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Evaluation of IPM adoption and financial instruments to reduce pesticide use in Thai agriculture using econometrics and agent-based modeling

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Abstract

Agricultural commercialization in Asia has led to an increased dependence on synthetic pesticides, especially for high-value fruit and vegetable crops. The present study uses the multi-agent modeling software MPMAS to *ex-ante* assess the impact of different pesticide use reduction strategies. The model is parameterized with data from an intensive and diverse production systems in the mountainous north of Thailand, where the adoption of cash crops has been accompanied by very high levels of pesticide use. The objective of this study is to compare different policy interventions in terms of their impact on pesticide use, farm incomes and land use. The adoption of integrated pest management (IPM) is assessed in combination with tax instruments and with adoption incentives, such as bio-pesticide subsidies and price premiums. The results show that a smart policy package can reduce pesticide use by up to 34% over five years without income trade-offs for farm households.

Keywords: Agent-based modeling, ex-ante assessment, innovation diffusion, pesticide policy, integrated pest management

1. Introduction

The intensification of crop production in many low and middle income countries is often accompanied by pesticide overuse and misuse (Ecobichon, 2001; Schreinemachers and Tipraqsa, 2012). Hazardous pesticides are regularly applied in large quantities, thereby not only harming human health, but also killing beneficial animals and contaminating soils and water bodies. Indirectly, pesticides threaten the resilience and long-term productivity of ecosystems by disrupting natural pest control processes. As natural predators disappear and pests become resistant, the application of pesticides needs to increase and expenditures rise. Despite high externalities and increasing input costs, farmers continue to use pesticides due to the perceived high withdrawal costs if giving up their present chemical pest control (Wilson and Tisdell, 2001). Scientific studies of pesticide use reduction strategies have remained relatively few and kept a focus on industrialized countries. Falconer and Hodge (2000) developed a case-study farm model for the UK to evaluate low-input farming in combination with pesticide taxation. The same topic is addressed by Jacquet et al. (2011) by means of a mathematical programming model at the national level for the French agricultural sector. Skevas et al. (2012) point out the lack of empirical research on the impact of different economic instruments on farm income, pesticide use and the environment in their econometric study of the effects of pesticide use reduction policies on Dutch cash crop producers. This lack of evidence is even more apparent in the context of tropical agriculture, where little attention has so far been given to investigating the options and implications for smallholders of reducing pesticide use.

This paper addresses the above research gaps and the lack of sound evidence on which to base advice by assessing strategies for pesticide use reduction for horticulture in a tropical country in transition, Thailand. Falconer and Hodge (2000) point out that simple economic models of pest management decisions could be unrepresentative or even misleading if used as a basis for policy recommendations due to a lack of adjustments options and the inability to simulate systems change. To assess the impact of different pesticide use reduction policies, this study uses the multi-agent modelling software MPMAS (Mathematical Programming-based Multi-Agent System), a tool developed and widely tested for *ex-ante* assessments (Schreinemachers and Berger, 2011). The present MPMAS application is parameterized with farm and plot level data and from intensive and diverse production systems in the mountainous north of Thailand, the Mae Sa Watershed, where the adoption of cash crops has been accompanied by very high levels of pesticide use. The model allows exploring the diffusion of policy-driven innovations in the farm population as well as the effect of policy interventions on heterogeneous farm households and the landscape over time. It is based on empirically estimated damage control functions to capture different levels of pesticide productivity and estimated adoption probabilities to assign innovativeness scores to agents. The adoption of IPM is assessed in combination with tax instruments and with various adoption incentives. The objective of this study is to compare these interventions in terms of their impact on pesticide use, farm incomes and land use and meet the demand for reliable advice on what would work best.

2. Materials

2.1 Study area selection and data collection

The Mae Sa watershed area in northern Thailand was selected as the primary data collection area for the study. It covers an area of 140 km^2, with altitudes ranging from 400 m to 1,600 m above sea level (masl). The study area is a good example of the benefits and problems that agricultural commercialization involves. Mountainous areas across the region have experienced a rapid intensification of agricultural productions in recent years. Farmers in the study area have been able to increase their incomes from agriculture substantially by growing a wide variety of horticultural cash crops. However, the increase in production of high value crops has been accompanied by heightened pest pressure and heavy pesticide use (Schreinemachers et al., 2011), and the build-up of pest resistance has led farmers to increase the frequency and intensity of pesticide applications over time.

To collect socio-economic and agricultural production data, a structured questionnaire survey was carried out in the Mae Sa watershed, which is comprised of twelve villages that practice agriculture. 20% of the farm households in each of these villages were randomly selected, which resulted in a total of 295 farm households being interviewed. A one-year recall period, from April 2009 to March 2010, was used for the face-to-face interviews, with detailed information being gathered about the farm households, the land-use and cultivation practices, such as quantities of active ingredients applied. For each plot and each crop, respondents were asked about inputs, outputs, their pest problems and how they have tried to control them. If using pesticides, respondents were asked to give the common names of each, the number of times they sprayed them, the quantity of undiluted chemicals used, and the price and volume per container. For each pesticide mentioned, data were collected on the active ingredients they contained from traders, shops and producers.

2.2 Land use and pesticide use

Cropping patterns in the Mae Sa watershed vary according to the land suitability, changing with elevation and slope, accessibility of the villages and the relationships of farmers with traders and extension services, here mainly the Royal Project. This results in a spatially diverse agricultural land-use mix. In total, 58 crops were recorded in the survey. However, the majority of these are minor crops, which are not significant in terms of harvested area, pesticide applications and sales revenues. For the purpose of assessing pesticide use reduction strategies, this study focuses on the economically most important crops, which tend to be those sprayed most intensively, as well as on those crops which cover large areas of the watershed. This includes the following land-use groups: leafy vegetables (Chinese cabbage, white cabbage, Chinese kale and lettuce, greenhouse vegetables (bell peppers and tomatoes), other vegetables (chayote, green beans and onions), flowers (chrysanthemums and roses), cereals (upland rice and maize) and fruit trees (litchis).

Figure 1 illustrates the relationship between profitability and input intensity, showing the gross margins generated per hectare and per month together with pesticide use in kg per ha and per month. The need to protect valuable crops from pests results in preventive as well as curative pesticide applications, which are extremely high for greenhouse vegetables, flowers and onions in particular. The risk of losing valuable crops, such as bell-peppers and tomatoes, during pest attacks is considerable, and so farmers spray excessively. As witnessed during many field visits, farmers frequently complain that the virulence of pest attacks has increased in recent years and that certain pesticides are no longer as effective or require large applications to produce the desired effect.

Figure 1

For most land uses, the majority of pesticide applications involve insecticides and fungicides, apart from cereals and fruit trees, where high quantities of herbicides are applied. The main insecticides used are *abamectin* and *cypermethrin,* while *mancozeb* is the most commonly used fungicide. Farmers also resort to toxic substances such as *mevinphos* on a regular basis. The WHO toxicity classification sheds light on the hazardousness of different pesticides (WHO, 2009), giving an indication of the risks they pose to human health, which also reflects the risks posed to other living organisms. It is the most widely used classification of pesticide toxicity, and enables researchers and policy makers to quickly differentiate the more harmful from the less harmful substances. Pesticides ranked as WHO 1a and 1b are extremely hazardous, those ranked as WHO 2 are considered moderately toxic, while the WHO 3 toxicity class refers to slightly toxic pesticides. WHO U pesticides are described as unlikely to cause any harm. As *Figure 2* shows, the proportion of applied pesticides belonging to different toxicity classes varies among the land-use groups. Large quantities of pesticides and most hazardous substances are applied on greenhouse vegetables and flowers, while the proportion of moderately hazardous pesticides used is largest for leafy vegetables.

Figure 2

2.3 Farm characteristics in the study area

Table 1 illustrates that land holdings in the study area are on average quite small, ranging from 0.7 ha in the villages of the central watershed, where most northern Thai farmers live, to 2 ha and above in the other parts of watershed, where the villages are inhabited by farmers of the Hmong ethnicity. The higher population densities in the central watershed lead to smaller farm sizes and more intensive production, with a greater use of greenhouses and cultivation of flowers. In the Hmong villages, many farmers are members of the Royal Project and the use of the GAP certification scheme is more widespread. The majority of Hmong farmers need to grow their crops on steep slopes, as they lack alternative locations among the higher elevations. In several Hmong villages the litchi orchards are an important land-use, which was promoted to prevent soil degradation and replace opium cultivation.

Table 1

2.4 Integrated Pest Management

This study uses the concept of IPM in an agro-ecological sense , incorporating factors such as the preservation of healthy soils, use of a diversity of cropping patterns and the conservation of beneficial insects. Farmers are need to develop knowledge of the agro-ecosystem and regularly observe their fields. Cultural, biological, genetic, mechanical and, as a last resort, chemical methods can be combined in a way that guarantees the long term environmental and economic viability of the farm.

While generally the practice of IPM among vegetable growers in the uplands of northern Thailand has remained rather insignificant, a pilot project of the national IPM program managed by the Royal Project station in Doi Angkhang is a good example of agro-ecological intensification of vegetable production. The lack of data available on alternatives to chemical pest management from the main survey, necessitated that observations from a similar environment be used. The climate and terrain of the Royal Project station at Doi Angkhang, which is located at 1400 m above sea level, is similar to that of the Mae Sa watershed. The land-use mix is also comparable, as leafy vegetables are an important crop in both places, and with the pest complex being very much alike. Average yields across the three crops are 25% lower for farmers at Doi Angkhang, but prices are higher and more uniform, and lie within the upper tercile range for leafy vegetable prices in the Mae Sa watershed. It should also be noted that variable input costs for IPM are lower, while labor requirements are higher.

Table 2

Growers of leafy vegetables in Doi Angkhang have, with the support of extension workers, successfully practiced IPM for several years now by combining different management practices to minimize the use of pesticides and grow healthy vegetables. Farmers combine cultural (rotations to break the pest cycle and soil conservation), biological (upkeep of high agro-biodiversity levels with many natural predators) and mechanical methods (traps) with well-monitored bio-pesticide applications. *Table 2* shows data for three typical rotations of the three of the main leafy vegetables grown by the farmers in Doi Angkhang: cabbages, lettuce and spinach. Data was collected following these rotations in 2012, representing one-third of all IPM farmers in Doi Angkhang. Since production is very homogenous among farmers and strictly controlled by the Royal Project, a relatively low number of representative cropping observations was sufficient. Each crop is managed according to a recommended cultivation plan developed by the Royal Project station. For cabbages, this involves the application of 3 to 5 kg of manure after planting, the spraying of a diluted organic fertilizer which has been produced from vegetable scraps, molasses and microorganisms every three days, and the application of bio-pesticides such as *Bacillus thuringensis* for use against worms, and *Bacillus subtilis* for use against parasites. *Trichoderma, azadirachtin* and *metazoan* are other bio-pesticides at the disposal of the IPM farmers, for which pre-specified quantities are applied at regular intervals, depending on the season. Specific substances or higher amounts are used when pest pressure crosses a particular threshold. Farmers closely observe their plots, and also resort to traps and hand-picking to protect them. For each cropping cycle and plot, the Royal Project obliges farmers to keep detailed records, and subsequently monitors applications, to make sure the recommended amounts are not exceeded. To guarantee the safety of its produce, staff from the Royal Project continuously test vegetable samples for residues.

3. Methods

3.1 The methodological context of MPMAS

ABMs in agricultural economics are useful in situations where model complexity leads to analytical intractability, that is, equilibrium conditions either cannot be identified or analytically solved (Nolan et al., 2009). MPMAS belongs to a category of models referred to as agent-based models of land-use and land-cover change (ABM/LUCC). These models are characterized by the combination of a cellular component representing the physical landscape with an agent-based component representing human decision-making (Parker, 2003). The interactions of autonomous individuals with each other, as well as with the landscape, are important features of ABM/LUCC, which are effective at analyzing a variety of resource management problems and which add to the capabilities of standard bio-economic models (Berger et al., 2006). MPMAS mainly distinguishes itself from alternative models in the ABM/LUCC category, such as Cormas (Becu et al., 2008) for example, through its use of whole farm mathematical programming (MP) to simulate the land-use decision-making of farm households, as the driver of land-use change in agriculture and forestry. The decision-making component is firmly grounded in the micro-economic theory of agricultural economics. The assumption of full economic foresight in MPMAS is relaxed by incorporating adaptive expectation formation and incomplete knowledge through a network model of innovation diffusion. On top of that, the software can be combined with a range of biophysical models to simulate crop yield responses to changes in the crop water supply or changes in soil nutrients. Altogether, MPMAS allows for the spatially-explicit modeling of human-environment interactions across a wide range of agro-ecosystems and for a variety of purposes (for examples of its applications, see Schreinemachers et al. (2011)). The model can be applied to help understand how the adoption of agricultural technologies or sustainable practices, how policy intervention and/or how global change processes affect a heterogeneous population of farm households and the resources on which they rely.

3.2 The model set-up, dynamics and initialization

The application of MPMAS to assess pesticide use reduction strategies for Thai upland agriculture is configured to suit the research topic and requires the following subset of the range of input files available in MPMAS: The agent population, which is subdivided into 15 clusters and which includes information on assets and resource endowments, and agent characteristics; Maps, including the spatial representation of agent plots and cluster memberships; The MP decision-making component, which is adjusted for each agent during each period; The network dynamics component, which defines investment objects and innovation diffusion; The perennial crops component, which defines yields and input requirements over the lifespan of a crop, for litchi, roses and IPM vegetables; The crop growth component (CropWat model), which specifies crop water requirements; Data on the prices of all inputs (pesticides, labor, etc.) and outputs; Water rights, a hydrological component regulating water supply (including local weather data), a demographic component defining the labor supply for different age categories, and basic data and a scenario manager, which include general model parameters and switches. The most important features for this application are explained in more detail in the following sections. *Figure 3* illustrates how the economic, social network and bio-phyisical components of the MPMAS application developed for the Mae Sa watershed are connected. The model is recursive, meaning that most factors are updated after each simulation period.

Figure 3

Investment and production decisions in MPMAS are separated into two MP matrices (Berger, 2001), and the acquisition of assets and the adoption of innovations are carried out before cropping choices are made. (Schreinemachers et al., 2010). The allocation of cash, labor, pesticides, etc. to a monthly cropping plan occurs after the right-hand side values in the MP matrix are updated for assets and cash, while the annuity values are replaced by actual costs and benefits (Schreinemachers, 2006). The theory of adaptive expectations was incorporated into MPMAS by Berger (2001), so that agents can form expectations on what would happen in the future based on what happened in the past, the development of foresight is in this context not possible. Agents revise their expectations after each simulation period proportional to the difference between actual X_{t-1} and expected vales X^{*}_{t-1}.As long as λ takes values greater than 0 and smaller or equal to 1, agent expectations are adjusted as follows:

$$X_t^* = X_{t-1}^* + \lambda * [X_{t-1} - X_{t-1}^*], 0 < \lambda \leq 1 \quad (1)$$

The simulation period in the study model is set to five years, reflecting the character of the pest management problem. The model is based on a cross-sectional dataset, which represents a great variety of cropping activities, meaning it is possible to predict how farmers change their behaviors in response to the incentives and disincentives that affect them in the short-term. Without some level of knowledge about pest pressure, yields and prices in the medium- and long-term, using an extended simulation period would involve a lot of uncertainty.

A lottery based on Monte-Carlo techniques was used to extrapolate data from the sample of 295 farm households to the population of 1491 farm agents, allocating characteristics and assets to agents. This methodology, the integration of which into MPMAS is described by Berger and Schreinemachers (2006), requires cumulative distribution functions to be used. A stochastic element of the Monte-Carlo simulation method is the seed values that are chosen to generate the random populations and check for the robustness of results. To take correlations into account, such as between the number of greenhouses and owned land, the sample was subdivided into clusters. Villages, where cropping habits and suitability due to altitude are similar, were grouped together (see *Table 1*) and each of these groups was then split into three clusters according to the tercile of the farm size (ha). Overall, this resulted in the creation of 15 clusters within the model, which display a higher degree of homogeneity than the agent population as a whole. The lottery was consequently carried out for each cluster separately.

3.3 The decision-making component

The decision-making relies on production functions and recursive mathematical programming (MP). As a first step, the cropping activities for the MPMAS model needed to be parameterized. For this purpose, empirical observations from the survey were directly included in the MP matrix. The parameterization approach produced 513 different cropping activities, for which a total of 82 active ingredients were needed.

Table 3

For crops with too few observations to estimate production functions, and which could not be easily grouped together with other crops, all data points between ± one standard deviation were selected (for maize, rice, chayote and chrysanthemums). For the perennial crop litchi, cluster analysis was used to generate three management options with different input levels, while the perennial rose, due to few observations, was inserted with just one average management option. For the remaining vegetable crops, it was possible to group similar vegetables together and to obtain sufficient observation numbers to estimate production functions. Estimations were carried out across three groups with similar pest management, input levels and growing lengths, these being leafy vegetables (open field system), greenhouse vegetables (closed system) and onions/beans (open field system). The production functions helped served as a means to identifying the empirical vegetable data for the model. All observations situated between the upper and lower confidence intervals of predicted output were selected as inputs into the MPMAS model. The Cobb-Douglas production function with a exponential damage control specification for pesticides, which had already been tested for the quantification of pesticide overuse (Grovermann et al., 2013), was used to parameterize vegetable cropping activities. This specification allowed the model to take into account the abatement effect of pesticides and is preferable to using a standard Cobb-Douglas production function, which tends to overestimate pesticide productivity (Lichtenberg and Zilberman, 1986, Praneetvatakul et al., 2013). Within each group of crops, the management, growing period and pest problems are similar, but output levels (Y) vary. Indicator variables C_i were introduced alongside growth-stimulating inputs Z_j and pesticides X to control for farm characteristics. These farm characteristics also included crop and location dummies that captured differences in crop management and agro-ecological conditions. Estimated coefficients include constant α, coefficients γi, βj and the damage control coefficient λ.

$$\ln Y = \alpha + \sum_i \gamma_i C_i + \sum_j \beta_j \ln Z_j + \ln[1 - \exp(-\lambda X)] + \varepsilon \qquad (1)$$

For each crop, the output as well as confidence intervals could thus be predicted from the estimated coefficients for the vegetable group, and then be adjusted by the crop coefficient. The values were predicted taking into account the different levels of the other variables used. Observations beyond the upper and lower bounds of the confidence intervals, as displayed in *Figure 4* for white cabbage and lettuce, denote the ‘outliers’, which were excluded.

Figure 4

The MP optimization problem at the core of MPMAS defines the behavior of the agents, which maximize their farm incomes by selecting an optimal combination of crops based on expectations about prices and yields, and satisfying a large set of resource constraints. Yield expectations, resources, as well as the access to technologies, are updated for every agent at every time step in the model run. The optimization problem is then repeatedly solved. The complete MP decision-making matrix contains 1129 columns and 862 rows. Permanent greenhouses and perennial crops need to be fully used, but idle activities allow agents to keep the greenhouses and perennial crops unmanaged. Similarly, all land needs to be used, but monthly fallow activities allow for not managing the land. Agents can choose to perform off-farm labor to some extend (remunerated with 70 Baht per manday) and have access to hired labor (paid with 96 Baht per manday). Individual activities and constraints are specified for all active ingredients classified according to the WHO toxicity classes. All other inputs (seeds, fertilizers, planting materials and hormones, among others) are aggregated to the balance row variable costs, and are expressed in 1000 Baht per hectare. Agents can also buy their pesticides and pay the variable costs using credit with a credit limit per agent for each simulation period of 200,000 Baht. Labor, water and sprinkler constraints for the cropping activities are set as monthly, so that different crops can be grown on the same plot in a year.

3.4 The diffusion of innovations

The decision-making of agents in the model is not only constrained by their resource endowments, but also by their access to investment objects. Parameters, such as acquisition costs and lifespan of each object as well as its availability and accessibility are defined in the network module. Investment objects required for this model included greenhouses for chrysanthemums, bell peppers and tomatoes, different perennials, IPM cropping, short term credit, off-farm labor, hired labor, and drip and sprinkler irrigation. Rogers' original model of technology diffusion (Rogers, 2003; Valente, 2005), yielding a classification of agents into adopter groups (innovators, early adopters, early majority, late majority, laggards) and corresponding network thresholds, was incorporated into MPMAS (Schreinemachers and Berger, 2011) and has been applied frequently (Berger et al., 2007; Quang et al., 2014; Schreinemachers et al., 2007).

The actual technology adoption process in MPMAS consists of two steps (Schreinemachers et al., 2009). As a first step, each agent assesses whether the level of overall exposure to the innovation and the related threshold level match its individual innovativeness, determined by adopter group affiliation. A completely new innovation such as IPM has an initial adoption of 0%; then only agents in the innovator segment (2.5% of the agent population) get immediate access. If the threshold is reached, during a second step an agent gains access to the innovation and includes it in the decision-making process. As illustrated in *Figure 5*, exposure to an innovation increases, giving access to further adopter groups. This process progressively permits agents to select innovations and if profitable, use them on a specific farm.

Figure 5

3.5 The Specification of the adoption model and innovativeness ranking

The decision to accept or reject is understood as a binary choice and can be used to predict adoption probabilities from a set of observable independent variables. Adoption here indicates whether a technology has ever been adopted, not whether it is used. Since knowledge of the innovation is limited to a part of the population only, a two-stage econometric procedure is suggested here. The first stage corresponds to the knowledge and persuasion parts of the innovation diffusion process, in which the awareness of the innovation is determined and the pre- condition for farm households to then consider adoption. The first and second stage estimations are based on probit regression models. When the error terms of these two models are correlated ($\rho \neq 0$), standard probit techniques applied to the first equation yield biased results. A probit model with sample selection provides consistent, asymptotically efficient estimates for all parameters in such cases (Van de Ven and Van Praag, 1981). The actual dependent variable y^* constitutes the scale of adoption and is an unobservable magnitude. X_j includes a vector of strictly exogenous variables that determine adoption, while z_j includes a vector of variables that determine knowledge of the innovation. β_j and γ_j are the vectors of parameters to be estimated, and u_{ij} is the household specific error term. The model assumes that there exists an underlying relationship, as follows:

$$y_j^* = x_j\beta_j + u_{1j} \quad \textit{latent equation} \tag{2}$$

Such that only the binary outcome is observed:

$$y_i^{probit} = (y_i^* > 0) \quad \textit{probit equation} \tag{3}$$

The dependent variable is however not always observed. Rather, the dependent variable for observation j is observed if:

$$y_i^{select} = \left(z_j\gamma_j + u_{2j} > 0\right) \quad \textit{selection equation} \tag{4}$$

And where:

$$u_1 \sim N(0;1); \quad u_2 \sim N(0;1); \quad corr(u_1;u_2) = \rho \tag{5}$$

When $\rho \neq 0$, a probit model of adoption is required that corrects for selection bias. The probability of observing a positive outcome for adoption is given by the following equation:

$$\Pr(\mathrm{y}|\mathrm{x}) = \{\psi(\beta x_i)\}^{y_i}\{1-\psi(\beta x_i)\}^{1-y_i}, \qquad y_i = 0{,}1 \tag{6}$$

Innovativeness is generally seen as a personal characteristic that distinguishes farm households, such that while the most innovative farmers eagerly test new technologies, other farmers might be more reluctant to do so. Innovativeness is difficult to measure directly and so is not usually recorded in surveys of farm households (Schreinemachers et al., 2009). As a result, econometrically estimated adoption probabilities can be used to predict the innovativeness levels of agents, given them a unique ranking. In the agent population, the exact innovativeness of each agent could be determined using a set of allocated regression variables and the estimated regression coefficients. In a last step, the innovativeness ranking was transformed into an adopter categorization in line with the five adopter threshold groups.

3.6 The econometric estimation of adoption probabilities

As explained above, farmers in the study area rely almost exclusively on chemical pesticides for their pest control. Recent government efforts have aimed to reduce these high levels of pesticide use by means of the voluntary public GAP standard. In total, 20% of farmers in the Mae Sa watershed are GAP certified, at the national level certificates were issued to about 212,000 farmers covering a crop area of 225,000 hectares in 2010 (Schreinemachers et al., 2012). The GAP standard is as such the most widespread pesticide use reduction initiative, even though it has been found not to deliver profound pest management changes at the farm level. Nevertheless, it provides an entry point for analyzing the determinants of innovativeness in this sector. In accordance with the two-stage econometric estimation procedure of adoption probability, the dependent variables are whether farmers know (y_j^{select} = 1) or do not know of (y_j^{select} = 0), as well as whether farmers do (y_j^{probit} = 1) or do not possess (y_j^{probit} = 0) GAP certification. The analysis is based on a set of explanatory variables, which represent farm characteristics, such as land size and wealth for example, as well as network characteristics. Of the network characteristics, exposure measures the links of an individual farm household to those households which are aware of the innovation. The variable reflects the proportion of contacts that know about an innovation when compared to contacts that don‘t know, indicating levels of communication among farm households (Valente, 2005). Royal Project membership and owning a motorbike are proxies for the number of ties an actor has with the outside world. The variable “Village head” in turn acts as a measure of the importance or prominence of a person in a network.

The low level of profitability of an innovation could also explain a prolonged adoption period. A t-test for differences in output per hectare and per month did not reject the null hypothesis of the difference in output between non-GAP certified and GAP certified cropping activities being smaller or equal than 0 (Ho: diff $\leq$ 0) for leafy vegetables (t = 0.807, p = 0.201), greenhouse vegetables (t = -3.042, p = 0.999) and litchis (t = 1.045, p = 0.176). The probit model with sample selection used to estimate the adoption probabilities resulted in a Wald chi2 of 342.77 (Prob > chi2 = 0.000). Therefore, as a whole, the model is statistically significant. At the same time, the likelihood-ratio (LR) test indicates that the results of fitting the combined model, which corrects for the sample selection bias, are significantly different from the outcomes produced when separately fitting the selection model for the knowledge of GAP and the probit model for GAP certification (chi2 = 3.88; Prob.> chi2 = 0.049). It is thus necessary to use the full model instead of a simple probit regression. *Table 4* shows the regression output. Even though some of the variables might be conceptually related, the variance inflation factor used was 1.99, which suggests that multi-collinearity is not an issue.

Table 4

Education, membership of the Royal Project extension organization, as well as exposure to peers who know about an innovation, have a highly significant, positive effect on the level of knowledge of the GAP standard. Also, farmers who regularly apply pesticides and own a motorbike, so increasing their mobility, are more likely to know about the GAP standard. The percentage of high value vegetables as well as litchi on the farm, which are included as control variables, the age of the household head, diversification (growing more than one crop) and liquidity per capita in the farm household, are other positive and significant determinants of certification with the GAP standard. In contrast, farm size, farm age and having a village head in the household have a significant negative impact on the adoption of the GAP standard. Bigger and older farm households or those with a household member in a traditional leadership position are therefore likely to be less innovative.

3.7 The perennial crop module

Perennial crops are handled differently to annual crops by MPMAS, since the crop yield is not only influenced by input use, but also by crop age. As shown in *Table 5*, the present application includes three crops that are processed as perennials: litchi fruit trees (30 years), IPM leafy vegetable crop rotations (six years) and roses (six years). Three different input-output levels or management options are distinguished for litchi, while for IPM vegetables the distinction is between three different rotation schemes. The switching between input-output guarantees that, after an investment in perennial crops has been made, adjustments are still possible for agents during each simulation period. However, For roses a uniform type of management is assumed in the model. In the case of having insufficient funds, agents also have the option to leave their plots idle, so receiving no income from these activities.

Table 5

The leafy vegetables grown with IPM methods are annual crops; however, integrated pest management requires that certain crop rotations are used to break the pest cycle and maintain soil quality. Therefore, several annual cropping activities over the course of one year are grouped together according to what was observed in the field, in order to create three rotation schemes. IPM is knowledge intensive and requires some upfront investments to be made. Light terracing, including the planting of grass strips, as well as plastic rain shelters make up the acquisition costs. Changing from the conventional production of cash crops with high external input use to agro-ecological IPM practices can be expected to involve some initial yield losses. In the model, this conversion period is taken into account by treating IPM vegetable rotations as perennial crops and specifying a yield factor for each year. Being a completely new innovation not yet adopted by any agent at the beginning of the simulation, each adopter thus incurs yield losses when starting to grow IPM leafy vegetables, based on examples can be found in the literature on the yield impact of conversion from conventional to organic practices. (Giovannucci, 2006; Seufert et al., 2012). *Table 6* shows how IPM vegetables are contained in the MP model as a perennial crop.

Table 6

3.8 Other input data

Crop yields depend on the amount of water supplied, and the CropWat model (Allen, 1998; Doorenbos et al., 1979) and can be incorporated within MPMAS as an optional crop growth tool, as is the case for the Mae Sa watershed application. As with previous applications of MPMAS with respect to land-use decision-making in Thailand (Schreinemachers et al., 2009; Schreinemachers et al., 2010), the present model uses the CropWat model to simulate yield responses to water supply. The water availability in a month is controlled by in MPMAS, based on Weather data from the Royal Project station and irrigation options.

Market data for is specified each simulation period and comprises buying prices for inputs, such as hired labor, pesticides and other variable inputs, as well as farmgate selling prices for the outputs of each cropping activity. Short-term credits and deposits, just like remunerations for off-farm labor, are also part of the market data. Due to the rather limited size of the Mae Sa watershed when compared to the overall area under horticulture in northern Thailand, the production output for the watershed is assumed not to affect price formation. Furthermore, due to the relatively short simulation period of five years, constant market data was assumed.

3.9 The scenario specifications of simulation experiments

The Scenario Manager in MPMAS enables the user to specify changes in parameters and run a sequence of simulation experiments that stepwise isolate the effects of parameter changes (Berger et al., 2006). This means it is possible to design pesticide use reduction scenarios which constrain or affect the decision-making of agents in different ways. For instance, prices for pesticide inputs can be increased, access to IPM can be granted or pesticide use constraints can be switched on or off for different simulation runs. For pesticide use reduction policies, a range of parameters can be used to evaluate the effect of an intervention. This is instrumental to test the sensitivity of results to different levels of change. The focus of this study is on financial instruments and innovation diffusion. *Table 7* gives an overview of the different policy interventions employed for assessing pesticide use reduction strategies within MPMAS, all of which can be simulated stand-alone or as combined interventions. The interventions can occur at different levels, denoted as low, medium and high. More precisely, the Mae Sa watershed model includes options to introduce taxes and combine them with lump sum compensation payments to agents according to farm size. Further scenarios involve subsidies and price premiums in conjunction with the introduction of IPM technology. The disincentives and incentives can be combined in policy packages. All instruments are evaluated in terms of their capability to reduce overall and toxic (WHO I and WHO II) pesticides use, their impact on farm incomes, their cost-effectiveness and how far they induce agents to adopt sustainable pest management practices.

Table 7

4. Model verification and validation

Verification implies checking that the resources allocated to agents are consistent with the observed resources available to farmers. Consistency is tested on six important assets: household size, liquidity, greenhouses owned, area under chrysanthemum cultivation, area under litchi orchards and area under rose cultivation. All of these are expressed as per household quantities. Using linear regression without a constant, the regression line is predicted. Slope coefficients and R-squared values close to unity indicate a good fit between the outcome of the asset allocation by the lottery and the asset allocation recorded in the survey. Seed values, used to initiate the Monte Carlo simulation of the lottery, affect the random allocation of assets, which requires testing the robustness of agent population configurations over different seed values. Here, the lottery proved to produce robust results.

Table 8

The validation process was carried out for three key outcome variables: land-use, sales revenues and pesticide use. Similar to verification, the goodness of fit between reality and the model outcomes is determined by regressing the observed data from the farm household survey against the simulated data generated by the model (forcing the intercept through the origin), evaluating the slope coefficient of the regression line and the R-squared. Coefficients between 0.95 and 1.05, and R-squared values between 0.95 and 1, are deemed sufficient for each of the three outcome variables at the aggregate level. The criteria are met for this application, across the various configurations of the agent population produced by 19 different seed values. As Table 8 shows, the model was able to produce a robust representation of real world land-use and associated agent revenues and pesticide use. As explained before, the agent population is subdivided into 15 clusters, and this allows for a validation of the model to take place at a less aggregated level. While the goodness of fit does not match the validation results at the aggregate level, average coefficients ranging from 0.805 to 1.040, with standard deviations between 0.075 and 0.207, can be regarded as acceptable. The same applies to the summary statistics of the R-squared values.

5. Results

Table 9 shows that even high taxes have only a moderate impact on pesticide use. With the high proportional tax rate, the reduction lies at 7.34%, which involves an income loss of 6.56%. Considering the differences between the high proportional taxes with and without compensation payments, it becomes apparent from the simulated outcomes that changes in pesticide use are negligible and income losses only partially offset. The changes in land-use induced by the tax levies prevent the baseline income levels being reached; therefore, lump sum payments only compensate for lost earnings to a minor or moderate degree. As far as land-use changes are concerned, crops involving less pollution, such as cereals or chayote become comparatively more attractive, but crops involving more pollution, such as onions or bell peppers become less attractive.

Table 9

In the following, the results of the pesticide use reduction strategies that promote the adoption of IPM rather than penalize the use of pesticides are presented. For this purpose, access to IPM is granted to the innovator segment in period 1. Price premiums are a mechanism used to increase the attractiveness of IPM. Here, farm gate selling prices are increased by 2, 5 and

10% respectively. Also, subsidies provided for IPM inputs are an important support measure that requires further study. The prices of bio-pesticides are then lowered by 20, 40 and eventually 60% to assess that effect on pesticide use, farm income levels and IPM diffusion. The IPM stand-alone scenario is included in the figures and tables below as a reference. IPM is comparatively profitable on average and should therefore be attractive to profit-maximizing agents. The diffusion of IPM does not differ between the IPM reference scenario and the low and medium price premium, as well as all the bio-pesticide subsidy scenarios. The innovation diffuses rather quickly, so that in year 4, agents in the early majority segment can already adopt IPM. However, for the high price bonus level scenarios, access to IPM becomes available to agents in the late majority segment in year 5. The change in pesticide use is also highest for this scenario, reaching 22% in period 5. As far as changes in incomes are concerned, farm agents are better off in all scenarios when compared to the baseline and the IPM stand-alone scenario.

Table 10

Even though overall and toxic pesticide use is the most reduced by the high price premium, in terms of expenditures, the scenario creates costs that are well beyond any potential tax revenues. In the case of the high proportional tax, as the tax scenarios showed, the government could generate revenues of ca. 6000 Baht for each of the 1941 agent households (see *Table 9*). This implies that, apart from high price premiums, roughly all of the scenarios could be financed by tax returns. The cost-effectiveness values shown in *Table 10* are a measure used to evaluate the policy costs of the IPM incentive against the amount of reduced toxic pesticide applications. The bio-pesticide subsidies turn out to be the most cost-effective interventions. Considering the cost-effectiveness of only 300 Baht costs per household for each percent of pesticide reduction, the high bio-pesticide subsidy scenario can be considered a suitable policy option. Land-use changes clearly differ across the scenarios in terms of the reduction of area under leafy and greenhouse vegetables. Table 11 illustrates that the area under IPM can only be substantially increased with high price premiums in place. The other interventions, where the diffusion process does not reach the late majority, bring about a smaller change in the area under IPM, when compared to the IPM stand-alone scenario.

Table 11

From the above scenarios it is possible to derive a series of policy packages. The high proportional tax now needs to be considered in combination with the introduction of IPM and a range of appropriate IPM adoption incentives. A high tax alone achieves only a moderate reduction in pesticide use, not exceeding 7% to 8% over the simulation period. Tax revenues can be employed to either directly compensate farmers through lump sum payments or promote less pesticide-intensive production practices. The following scenarios show that spending the tax money on IPM promotion rather than redistributing it as a lump sum achieves higher pesticide use reduction rates. Contrary to the tax-compensation scheme, investing in IPM adoption has a clear temporal dimension, since impacts can be assumed to become more significant over time. According to the experts from Kasetsart University in Thailand, a subsidy for bio-pesticides would most likely be put into practice, since it fits the existing policy framework which already allows for the subsidizing of various agricultural inputs. Price-sensitive consumers in Thailand might however be reluctant to pay a price premium for sustainably produced vegetables. The cost-effectiveness analysis also comes out in favor of advocating a bio-pesticide subsidy over other policy measures. As *Table 12* shows, the same reduction of pesticide use is achieved using a 5% price premium involving average costs of 4,110 Baht per household, and a 60% subsidy for bio-pesticides for which average costs only lie at 3,170 Baht per household. This cost is well below tax revenues, which leaves room for the augmentation of bio-pesticide use and the related, additional government expenditures. Therefore a policy package with an 80% bio-pesticide subsidy has been simulated is also shown in *Table 12*. Here costs on average are still covered by tax revenues and, as diffusion takes IPM adoption to the late majority, the area under IPM is much larger. Therefore pesticide use in period 5 is also reduced to a greater extend, by 34%.

Table 12

It is of interest to examine more closely which agents gain or lose from the introduction of IPM. *Figure 6*, for the scenario involving a tax and a 80% bio-pesticide subsidy, helps to understand that reductions in pesticide use and changes in income with regard to the baseline situation are experienced across the agent population. The graph on the right shows that income gains occur across the lower and middle ranges of the cumulative agent distribution, while for the upper range losses are evident. Gains clearly outweighing losses in terms of agent count and magnitude. The innovativeness of agents and the adoption of IPM are the main drivers of positive changes in income. The less innovative agents register most losses.

Figure 6

6. Discussion and conclusion

6.1 Strength and weaknesses of the MPMAS application

Overall, the temporal and spatial dimensions of the model, the combination of social network and optimization dynamics, as well as the analytical gains due simulating impacts on a heterogeneous population, are original features of MPMAS. The present MPMAS application harnesses these features and applies them to a new field of study. Agent-based modeling has so far not been used to assess crop protection policies. It increases the complexity of modeled processes and helps avoid problems of over-specialization and aggregation bias inherent in previous research using representative farm MP modeling (Falconer, 2000) or aggregate sector MP modeling (Jacquet et al., 2011). The results obtained with MPMAS illustrate the adjustments and reactions of individual farm agents to crop protection innovation and pesticide policy interventions, permitting an analysis of impacts for different polluter groups, including a more detailed representation of the dissemination of IPM among agents. The incorporation of network constraints alongside optimization in a multi-agent system generally distinguishes MPMAS from other bio-economic farm models used to assess innovations and responses to policies (Janssen and van Ittersum, 2007). Compared to a rule-based multi-agent system (Becu et al., 2003), MPMAS stands out, as optimizing agents with innovation access can evaluate adoption more effectively against the full range of existing cropping activities.

The level of agent access to an innovation is defined by the stage of innovation diffusion and by the agent's innovativeness. This presumes that the discrete innovativeness variable, which is calculated for each agent, can capture a range of factors such as social position, farm characteristics, and risk perceptions and attitudes. Therefore, the default random allocation of innovativeness in MPMAS has recently been replaced by a more refined direct assignment approach, which goes beyond previous improvements (Quang et al., 2014; Schreinemachers et al., 2009). It has been argued that risk perception is often absent from adoption research A concern raised by Abadi Ghadim and Pannell (1999) refers to the learning process, which according to them consists of a trial and error period in which farmers evaluate an innovation. The lack of learning-by-doing limits the scope of action of farm agents and constitutes an important shortcoming of the innovation diffusion approach, as modeled in this MPMAS application. It is the result of implementing IPM for leafy vegetables as a perennial crop which prevents agents from abandoning it in the years after adoption, though they can keep the land under IPM idle. The disadvantage of this needs to be weighed against the advantage of using the perennial crop feature for IPM, which allows the model to represent changing yields over the lifetime of an innovation.

In their assessment of economic incentives for pesticide use reduction, Skevas et al. (Skevas et al., 2012) extended the standard econometric model of production function with exponential damage control term, in order to capture the effect of environmental spill-overs such as biodiversity loss. They used data from three cropping seasons and focused on potato farmers only. Predicted coefficients served to model the impact of taxes or quotas on reducing pesticide use, which was split into two toxicity classes. Unlike MP-based models, such a statistical modeling approaches cannot fully represent the substitutions made between a big range of active ingredients. Falconer and Hodge (Falconer, 2000) confirmed that an important reason, why actual responses may be higher than theoretically predicted, is related to the assumptions and reductionist approaches used when modeling, especially with regard to the range of options available to producers. Falconer and Hodge's seminal case study of pesticide use reduction policies in the UK is based on a representative MP farm model and focuses on taxes and levies. The data used for their model stems from experimental trials for 12 crops, those which serve as approximations of conventional and low-input farming production activities (Falconer, 2000, 2001). Similarly, an MP-based pesticide policy model for the French agricultural sector developed by Jacquet et al. (Jacquet et al., 2011) is built on agronomic trial results and expert knowledge. In contrast to these two models, the MPMAS model developed here exhibits a more data driven model set-up, because it contains actual empirical observations with varying pesticide observations. Instead of empirical observations, it would have been possible to resort to expert opinion in order to parameterize the cropping activities for the model. While the entomological and ecological aspects of crop-pesticide interaction could have been represented more accurately, the empirically-grounded model implementation more closely reflects the actions of the farmers themselves. This allows the model to create a vast range of realistic substitution possibilities that fit the agro-ecological conditions, whereas the fit between expert knowledge or site-specific data from well-managed trails and actual farming practices can sometimes be unclear. The simulation period over which these interventions are assessed is deliberately kept brief, so ignoring the interaction of farm-level decision-making and ecological processes, or environmental spill-overs such as pesticide resistance build-up and changes in natural pest control, is less pertinent than when dealing with an extended simulation period. In terms of temporal analysis, the focus of this study is mainly on the short-run diffusion of IPM in relation to different adoption incentives.

6.2 Implications for pesticide policy-making

The issues of food safety and pesticide risk reduction continue to be high on the agenda of Thai policy-makers. This thesis analyses a range of economic instruments that can help to tackle the problem of heavy pesticide use, though not all of these instruments are equally effective, practicable or relevant.

First of all, it needs to be stressed however that policy implications are related to methodology. Skevas et al. (2012) found that a lack of response by Dutch farmers to increases in the price of pesticides is critically influenced by their choice of model. As they used an econometric simulation model based on an exponential damage control specification, the impact of the tax is determined by the low output elasticity of pesticide use. Therefore, a 120% tax only reduced pesticide applications by 4%. The high values of pesticide overuse that result from the econometric pesticide productivity analysis carried out for Thai farmers with a similar methodological set-up, also suggests that the responsiveness of farmers to higher pesticide tax levels of is very low. From their review of 17 studies and an analysis of the potential for pesticide taxation in Mexico, Pina and Forcada (2004) ascertained that own-price elasticities of pesticide demand are generally low, which leads them to conclude that farmers will not change their on-farm practices, but instead decide to absorb impacts through their incomes. The representative MP farm model of Falconer and Hodge (2000, 2001) showed that only high taxes can achieve significant pesticide use reductions. This is in line with the results of the model used here, which demonstrates that, while the tax impact is far from great, a 50% tax can reduce pesticide use by 8.5%. While the model parameterization is influenced by the exponential damage control term, the dynamic optimization process is based on a vast array of activities, constraints and pesticide substitution options, and thus provides a more detailed representation of the actual farm household decision-making environment. In conclusion, MP-based farm models seem to yield more perceptible tax impacts than econometric analyses. At first glance, the sector MP model of Jacquet et al. (2011) produced extra-ordinary results, since a 16% tax reduced pesticide use by 20%. It must be said however that, in contrast to MPMAS, the model was not calibrated to reproduce observed behavior, but set up to explore the capacities of a series of low-input technologies without access constraints. In the MPMAS simulation scenario, in which a 50% tax is combined with low-input IPM access, the innovation becomes available to the first three innovator segments and the reduction of pesticide use rises to 13.5%. The availability of technologies and the sequence of access, both of which are a function of individual characteristics and time, influenced the results significantly. Also, the redistribution effect of the tax revenues has an essential impact on the model outcomes. In this regard, the results here are in line with those of Jacquet et al. (2011), who tested the direct compensation of farmers against the provision of subsidies to organic farming. Their model and the MPMAS application used here provide evidence that financially supporting sustainable farming technologies are more effective at achieving the environmental goal of lower pesticide applications, than the per hectare redistribution of collected taxes. The simulation results of both models indicate that, due to the good rate of return provided by low-input innovation, incomes are on average not negatively affected by policy-induced land-use changes.

For policy makers, it is important of know which policy mix works best. It turned out that the high level bio-pesticide subsidy is the most cost effective, practicable and realizable adoption incentive policy. The MPMAS model demonstrates that the combination of a high proportional tax and a 60% bio-pesticide subsidy, one financed by tax revenues, reduces overall pesticide use after five simulation periods by 18%, and more toxic pesticide use by almost 25%. With additional funds it could be possible to sustain a 80% bio-pesticide subsidy and, as a result, increase toxic pesticide use reductions to almost 35%. On the whole, reductions of that magnitude can be considered significant over a short time horizon. This finding is in line with those of Falconer and Hodge (Falconer, 2000), who stated that taxes can be more effective if farmers are provided with pest control alternatives. The lack of alternatives to synthetic pesticides among Thai farmers has been described as one of the main factors causing the high levels of pesticide use in the country (Lamers et al., 2013; Schreinemachers et al., 2011). Praneetvatakul et al. (2013) concluded that it is best to introduce a package of policies that combines an environmental tax with supportive measures to help farmers change their on-farm practices. This research has confirmed this, by showing that the availability of IPM for one group of vegetable crops can bring down pesticide pollution levels, especially if accompanied by policies to incentivize adoption. Due to a lack of data, IPM methods are only included in the model for leafy vegetables. With integrated pest control available for other cropping activities, in particular bell peppers, tomatoes and flowers, even more far-reaching reductions can be achieved. The same is likely to be the case for a time horizon above five simulation periods; however, due to the innovation diffusion over time, the long-term financing of bio-pesticide subsidies or price premiums might not be covered by tax revenues. One way to guarantee financing for subsidies and price premiums would be to cap the number of eligible farmers or the amount of eligible land. Transaction costs, for which no estimates were available in the model, can be assumed to be lower when implementing a single incentive policy with a policy infrastructure already in place, rather than a mix of payments, subsidies and price premiums. At the moment however, subsidies for conventional agriculture continue to dominate, and there is a lack of government will to promote sustainably produced products in the domestic market, despite official commitments to the contrary. Kasem and Thapa (Kasem and Thapa, 2012) pointed out that there is a clear divergence between the commitments of policy-makers, and actual practice in Thailand.

In addition, a crucial factor in the impact of policies on pesticide use is the nature of the accompanying innovation. GAP certification is not the subject of innovation diffusion in the MPMAS model, as evidence suggests that the public GAP standard in Thailand has little impact on reducing pesticide use due to a lack of standard compliance and changes in on-farm practices (Amekawa, 2013; Schreinemachers et al., 2012), but it was decided to use a more far-reaching sustainability innovation, that is the IPM system practiced by farmers belonging to Royal Project station in Doi Angkhang. The transfer of data from that location to the Mae Sa watershed can be regarded as unproblematic in terms of crop suitability, since the climate, soils and topography are similar in both locations. Extension services, which supports farmers through the provision of production and marketing advice, need to be further developed. In places, with a lack of solid advisory structures, an innovation, such as a comprehensive agro-ecological IPM system, which requires a high degree of skill transfer and logistics to be in place, is more difficult to become established. The preparation of biological pest control and fertilizing inputs, as well as the sequence of input applications for IPM is knowledge-intensive. Investments are required to improve the capacity of government agencies and NGOs to better respond to farmers' demands, facilitate knowledge exchange and strengthen community initiatives. Farmer field schools have been successfully tested in Southeast Asia in order to implement community IPM (Pontius et al., 2002), but they need to be tailored to the local circumstances. In the context of northern Thailand, agro-ecological IPM practices are not widespread. The example of Doi Angkhang, as well as the econometric analysis of GAP certification adoption provided here, suggests that formal institutions providing effective extension services are important. This however does not rule out to link formal advisory services to informal farmer networks and promote participatory approaches that take into account the diversity of demand for innovations, and allow farmers to adapt innovations to their needs. Their role in Thailand has been found to be important (Schreinemachers et al., 2013). Also in this study, exposure, that is the links between farmers who are aware and those who are not aware of an innovation, is also shown to be vital for innovation adoption. For public investments this means policy-makers needs to prioritize the building of long-term interactive knowledge partnerships and innovation networks (Neef et al., 2013).

The outcomes of the MPMAS model imply that, if the institutional context allows for knowledge of IPM innovations to take root among local communities, the integrated management of pests will be widely adopted, implemented and due to its profitability sustained in the long run. Different types of interventions need to be balanced. Policies aimed at addressing the environmental externalities caused by market participation for example should be combined with socially-oriented policies that target poorer segments of the population (Zeller et al., 2013). The prediction of innovativeness and the simulation results regarding IPM adoption shown here demonstrate that poorer households can be innovative and so benefit from the introduction of farm-income increasing innovations, such as IPM. Only the wealthier and highly polluting households benefit little. In a nutshell, integrated pest management can partly mitigate the environmental impacts of agricultural intensification, without negatively affecting livelihoods. A trade-off between environmental protection and livelihoods can be avoided if policy-makers manage to introduce economic incentives to motivate changes in growing practices as well as create an enabling environment in which farmers can learn about IPM.

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Tables

Table 13: Basic farm household and farm characteristics

Part of the Mae Sa Watershed	Hh size	Education	Liquidity per cap.	Debt per cap.	On-farm labour	Off-farm labour	Hired labour	Farm age	Farm size	No. of greenh.	Irrigated	Land w/o title	GAP certific.	Grow > 1 crop	Royal Project
	Pers.	%	1000 baht	1000 baht	md/ m/hh	md/ m/hh	md/ m/hh	y.	ha	#	%	%	%	%	%
Central-Mid	3.6	95	66.3	32.6	51.8	21.3	8.8	22	0.8	8.4	50	35	11	56	9
Central-High	3.2	100	74.9	41.6	50.1	15.6	10.7	23.8	0.7	11.0	1	29	23	69	14
Southern-High	6.6	58	28.6	10.8	81.6	22.3	14.1	24.8	2.0	1.8	1	97	45	78	58
Western-High	6.1	62	35.4	7.2	75.9	11.6	19.1	24	2.2	1.6	11	100	0	62	33
Northern-High	7.1	66	28.1	4.9	94.4	18.2	17.6	21	2.2	0.5	52	96	26	100	64

Note: md = mandays, m = months, hh = household

Table 14: Production data for IPM vegetable rotations as practiced by farmers at Doi Angkhang (2012, n = 34)

Growing length	Labor requirement	Bacillus turingh.	Bacillus subtilis	Tricho-derma	Azadi-rachtin	Metazan	Bio-pesticide costs	Other var. costs	Sales revenues
(months)	(mandays /ha/ month)	(kg/ha/ month)	(kg/ha/ month)	(kg/ha/ month)	(kg/ha/ month)	(kg/ha/ month)	(baht/ha/ month)	(baht/ha/ month)	(baht/ha/ month)
Rotation option 1: Cool season cabbage -> Hot season lettuce -> Rainy season spinach									
2.33	693	11.15	4.00	4.00	0.82	1.16	7,334	18,412	202,499
Rotation option 2: Cool season lettuce -> Hot season spinach -> Rainy season cabbage									
2.33	407	6.46	11.15	4.00	4.00	0.81	7,334	21,063	114,488
Rotation option 3: Cool season spinach -> Hot season lettuce -> Rainy season cabbage									
2.33	334	10.56	6.46	5.21	5.21	0.00	5,479	14,535	82,962

Table 15: Crop data selected for the MP matrix

Crop	Observations by land – flat (1) to steep (4)				Growing length	Yield	Labor	Variable inputs	Pesticide use	Irrigated
	1(#)	2(#)	3(#)	4(#)	Months	tons/ha	mandays/ha	1000baht/ha	kg/ha	%
Upland rice	3	2	2	2	5.73	1.68	15.61	2.04	0.20	0
Maize	1	2	4	4	4.73	2.24	9.79	0.59	0.07	9
White cabbage	6	14	26	20	3.36	25.64	95.19	30.55	1.58	26
Chinese cabbage	6	14	26	20	2.49	23.66	97.84	21.17	2.09	56
Chinese kale	8	3	8	4	2.32	5.93	211.83	15.91	1.62	96
Lettuce	2	9	10	3	2.48	9.45	100.12	23.68	0.94	54
Bell pepper	32	13	6	4	5.64	45.99	247.02	434.08	29.45	100
Tomato	2	4	7	2	5.20	68.68	416.18	591.52	14.34	100
Onion	3	3	3	3	4.00	26.30	165.29	85.72	8.61	100
Green bean	5	11	8	4	3.00	8.97	152.06	13.25	1.59	89
Chayote	10	9	2	6	6.23	18.67	178.99	85.76	0.09	96
Chrysanthemum	12	2	11	0	4.33	52.12	198.85	32.91	12.23	100
Roses	2	2	2	2	12.00	164.37	133.46	131.92	19.44	100
Litchi	12	12	12	12	12.00	4.05	11.80	3.32	0.82	67

Table 16: Probit regression with sample selection - Output

	GAP standard certification (probit model)		GAP knowledge (selection model)	
Variables	Coef.	SE	Coef.	SE
Household size (#)	0.023	0.051	0.007	0.042
Farm size (ha)	-0.386***	0.103	-0.093	0.081
Percentage of high value vegetables (%)	0.860**	0.399	0.315	0.251
Percentage of litchi (%)	2.023***	0.418	0.363	0.349
Farm age (years)	-0.045**	0.020	0.014	0.012
Age household head (years)	0.070***	0.024	-0.006	0.012
Education (yes=1)	1.148***	0.291	0.809***	0.223
Grow more than 1 crop (yes=1)	0.821**	0.396	0.339	0.214
Applying pesticides regularly (yes=1)	0.361	0.223	0.345**	0.174
Liquidity per capita (1000 baht)	0.003***	0.001	0.001	0.001
Own motorbike (yes=1)	0.668*	0.344	0.379*	0.237
Member of Royal Project (yes=1)	1.502***	0.229	1.054***	0.163
Exposure (#)	2.201***	0.607	2.194***	0.439
Village head (yes=1)	-1.009*	0.543	-0.021	0.454
Born in the Mae Sa watershed (yes=1)			-0.014	0.168
Constant	-7.506	1.072	-3.163	0.669
N	111		295	
Wald chi2 = 342.778, Prob. > chi2 = 0.000				
LR test of independent equations (rho = 0): Chi2 = 3.88; Prob. > chi2 = 0.049				

Note: Significance levels: *P < 0.10, **P < 0.05, ***P < 0.01

Table 17: Data of perennials crops in the model

Perennial crop	Lifespan	Acquisition cost	Price	Av. yield potential	Av. crop yield factor	Av. labor	Av. cash cost
	Years	1000 baht/ha	1000 baht/ton	ton/ha		mandays/ha	1000 baht/ha
Litchi low input	30	2.43	9.23	2.10	0.78	106.02	0.00
Litchi average input	30	2.43	9.23	3.08	0.78	111.88	2.35
Litchi high input	30	2.43	9.23	5.53	0.78	217.92	6.43
IPM veg. rotation 1	6	9.12	11.70	56.77	0.90	3,378.51	165.4
IPM veg. rotation 2	6	9.12	11.00	64.07	0.90	3,751.65	176.2
IPM veg. rotation 3	6	9.12	12.60	42.86	0.90	3,008.31	130.5
Roses	6	96.21	8.20	157.64	0.90	1,565.81	141.5

Note: The price for flowers is given in 1000 baht/1000 flowers and the yield in 1000 fl./ha.

Table 18: Part of the MP model showing simplified implementation of IPM vegetables as perennial crops

	Units	Constraints (#)	Sell IPM produce	Buy bio-pestic.	IPM vegetables – rotation 1				IPM vegetables – rotation 2				Transfer land	Transfer labor	Sign	RHS
					Invest	Grow	Switch to rotation 2	Idle	Invest	Grow	Switch to rotation 1	Idle				
Units			kg	kg	ha	ha	ha	ha	ha	ha	ha	ha	ha	md.		
Activities (#)			2	5	12	12	24	12	12	12	24	12	4	1		
Objective function			E(+C)	E(-C)												
Invest land	ha	4			1				1						≤	0
Land	ha	4											1		=	**(+R)**
Labour	md.	1												1	≤	**(+R)**
Monthly water	l/sec	12			(+A)	(+A)	(+A)		(+A)	(+A)	(+A)				≤	**(+R)**
IPM land	ha	12			+1	+1	+1	+1	+1	+1	+1	+1			=	**(+R)**
IPM innov. Access	-	1			**(+1)**	**(+1)**	**(+1)**	**(+1)**	**(+1)**	**(+1)**	**(+1)**	**(+1)**			≤	**(+I)**
Capital use	Baht	1			(+A)	(+A)	(+A)		(+A)	(+A)	(+A)				≤	**(+R)**
Sprinkler irrigation	ha	12			+1	+1	+1		+1	+1	+1				≤	**(+R)**
Balance bio-pestic.	Kg	5		-1	+A	+A	+A		+A	+A	+A				≤	0
Balance monthly land	ha	48			+1	+1	+1		+1	+1	+1			-1	≤	0
Bal. labor IPM veg.	md.	1			(+A)	(+A)	(+A)		(+A)	(+A)	(+A)			-1	≤	0
Balance IPM veg.	kg	6	+1			**E(-Y)**	**E(-Y)**			**E(-Y)**	**E(-Y)**				≤	0

Note: E = Expected values, C = Price coefficients, Y = Crop Yields, A = Technical coefficients, R = Available resources, I = Available innovations. Values in round brackets are adjusted inside the model. Bold values are agent-specific. md.= mandays

Table 19: Overview of policies at different intervention levels

Intervention	Low (1)	Medium (2)	High (3)
Prop. tax (+ compensation payment)	WHOIa & Ib: 20% WHOII: 15% WHOIII: 10% WHOU: 5% WHONL: 5%	WHOIa & Ib: 50% WHOII: 40% WHOIII: 30% WHOU: 20% WHONL: 20%	WHOIa & Ib: 70% WHOII: 50% WHOIII: 40% WHOU: 30% WHONL: 30%
Price premium for IPM produce	2% price increase	5% price increase	10% price increase
Bio-pesticide subsidy	20% price decrease	40% price decrease	60% price decrease

Table 20: Summary statistics for validation results for three outcome variables across all seed values

	Land-use		Sales revenues		Pesticide use	
	Coef.	R2	Coef.	R2	Coef.	R2
Obs.	19	19	19	19	19	19
Mean	0.991	0.995	0.960	0.962	0.980	0.981
Std. dev.	0.008	0.001	0.008	0.004	0.001	0.001
Min.	0.976	0.994	0.944	0.951	0.978	0.980
Max.	1.004	0.997	0.973	0.970	0.985	0.982

Table 21: Evaluation of interventions for tax scenario impacts when compared to the baseline

Scenario name	Δ income		Tax revenues	Δ pesticide use		Δ toxic pesticide use	
				Av.	P. 5	Av.	P. 5
	(%)	(1000 baht/hh)	(1000 baht/hh)	(%)	(%)	(%)	(%)
Low proportional tax	-1.24	-3.17	1.48	-2.06	-2.08	-2.67	-2.74
Medium proportional tax	-3.96	-10.10	4.21	-5.03	-5.12	-6.26	-6.29
High proportional tax	-6.56	-16.71	6.74	-7.34	-7.38	-8.26	-8.27
High prop. tax + compensation	-4.81	-12.28	6.73	-7.47	-7.46	-8.27	-8.21

Note: Averages over all agents and simulation periods, values represent the difference between the respective scenario and the baseline

Table 22: Evaluation of policies for IPM + adoption incentives

Scenario	Δ income		Policy costs	Net benefit	Δ pesticide use		Δ toxic pes. use		Cost-effectiveness
					Av.	P. 5	Av.	P. 5	
	%	1000 baht/hh	1000 baht/hh	1000 baht/hh	%	%	%	%	policy costs/ av. Δ toxic pes. use
IPM, stand-alone	10.93	28.31	0.00	28.31	-5.53	-9.71	-7.81	-12.95	-
IPM + low price prem.	11.74	30.43	1.50	28.93	-5.74	-10.11	-8.26	-13.47	-0.18
IPM + med. price prem.	12.08	31.36	3.85	27.50	-6.62	-11.04	-9.30	-14.69	-0.41
IPM + high price prem.	17.01	44.32	10.48	33.85	-10.09	-22.17	-13.10	-27.25	-0.80
IPM + low subsidy	11.20	29.02	0.96	28.06	-5.92	-10.65	-8.28	-13.63	-0.12
IPM + med subsidy	11.97	31.02	1.95	29.07	-6.02	-10.81	-8.60	-14.15	-0.23
IPM + high subsidy	12.07	31.36	3.01	28.35	-6.49	-11.17	-9.29	-14.90	-0.32

Note: Averages over all agents and simulation periods, values represent the difference between the respective scenario and the baseline, for pesticide use reductions average (Av.) & period 5 (P.5) values are reported.

Table 23: Land-use changes for IPM + adoption incentives

Scenario	Cereals	Leafy veg.	Greenh. veg.	Other veg.	Flowers	Fruit tree	IPM
Name	%	%	%	%	%	%	ha
IPM, stand-alone	-0.81	-19.31	-12.36	-34.71	-2.37	-1.17	207.25
IPM + low price prem.	-0.81	-19.65	-12.37	-36.77	-2.41	-0.52	218.60
IPM + med. price prem.	-1.31	-20.45	-13.21	-38.47	-2.82	-0.77	230.44
IPM + high price prem.	-7.90	-34.32	-29.92	-72.21	-6.25	-0.20	413.92
IPM + low subsidy	-0.73	-19.66	-12.58	-36.52	-4.06	-0.52	216.89
IPM + med subsidy	-1.41	-20.23	-13.02	-37.51	-2.63	-0.69	224.04
IPM + high subsidy	-1.37	-20.78	-13.55	-38.50	-2.80	-0.42	233.16

Note: Results of period 5 averaged over all agents, values represent the difference between the respective scenario and the baseline, total cultivated area in the model: 1100 ha

Table 24: Evaluation of policy packages

Scenario	Δ income Av.	Tax revenues Av.	Policy costs Av.	Δ pesticide use Av.	P. 5	Δ highly toxic pesticide use Av.	P. 5	Innov. access P. 5	IPM area P. 5
IPM + tax +	(%)	(1000 baht/hh)	(1000 baht/hh)	(%)	(%)	(%)	(%)	(Adopter group)	(ha)
No other intervention	4.9	6.2	0.0	-12.9	-17.8	-16.3	-21.7	Early majority	215.7
Direct compensation	6.0	6.2	-6.2	-12.8	-17.9	-16.3	-21.8	Early majority	215.9
Price premium 5%	5.7	6.1	-4.1	-14.4	-20.1	-17.9	-24.4	Early majority	237.5
Bio-pesticide subsidy 60%	5.5	6.1	-3.2	-14.9	-20.1	-17.9	-24.5	Early majority	239.9
Bio-pesticide subsidy 80%	8.7	5.9	-5.4	-17.4	-29.0	-20.7	-34.3	Late majority	414.5

Note: Averages over all agents and simulation periods; values represent the difference between the respective scenario and the baseline, for average pesticide use reductions (Av.) and period 5 (P.5), values are reported.

Figures

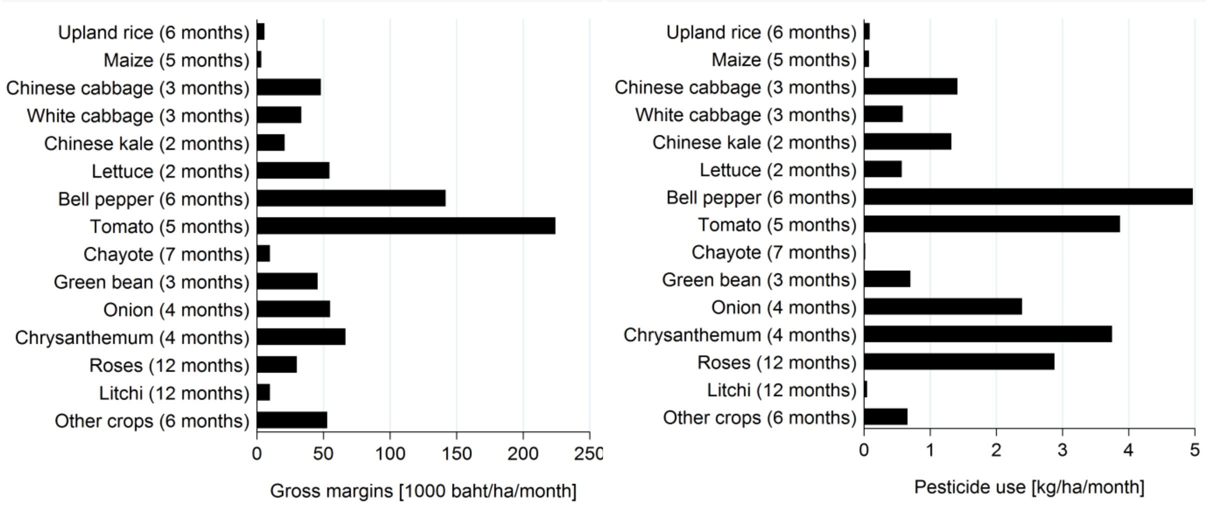

Figure 7: Gross margins and pesticide use for different crops (growing period in brackets)

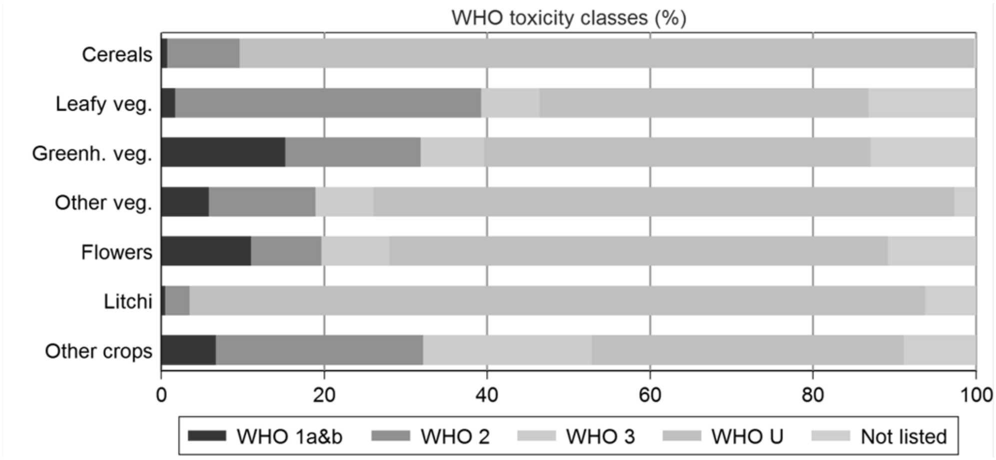

Figure 8: Proportion of pesticides used by different types and WHO toxicity classes

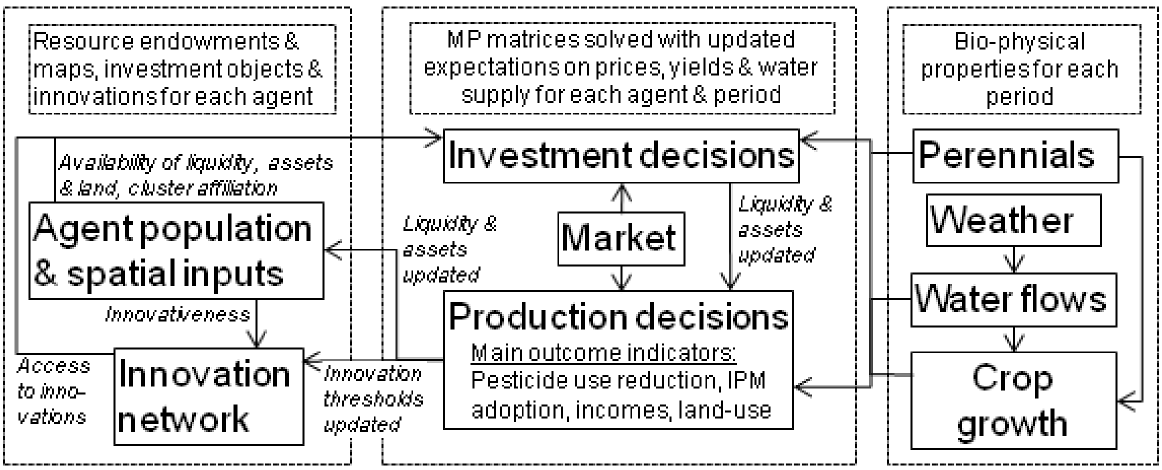

Figure 9: Dynamics of the MPMAS Mae Sa watershed model

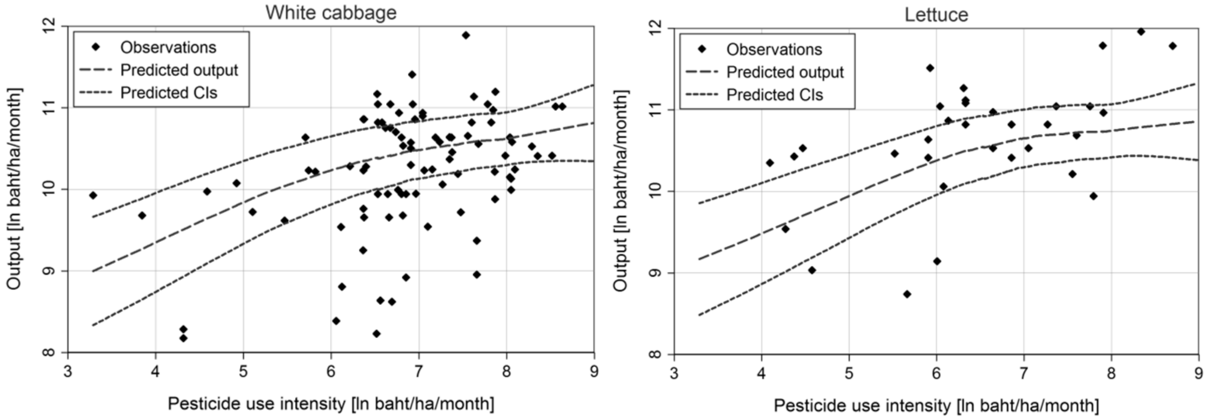

Figure 10: Representation of the estimated confidence intervals (CIs) used for data selection

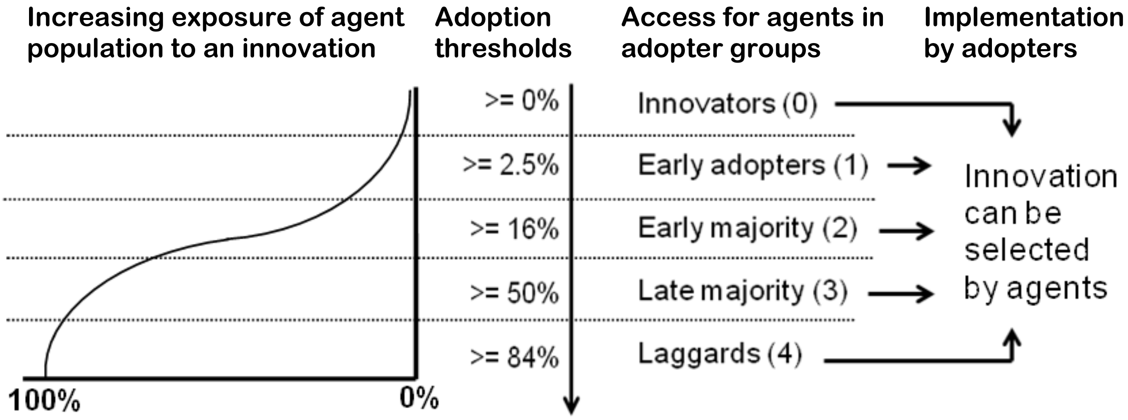

Figure 11: Model of innovation diffusion in MPMAS

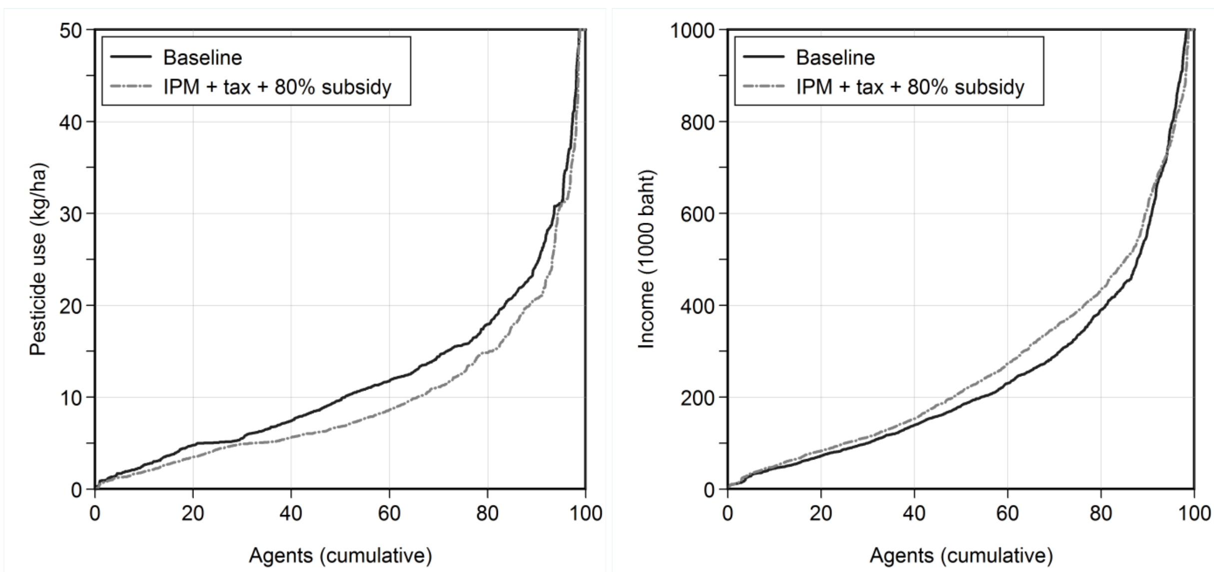

Figure 12: Disaggregated pesticide use and income changes