at first glance. However, as the researcher had observed in the field, the improper use, *i.e.* putting the trouser inside the boots may offer a partial explanation of this apparently perverse result.

⁷ WHO category Ia or Ib (extremely or highly hazardous), WHO category II (moderately hazardous), WHO category III (slightly hazardous), WHO category U (unlikely to present any acute hazard in normal use).

This finding is analogous to that found by Ohayo-Mitoko (1999), where use of gumboots was associated with high acetyl cholinesterase⁸ inhibition.

Location control for agro-ecology and differences in institutional settings shows that, farmers in the districts of Kiambu, Meru Central, Makueni, Nyandarua and Nyeri North experience significantly high cases of pesticide ascribed health symptoms as compared to the Kirinyaga (base). Perhaps this is due to the use of protective equipment by farmers located in Kirinyaga.

Contrary to the expectations, the analysis does not support the hypothesis of a significant influence of GLOBALGAP certification on the outcome of health, but the variable has the correct signs. Once again, the low number of farmers who were certified and the failure of the certified farmers to maintain their certification may be the cause of the insignificance. The hypothesis that gender and age have a stronger relation to the acute symptoms is also not supported by the results.

The likelihood ratio test used to assess the statistical quality of the model showed that the model was statistically valid⁹. The reduced model with only the variables that had a significant effect on the dependent variable shows that the statistical quality of the model does not differ much and the direction of the coefficient are identical, suggesting the robustness of the model.

Table 4 here

4. Conclusions and recommendations

The results of the study give indications of increase of pesticide related health impairments with over 70% new episodes. The most frequently reported symptoms were sneezing, dizziness, headache and blurred vision and skin irritations. The result further shows that farmer loses on average US\$ 3.54/farmer/year on pesticide related indirect health costs. These costs are significantly explained by variation in number of symptoms and severity of the symptoms. Pesticide-related acute symptoms increase significantly with the number of pesticide products handled and considerably reduce with level of education, use of PPE, and record keeping. These findings hint at some important points for policies aiming to reduce pesticide poisoning among vegetable farmers. Firstly, the results support the already widely know notion that proper use of PPE (coat/apron and facemask) reduce the pesticide related impairment. Encouraging the use of PPE and record keeping of pesticide use activities by farmer is thus recommended.

⁸ An enzyme that breaks down acetylcholine (ACh) into choline and acetic acid. It is released onto the sarcolemma of muscle fibres and destroys ACh after the ACh has combined with receptors on the muscle fibre. Thus, it prevents continued muscle contraction in the absence of additional nervous stimulation.

⁹ Dispersion parameter alpha was greater than zero.

Future efforts to measure pesticide related health costs should cover the health costs of all individuals exposed to pesticides e.g. entire public, consumers and hired workers and also incorporate pesticide-induced chronic illnesses and deaths.

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Table 1: Regional distribution of survey respondents

Province	District	Main vegetable crops		Previous surveys (2005)	No. of farmers sampled (2008)
		Domestic	Export		
Central	Kiambu	Cabbages, kales, spinach		48	27
	Kirinyaga	Peas, tomatoes	French beans	155	74
	Muranga	Tomatoes, kales	French beans	51	24
	Nyandarua	Cabbages, potatoes		119	52
	Nyeri North	Peas, cabbage, onions, carrots	French beans	277	116
Eastern	Makueni	Cabbages, kales	Asian vegetables ^{a)}	49	22
	Meru Central	Peas, tomatoes, cabbage, onions	French beans	140	110

^{a)} Brinjals, karella, dudhi, okra, turia, valore and aubergine

Source: Own presentation

Table 2: Descriptive statistics of variables used in empirical estimations (N = 726)

Variables	Definition	Unit	Mean ^{a)}		t or z stat ^{b)}
			2005	2008	
Dependent variables					
TACUTE ^{c)}	Number of symptoms	count	1.89 (0.13)	1.09 (0.03)	-7.07***
TACUTE	Number of symptoms	count	0.38 (0.48)	0.37 (0.03)	-0.15
HealthCost ^{c)}	Cost of illness	US\$	4.15 (1.70)	7.98 (1.57)	1.57
HealthCost	Cost of illness	US\$	0.84 (0.35)	2.72 (0.58)	2.80**
Farmer characteristics variables					
AGE	Age of the farmer	years	43.19 (0.66)	46.18 (0.67)	6.30***
AGESQ	Age of the farmer (years squared)	years	2024.43 (62.80)	2292.64 (66.85)	65.21***
EDUCATION	0=None; 1=Pre-primary; 2=Primary; 3=Secondary; 4=College	ordinal	2.45 (0.05)	2.51 (0.04)	1.09
GENDER	Male	1/0	0.70 (0.02)	0.70 (0.02)	0.00
EXPERIENCE	Farming experience	years	18.42 (0.74)	20.56 (0.07)	2.38**
Health-related and pesticide exposure variables					

Variables	Definition	Unit	Mean ^{a)}		t or z stat ^{b)}
			2005	2008	
HEALTH	Farmer reported a symptom	1/0	0.20 (0.02)	0.34 (0.02)	4.26***
SEVERE	1=mild, 2=severe, 3=very severe	ordinal	1.11 (0.08)	1.59 (0.36)	1.22
PWHOlab	WHO Ia and Ib (extremely hazardous)	g	8.79 (2.32)	33.55 (12.79)	1.92**
PWHOII	WHO category II (moderately hazardous)	g	129.87 (10.15)	432.63 (25.20)	10.97***
PWHOIII	WHO category III (slightly hazardous)	g	18.95 (3.39)	166.12 (19.23)	7.45***
PWHOU	WHO category U (no hazard)	g	79.87 (7.47)	167.79 (16.86)	4.87***
PESTHA	Total amount applied	g/ha/season	1,473.00 (201.82)	2,124.87 (118.28)	2.97***
NPEST	Pesticide products	count	2.89 (0.09)	3.32 (0.08)	3.37***
COAT	Wear coat/apron	1/0	0.49 (0.03)	0.71 (0.02)	6.06***
GLOVE	Wear gloves	1/0	0.26 (0.02)	0.35 (0.02)	2.49**
GUMBOOT	Wear boots	1/0	0.26 (0.02)	0.89 (0.02)	17.35***
MASK	Wear facemask	1/0	0.24 (0.02)	0.40 (0.02)	4.36***
TPPE	Protective equipments	count	2.81 (0.07)	4.00 (0.11)	10.85***
Farm management variables					
FARMSIZE	Total farm size	ha	1.46 (0.08)	1.06 (0.05)	-4.46***
GLOBAL-GAP	GLOBALGAP certified	1/0	0.07 (0.01)	0.19 (0.02)	0.15
RECORD	Keeps records	1/0	0.71 (0.02)	0.32 (0.01)	-10.47***

All monetary variables *e.g.* health cost were adjusted (normalized) to US\$ of 2008 to take account of inflation. US\$ = 72 KSh (2005) and 75 KSh (2008)

^{a)} Figures in parenthesis are standard errors

^{b)} Statistical significant at the 0.01 (***), 0.05 (**), 0.1 (*) level of probability. Categorical variables were analyzed using z-test

^{c)} With only farmer who reported the health impairment

Source: Own survey

Table 3: Tobit model for Cost of illness estimations

Model	Unrestricted		Restricted	
	(coefficient) ^{a)}	z- value	(coefficient) ^{a)}	z- value
TACUTE	7.45(4.08)**	1.83	6.20 (2.00)***	3.10

Model	Unrestricted		Restricted	
SEVERE	9.01 (2.52)***	3.58	11.07 (2.17)***	5.12
AGE	-0.48 (1.09)	-0.44		
AGESQ	0.01 (0.01)	0.61		
EDUCATION	1.46 (2.36)	0.62		
GENDER	-2.84 (4.33)	-0.66		
FARMSIZE	3.25 (2.88)	1.13		
GLOBALGAP	-21.75 (3.40)*	-1.62	-18.71 (7.47)**	-2.50
RECORD	-1.08 (4.89)	-0.22		
KIAMBU	2.50 (10.31)	0.24		
MAKUENI	-15.08 (17.25)	-0.87		
MERU CENTRAL	1.65 (8.71)	0.19		
MURANGA	-5.48 (11.75)	-0.47		
NYANDARUA	-5.61 (8.81)	-0.64		
NYERI NORTH	6.62 (8.47)	0.78		
YEAR2008	7.93 (9.15)	0.87		
Constant	-23.23 (29.41)	-0.79	-19.54 (4.45)***	-4.39
Log Likelihood	-464.10		-549.55	
Wald χ^2 / LR χ^2	40.18***		43.22***	

^{a)} Figures in parenthesis are robust standard errors, statistical significant at the 0.01 (***), 0.05 (**), 0.1 (*) level of probability

Source: Own survey

Table 4: Binomial Regression Model for the acute symptoms estimations

Model	Unrestricted		Restricted	
Variables	(coefficient) ^{a)}	z- value	(coefficient) ^{a)}	z- value
AGE	0.04 (0.04)	1.13		
AGESQ	-0.00 (0.00)	-1.21		
EDUCATION	-0.16 (0.07)**	-2.13	-0.14 (0.07)*	-1.94
GENDER	-0.10 (0.16)	-0.67		
GLOBALGAP	-0.33 (0.29)	-1.11		
RECORD	-0.44 (0.17)***	-2.57	-0.55 (0.15)***	-3.77
NPEST	0.09 (0.05)**	1.88	0.10 (0.05)**	2.39
PWHOlab	0.00 (0.00)	1.28		
PWHOII	0.00 (0.00)	0.68		
PWHOIII	-0.00 (0.00)	-0.28		
PWHOU	-0.00 (0.00)	-0.13		
COAT	-0.29 (0.16)*	-1.82	-0.29 (0.15)**	-2.03
GLOVE	-0.26 (0.21)	-1.23		
GUMBOOT	0.32 (0.23)	1.36		

Model	Unrestricted		Restricted	
MASK	-0.35 (0.20)*	-1.74	-0.39 (0.17)**	-2.30
KIAMBU	1.69 (0.36)***	4.67	1.63 (0.32)***	5.20
MAKUENI	1.74 (0.49)***	3.55	1.50 (0.46)***	3.35
MERU CENTRAL	1.18 (0.31)***	3.82	0.95 (0.25)***	3.77
MURANGA	0.64 (0.46)	1.40		
NYANDARUA	0.90 (0.34)***	2.66	0.80 (0.28)***	2.81
NYERI NORTH	0.93 (0.30)***	3.07	0.79 (0.24)***	3.26
YEAR2008	-0.05 (0.21)	-0.23		
Constant	-1.22 (1.06)	-1.15	-0.01 (0.48)	-0.02
Log Likelihood	-518.85		-535.52	
Wald χ^2	73.74***		60.96***	

^{a)} Figures in parenthesis are robust standard errors, statistical significant at the 0.01 (***), 0.05 (**), 0.1 (*) level of probability

Source: Own survey

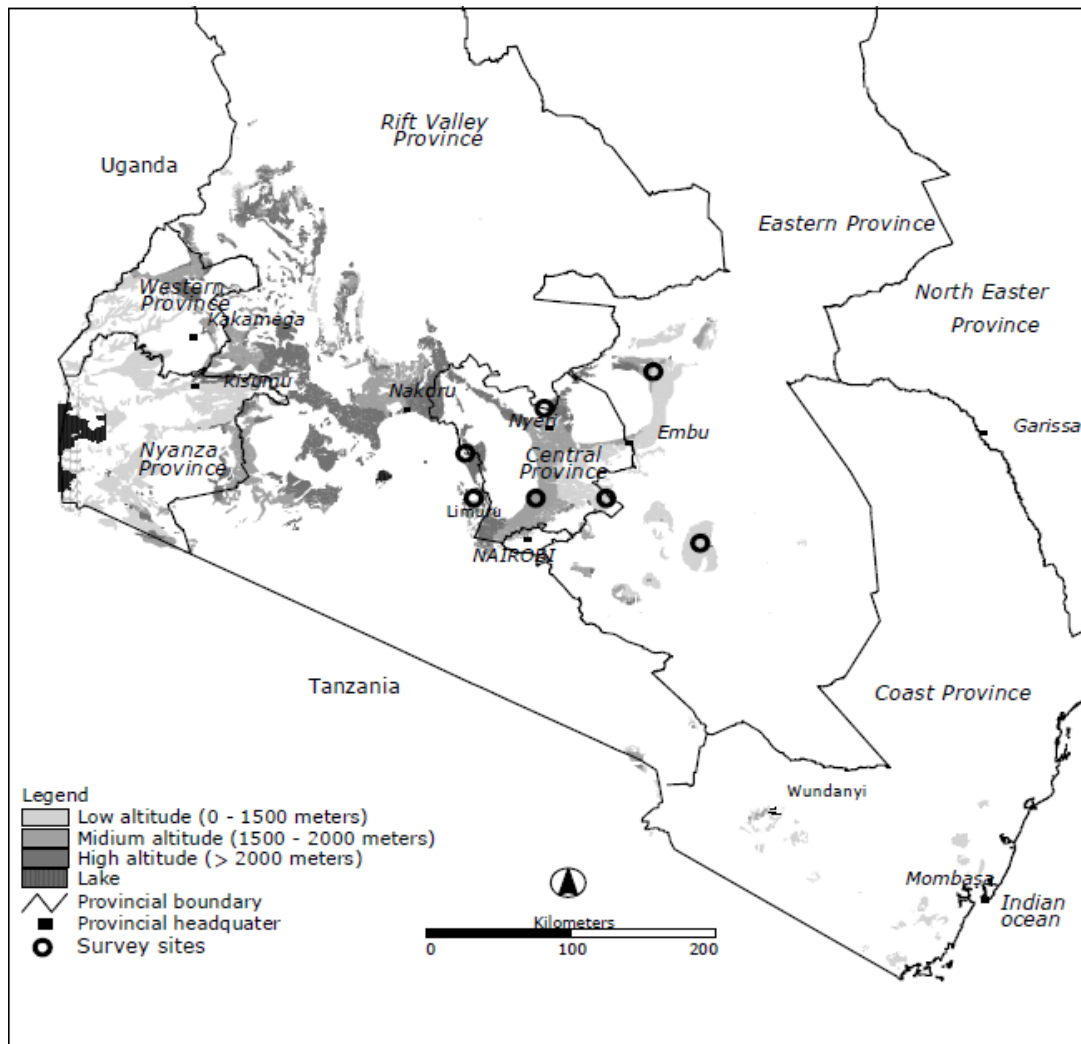


Figure 1: Study sites

Source: Own presentation based on GIS mapping of potential vegetable production areas