

Economic Benefits of Sustainable Agricultural Production: The Case of Integrated Pest Management in Cabbage Production

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Abstract

Environmental protection is a basic element of sustainable agricultural development. Agricultural production practices, however, can cause negative externalities. One main concern of the externality is the negative effects of pesticide use. This has motivated the application of Integrated Pest Management (IPM) program. This study attempts to evaluate the economic benefits of IPM to address the widespread misuse of pesticides in cabbage production. IPM application in cabbage production includes initiatives on the optimal use of pesticides, complementary weed control strategies, and alternative cultural and biological controls. Results of this study showed that the programme would generate economic benefits which include improvements in water quality, food safety, pesticide application safety, and long term sustainability of pest management systems. Thus there is justification for public investment of resources in training and educational programs to increase awareness about IPM and promote IPM adoption.

Keywords: integrated pest management; economic benefits; cabbage production

1. Introduction

Sustainable agricultural development continues to be emphasized to ensure that the well-being of the present generation is not met at the expense of future generations. Economic, social and environmental aspects are increasingly integrated into the development process. Thus environmental consideration is now integrated into the Malaysian agricultural sector policy in order to ensure a sustainable economic and social development, as mentioned in the Third National Agricultural Policy (1998). The primary interest in sustainable agriculture is to develop farming systems that promote equally farming profits, agro-ecosystem, and local communities. Unsustainable practices, as it is argued, often focus solely on farm profits, at the expense of ecosystems, farming communities, and externalities.

One main concern of the sustainability issues in the Malaysian agricultural production is the use of pesticides in vegetable cultivation. It is often argued that pesticide is often applied in inappropriate amounts to cabbage, as there is a premium attached to unblemished and fresh looking produce. A study on pesticide residues in Malaysia reported that 34.5% of samples contained pesticide residues exceeding maximum residual limit (MRL) (Jusoh *et al.*, 1992). According to Tay *et al.* (2004), RM326 million and RM307 million worth of agricultural chemicals were used in Malaysia in 2001 and 2002, respectively. Among the agricultural chemicals, a large percentage of expenditure was herbicides (73%), insecticides (17%), fungicides (6%), and rodenticide (4%).

An Initiative towards sustainable agricultural production is the adoption of Integrated Pest Management (IPM) program in vegetable production. The adoption of IPM includes initiative on the optimal use of pesticides, complementary weed control strategies, and alternative cultural and biological controls. If successful, the program could generate benefits that can be measured in economic terms. These benefits include improvements in water quality, food safety, pesticide application safety, and long run sustainability of pest management systems. The study therefore aims to assess on the economic benefits, impacts and factors associated with the adoption of IPM program. A case study was conducted in cabbage production in Cameron Highlands, the main producing area in Malaysia, in 2006.

2. Methodology

Farmers have to make decision on the appropriate technology for adoption that will increase their farm productivity. For this purpose, this study employed McFaddenûs Random Utility Model which was used by Antle and Prabhu (1994). In this model, the decision makerûs unobserved net gain in utility of adopting practice j, denoted by U*j is the difference between an individual's utility from deciding to adopt the technology and utility from not adopting the technology. This net gain can be interpreted as being explained by the variables X_j that would have explained utility levels with adoption or without adoption, plus the disturbance term , such that:

$$U_{j}^{*} = U_{adaption} - U_{non-adaption} = X_{j}\beta_{j} + \varepsilon_{j}$$
(1)

Since only the decision on whether or not to adopt is observed, it can be inferred that

$$\mathbf{Y}_{j} = \begin{cases} 1 \text{ if } U_{j}^{*} - \varepsilon_{j} \ge X_{j}\beta_{j} \\ 0 \text{ if } U_{j}^{*} - \varepsilon_{j} < X_{j}\beta_{j} \end{cases}$$
(2)

where Y_j is a binary variable representing adoption of practice j and X_j is a vector of regressors relevant in explaining adoption.

The likelihood function is formed as: $L = \pi_i (e^{Xi\beta} / (1 + e^{Xi\beta})) \pi_j (1/(1 + e^{Xi\beta}))$; the subscript i denotes adopters and j denotes non-adopters. This likelihood function is maximized with respect to β (using an iterative procedure, usually Raphson-Newton) to get the maximum likelihood estimates of β (β^{MLE}).

Data for the analysis was collected from 102 cabbage farmers in the Northern, Central and Southern zones of Cameron Highlands. The collected data includes farms and farmers' characteristics, farm structure, managerial factors, physical and location factor, pesticide usage, pest management practices, perceptions about pesticidesû hazards, awareness of IPM and willingness to adopt IPM program. The variables names used and definitions are presented in Table 1.

3. Results and Discussion

A synthesis of results from the estimation and evaluation procedures described in the methodology section is presented here. It begins with a discussion of the results from descriptive statistics analysis of the survey data, and is followed with a discussion of the results from the step-by-step evaluation of the IPM program.

3.1. Socio-economic Profile of Respondents

The number of respondents from Northern, Central and Southern zones of Cameron Highlands was 32 (31.4%), 36 (35.3%) and 34 (33.3%), respectively. Among the respondents, 73.5% were Chinese, 21.6% were Indian and 4.9% were Malay. Majority (91.1%) of the respondents interviewed were above 31 years old. Only 2.9% of the respondents were females. Because of the very limited number of females in the sample, further analysis considering gender differences could not be explored.

Most of the respondents (59.8%) had obtained secondary school education; and 36.3% had only primary school education, 1.0% received higher education at Bachelor's level, 2.0% at Diploma level and the remaining (1.0%) has no schooling at all.

The majority of the respondents (88.2%) treated agricultural as their full-time job. About 38% spent 31 to 40 hours per week on the farm which was equivalent to 5-8 hours per day working on the farms. About 19% were working for more than 50 hours per week, which was more than 8 hours per day working on their farm.

3.2. Farm Characteristics and Operations

Farmers selected across the three zones showed no significant differences in terms of farm characteristics. In terms of land tenure status, 22 farmers (61.1%) of farmers in the Central zone had Temporary Occupational License (TOL). Under TOL, farmers lease land from the government on a year-by-year basis. In the Northern and Southern zones, 46.9% and 41.9% respectively, of the respondents were operating TOL farmlands. The percentage of all the surveyed farmers operating under TOL was 50%.

Cabbage was usually planted two seasons a year, the first round in October and harvested before the rainy season starts in December. The second season was from April to June. The average farm net income per month for each acre of the cabbage planted in the Central zone was RM10,518 which was substantially higher as compared to those planted in the Northern and South zones which were RM8,132, and RM8,913, respectively.

3.3. Indicators of Pesticide Exposures

Several questions about respondentsû immediate farm environment and the precautionary measures they took against pesticide exposures were incorporated in the survey to assess the degree of environmental risks in the areas. Surface water in the regions was at risk from pesticide runoff. The distance of the cabbage farms to surface water ranged from as close as 5 metres to about 300 metres, and the average distance was 27.5 metres (Table 2).

Definition variable	Unit
Farmer characteristics	
Age (AGE)	No. of years
Educational attainment (EDUC)	No. of years
Experience of farming (EXPER)	
Tenure status (OWNER)	1 = owner-operator or $0 = $ otherwise
Managerial factors	
Farm hours (FHOURS)	Time spent on farm per week; number of hours
Off-farm work (OFFWORK)	1 = farmer has off-farm employment or $0 =$ otherwise
Pesticide costs (PESCOST)	Ratio of pesticide expenses to total operating costs; percent
Farm structure	
Farm size (FARMSIZE)	No. of hectares
Cabbage profit share (PSHARE)	Ratio of profits from cabbage to total farm income; percent
Physical/location factor	
Site dummies	1 = farm is located in that site or $0 =$ otherwise
North zone (NORTH)	
Central zone (CENTRAL)	
South zone ^a (SOUTH)	
Institutional/informational factors	
IPM awareness (ADVICE)	1= farmer obtained pest control from the specified source; 0= otherwise
IPM training (ATTEND)	1= farmer attended an IPM training; 0= otherwise
Experiences and awareness about i	mpacts of pesticide use
Preventive against pesticide exposure (PREVENT)	Use of preventive measures against pesticide exposure
Health impact (SICK)	1= farmer got sick after spraying pesticide; 0= otherwise

Table 1. The explanatory variables (regressor) used in the logit analysis

^a Variable dropped from the model to avoid a singular matrix

Table 2. Indicators of pesticide exposure

Pesticide exposure	Percen	tages of "yes" re	esponses	
	NORTH $n = 32$	CENTRAL n = 36	$\begin{array}{c} \text{SOUTH} \\ n = 34 \end{array}$	TOTAL n=102
Do you boil your drinking water?	29(90.63)	34(94.44)	32(94.12)	95(93.14)
Drinking water source (pond, mountains).	7(21.87)	4(11.11)	6(17.64)	17(16.67)
Do you wear the following?				
Face mask	21(65.62)	34(94.44)	28(82.35)	83(81.37)
Long pants	31(96.88)	36(100.00)	31(91.18)	98(96.08)
Long-sleeved shirts	27(84.38)	34(94.44)	32(94.12)	93(91.18)
Shoes	27(84.38)	35(97.22)	32(94.12)	94(92.16)
Distance between surface water and cabbage fields (averages meters)	52.76	15.61	14.20	27.52

Note: Figures in parenthesis indicate percentage of 'n'

Measure o of-Fit	f Goodness-				Logit models			
		REPRUN	MULC	TRIWKLY	ONEHERB	MICROBIO	TRAP	ETL
Percentage prediction		97.5	91.4	91.7	93.9	93.7	87.0	68.8
Percentage prediction:	of correct Non - Adopti	77.3	50.0	83.3	88.9	91.7	87.5	97.7
Count R ²		71.57	28.59	65.19	72.84	75.24	75.24	56.77
-2 Log L	λ^2 value p-value	65.491 0.2661	36.277 0.6354	90.091 0.7471	96.475 0.7284	99.647 0.5568	99.647 0.7591	50.307 0.5216

Table 3. Goodness-of-Fit measures/Predictive ability of the logit models

In general, the respondents knew about protection against pesticide exposures. More than 80% of the respondents wore face masks (or any substitute), and more than 90% wore long pants or long sleeved-shirts and shoes when applying pesticides.

About 83% of the farmers used government water supply as their main source of drinking water, and only 17% from other sources (river, mountain water and pond). As an indication of how important it was to farmers to avoid being sick from contaminated water, they were asked whether they boiled their water before drinking. About 93% said they did boil their water before use.

3.4. IPM Program Adoption

The likelihood ratio tests indicate that the amount of variations explained in each of the model (REPRUN, MULC, TRIWKLY, ONEHERB, MICROB, TRAP, and ETL) was significantly different from zero. Two criteria for goodness of fit are reported in the table, the -2LogL statistics. Two values for both measures were highly significant (99% confidence level), providing evidence that the regression coefficients were significantly different from zero (Table 3). Count R² which is a ratio of correct predictions to the total number of observations was 0.71 for the REPRUN model, 0.75 for the TRAP model, and 0.75 for the MICROBIO model. This suggested that the selected regressors were good predictors of adoption and non-adoption of IPM program.

The proportion of correct prediction compares the correct predictions of both adoption and non-adoption with the observed outcomes based on explanatory variable information. Results showed that the REPRUN model correctly predicts 97% of adoption cases and 77% of non-adoption cases. For the other two models, 87% (TRAP) and 93% (MICROBIO) adoption cases were correctly predicted, while non-adoption was correctly predicted for 87% (TRAP) and 91% (MICROBIO) of the observations. The strong predictive ability of each of the models in estimating the probabilities of adoption provides justification for using these probabilities to project adoption rates in the area.

3.5. Estimated Adoption Rates Based on Logistic Regression

The estimated adoption rates for each technology in each of the sites were based on the logistic

VARIABLES	SOUTHERN	NORTHERN	CENTRAL	Average
REPRUN	64.71	84.38	91.67	80.39
MULC	64.71	68.75	91.67	75.49
MICROBIO	50.00	53.13	94.44	66.67
ONEHERB	44.12	53.13	91.67	63.73
TRIWKLY	50.00	53.13	77.78	60.78
TRAP	38.24	25.00	61.11	42.16
ETL	14.71	9.38	13.89	12.75

Table 4. Predicted adoption rates by site (region)

IPM Model	REPRUN	Z	MULCH				UNALIAND		MICKUBIU		INAL	~
Variable ^a	Parameter Odd-	-ppO	Parameter Odd-	-ppO	Parameter	-ppO	Parameter	-ppO	Parameter	-ppO	Parameter	-ppO
	estimate	ratio	estimate	ratio	estimate	ratio	estimate	ratio	estimate	ratio	estimate	ratio
INTERCEPT	-7.8593	0.0004	-4.5726	0.0103	-12.5572**	0.0000	-20.8104 **	0.0000	-21.2184**	0.0000	-12.3294	0.0000
AGE	0.0310	1.0315	-0.0169	0.9832	-0.0523	0.9490	-0.2136	0.8076	-0.2689***	0.7642	0.0747	1.0775
EDUC	0.1782	1.1951	0.1584	1.1717	0.1227	1.1305	0.4775	1.6121	0.4953	1.6411	0.1394	1.1496
EXPER	-0.0264	0.9740	0.0478	1.0490	-0.0120	0.9881	0.0227	1.0230	0.0894	1.0936	-0.1279*	0.8799
OWNER	0.7031	2.0201	-1.6630^{**}	0.1896	1.8121	6.1230	-0.6002	0.5487	-1.3003	0.2725	-0.2091	0.8113
FHOURS	*7660.0	1.1048	-0.0003	7666.0	0.0169	1.0171	0.1005	1.1057	0.1124	1.1189	-0.0596	0.9422
OFFWORK	2.6897	14.726	0.2625	0.7691	0.1133	1.1199	2.9030	18.227	3.4012	30.0013	-1.5361	0.2152
PESCOST	-0.0022*	0.9978	-0.0017**	0.9983	-0.0050***	0.9950	-0.0036***	0.9964	-0.0050**	0.9950	-0.0051***	0.9949
FARMSIZE	1.0761	2.9332	1.0096^{**}	2.7445	2.6672***	14.399	2.2142**	9.1544	3.2112**	24.8086	2.4057***	11.086
PSHARE	-0.0165	0.9836	0.0240	1.0243	0.0325	1.0331	0.0356	1.0363	0.0423	1.0432	-0.0093	0.9908
NORTH	2.2714*	9.6934	-0.0301	0.9703	0.6896	1.9929	3.5750**	35.692	3.1484^{*}	23.2983	1.4429	4.2330
CENTRAL	3.0691^{**}	21.522	0.7495	2.1159	0.1391	0.8701	4.8216^{***}	124.15	5.3073***	201.8006	1.3020	3.6765
ADVISE	0.4820	1.6193	-0.3140	0.7305	1.8937*	6.6438	2.5212	12.443	3.5404^{*}	34.4821	3.7872**	44.130
PREVENT	0.3627	1.4372	0.1600	1.1735	2.2079**	9.0966	3.8734**	48.105	3.7575**	42.8395	1.1781	3.2483

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Table 5. IPM willingness to adopt models

regressions. The logit models estimated the predicted probabilities of adoption which were shown in Table 4. A farmer is classified as an adopter if the predicted probability of adopting a particular technology for an individual farmer given his or her specific set of attributes, is greater than his or her probability of nonadoption i.e. greater than 50% of the predicted probability of adoption practices REPRUN, MULC, MICROBIO, ONEHERB, and TRIWKLY. While the TRAP adoption was 42.2%, the ETL had only 12.8% of the respondents from the survey.

3.6. Factors Affecting Adoption of IPM Program

Influence of the explanatory variables on the adoption of IPM technologies is shown in Table 5. Logit regression results for the REPRUN model revealed that farm experiences negatively affect willingness to adopt cabbage pruning and leaf burning as an alternative control for pest larvae and nematodes. The coefficients for AGE and EDUC turned out to be positive while PSHARE and PESTCOST variables turned out to be negative. One possible explanation for these results could be that farmers who are younger, are more highly educated, have smaller farms, have more secure land tenure, and have less experience in vegetable farming follow more IPM practices. Only the Central zone showed a significant relationship at alpha 5%, while variables FHOURS, PESCOST, NORTH were significant at alpha 10% and FARMSIZE with PREVENT at 15% level of significance. It shows that the significant variables increased the probability of REPRUN adoption. Table 5. IPM willingness to adopt models

The probability of adoption of the MULC model

using plastic mulching increased when farmers are young and can spend more hours in their farms. This was proven by the coefficient OFFWORK which was positively correlated with the increase of MULC adoption. Positive correlation was also due to FARMSIZE. It showed that bigger farm size farmers tended to increase MULC adoption. Adoption of more MULC meant that controlling weed was more efficient and at the same time it reduced the amount of weedicide used. On top of savings in environmental costs, the reduction in pesticide use also reduced operating expenses (Table 6). Calculated reduction in economic costs showed the aggregate cost saving per season (of 102 cabbage farmers) were RM57,433.60 for insecticides, RM1, 840.66 for herbicides, and RM 311.00 for fungicides.

4. Conclusion

The results of the study indicate that there are economic benefits with the adoption the IPM program. The program can reduce pesticide use in cabbage production, and may also in other vegetable production, without loss of efficacy. This finding is supported by Shamsudin and Awang (2007) that agricultural policy development and environmental protection policy can be reinforcing, or complementary, rather than conflicting. Thus this study provides justification for public investment of resources in training and educational programs to increase awareness about IPM and promote IPM adoption to ensure that the well-being of the present generation is not met at the expense of the future generationsû well-being. Economic, social and environmental aspects should be increasingly integrated into the agricultural development process.

IPM Technology	Cost Savings Per Season					
	Insecticides	Herbicides	Fungicides			
MICROBIO	14,694.36	NA	NA			
TRIWKLY	12,831.46					
TRAP	11,201.77					
ETL	3,710.20					
REPRUN	14,995.81		311.00			
ONEHERB	NA	853.13				
MULC	NA	987.53				
TOTAL	57,433.60	1,840.66	311.00			

Table 6. Cost savings from adoption of IPM technologies

Note: The value is in Ringgit Malaysia. NA = Not available

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