Received: 7 June 2022 | Accepted: 6 May 2023

DOI: 10.1111/1467-8489.12521

The Australian Journal of Agricultural and Resource Economics | AARES Australasian Agricultural & Resource Economics Society

ORIGINAL ARTICLE

Measuring pesticide overuse and its determinants: Evidence from Vietnamese rice and fruit farms

Lan Tran[1,2] | **Theodoros Skevas**[1] | **Laura McCann**[1]

[1]Division of Applied Social Sciences, University of Missouri, Columbia, Missouri, USA

[2]University of Business and Economics, Vietnam National University, Hanoi, Vietnam

Correspondence
Laura McCann, Division of Applied Social Sciences, University of Missouri, 214 Mumford Hall, Columbia, MO 65211, USA.
Email: mccannl@missouri.edu

Abstract

Pesticides have long been important for the development of agricultural production. However, improper use of pesticides may result in inefficiency with respect to farm profitability, in addition to external effects of pesticide use on environmental and human health. This paper employs a production function that explicitly accounts for the role of damage abatement inputs (i.e. pesticides) in the production process, to examine the optimal use of pesticides. It then investigates determinants of pesticide overuse versus underuse and the intensity of overuse. The empirical application uses data on Vietnamese rice and fruit farms drawn from the 2016 Vietnamese Household Living Standards Survey. Results show about 95% of farmers overused pesticides for both rice and fruit farming systems. The Mekong Delta, also known as the 'Rice Bowl' of Vietnam, has higher levels of overuse on rice farms than two other regions. Overuse intensity is lower for female and poorer rice farmers while intensity is higher for those with more income and more family members. For fruit farms, younger farmers or those with more family members were more likely to overuse versus underuse pesticides.

KEYWORDS

fruit trees, overuse intensity, pesticide overuse, rice, Vietnam

1 | INTRODUCTION

Pesticides are important inputs in modern agriculture for ensuring high quantity and quality of agricultural production. In 2017, about 4.1 million tonnes of pesticides were used in agriculture worldwide (FAOSTAT, 2019). The use of these chemicals has been dramatically increasing during the last three decades especially in developing countries (Ecobichon, 2001; Schreinemachers & Tipraqsa, 2012; Sharma et al., 2019). Despite the benefits of pesticides, their indiscriminate use has led to serious health and environmental risks (Antle & Pingali, 1994; Dasgupta, Meisner, & Wheeler, 2007; Lamers et al., 2013; Pingali, 2004; Sarkar et al., 2021; Teklu et al., 2022; WHO-FAO, 2019). The growing concerns regarding the environmental and health effects of pesticides have stimulated intensive research efforts into understanding farmers' pesticide use behaviour and its determinants.

Vietnam has widely promoted pesticide use in agricultural production since the 1990s (Meisner, 2005). Pesticide consumption drastically increased from about 20,000 tonnes of 96 different pesticide formulations in 1991 to more than 150,000 tonnes of about 4000 formulations in 2017 (General Statistics Office of Vietnam, 2018). The rising quantity and types of pesticides indicate the increasingly heavy reliance on pesticides for pest control.

While pesticides indeed have benefited agricultural crop production in Vietnam, their improper use has caused a variety of problems, such as environmental pollution and adverse health impacts on animals and humans. Pesticides, even highly hazardous pesticides, have been misused in Vietnam due to the absence of pesticide regulations, and farmer's lack of knowledge and proper equipment (Hoi et al., 2013; Toan et al., 2013). Minh et al. (2008) showed that in Vietnam, contamination of air, water and sediment due to persistent organic pollutants, especially organic chlorinated insecticides, is higher than in developed countries such as Japan. In another study, Hoai et al. (2010) also indicated many water samples have been seriously polluted with dichlorodiphenyltrichloroethane, hexachlorocyclohexane and endosulfan. According to Dang et al. (2007), improper use of pesticides has been an important factor leading to an increase in noncommunicable diseases including neurobehavioural development, cancer, infertility and other reproductive problems. Vietnamese farmers and their families are directly and indirectly exposed to pesticides from their work in fields, their contaminated clothes or the pollution of local water supplies. They are faced with multiple symptoms of chronic poisoning: skin irritation, headache, dizziness, eye irritation and respiratory problems (Dasgupta, Meisner, & Wheeler, 2007; Murphy et al., 2002). Continuous misuse and overuse of pesticides have also caused negative effects on fish or shrimp farming, which are often combined with rice cultivation in the Mekong Delta (Berg, 2001; Klemick & Lichtenberg, 2008; Tam et al., 2015).

Understanding pesticide use in Vietnam is thus important for farmers' incomes and health status, as well as the environment. Identifying significant factors affecting the overuse of pesticides is also important for designing improved policies and educational efforts in Vietnam aimed at improving pesticide use efficiency and protecting public health and the environment. We examine rice and fruit farming because they have special roles in Vietnam's agriculture. Rice is the major crop in Vietnam, grown by 80% of the rural population, and Vietnam is the second largest rice exporter in the world, but fruits have seen considerable growth in recent years (GSO, 2018). Moreover, while rice farms represent 63% of all pesticide use, the largest average expenditure for pesticides is on fruit farms.

In this study, we add to previous research by examining whether pesticides are overused or underused on Vietnam's rice and fruit farms, and the factors leading to pesticide overuse versus underuse. The study utilises a Cobb–Douglas specification for the production function where pesticides are treated as damage abatement inputs to estimate a privately optimal pesticide use level. The difference between actual and optimal use of pesticides at the farm level would measure pesticide overuse (underuse) on each farm. For the identification of determinants of pesticide overuse versus underuse, we employ probit models to examine factors affecting the probability of overusing pesticides. Truncated regression models are then used to assess the effects of these same factors on the intensity of pesticide overuse. This research contributes to the literature in several ways. First, it provides the first nationwide assessment of pesticide overuse at the farm level in Vietnam. Second, unlike other pesticide overuse studies focussing on relatively homogeneous groups of crops such as vegetables (Schreinemachers et al., 2020; Singbo et al., 2015), rice (Wang et al., 2018) or arable crops (Skevas et al., 2012), this study examines pesticide overuse in two important but divergent crops, rice and tree fruits. Third, it adds to the scarce literature on the determinants of pesticide overuse in agriculture (Schreinemachers et al., 2020; Wang et al., 2018).

In the next section, we present relevant empirical studies and theoretical literature about pesticide use in crop production, especially in developing countries. We then describe the methodology used and provide data descriptions for the study. In the subsequent section, we report empirical results of pesticide overuse measurements and present significant factors affecting pesticide overuse in rice and fruit farming, separately. The paper ends with a brief summary and a discussion of the implications and limitations of the study.

2 | LITERATURE REVIEW

2.1 | Defining and measuring pesticide overuse

Agricultural production has always involved the use of resources or inputs such as farmland, labour, physical capital and variable inputs such as fertilisers, pesticides, energy and custom services to produce outputs (e.g. crops). Since the Green Revolution, there have been considerable changes in input use in agriculture (e.g. increased use of fertilisers and pesticides, and decreased use of labour and land). Increased efficiency of input use can lead to reduced production costs and, in the case of polluting inputs such as pesticides, higher environmental quality. The efficiency of input use has become a focus for enhancing agricultural productivity growth, especially in developing countries where existing technology has usually not been used efficiently (Belbase & Grabowski, 1985; Bravo-Ureta & Pinheiro, 1993; Fan et al., 2012).

Although the literature on the measurement of farm-level pesticide use efficiency is limited, this is not the case with the literature on farm-level pesticide overuse. The term 'pesticide overuse' has been used in numerous pesticide studies, especially in developing countries, but with different definitions. Legally, 'overuse' refers to pesticide applications that exceed the standard dosage recommended by the pesticide label or experts such as agronomists, extension agents or retail sellers (e.g. Aniah et al., 2021; Jallow et al., 2017). This definition conforms to pesticide laws and regulations, description of agrochemical companies and farmers' knowledge. From an economic point of view, pesticide overuse occurs when the amount used is greater than the economic optimum or the profit maximising level of pesticides (e.g. Schreinemachers et al., 2020). The estimated value of marginal product (VMP) and marginal cost of pesticides are crucial to determine the presence of pesticide overuse. When the estimated VMP is lower (higher) than the marginal cost, pesticides are overused (underused) according to the economic approach.

Various attempts have determined pesticide overuse in the literature. Most studies found overuse of pesticides is common in Asian developing countries, either using the agronomic approach (Aniah et al., 2021; Dasgupta, Meisner, Wheeler, Xuyen, et al., 2007; Jallow et al., 2017; Khan et al., 2015; Qin & Lü, 2020; Shetty, 2004; Wu et al., 2018; Zhang et al., 2015) or using the economic approach (Huang et al., 2020; Schreinemachers et al., 2020; Sun et al., 2020; Wang et al., 2018). A few studies have examined both pesticide efficiency and overuse, all using a Data Envelopment Analysis modelling framework and the economic definition of pesticide overuse at the farmer level (Lansink & Silva, 2004; Singbo et al., 2015; Skevas et al., 2014). For instance, Skevas et al. (2014) showed pesticides on average are overused in cash crop farms in the Netherlands, although there are a small number of farms that underuse insecticides and fungicides. In a developing country setting, Singbo et al. (2015) also found the general presence of pesticide overuse in vegetable production in Nigeria. While beyond the scope of our research, several studies also accounted for the negative effects of pesticide use on human health and the environment (e.g. Grovermann et al., 2013; Pimentel, 2005; Veettil et al., 2017).

2.2 | Determinants of pesticide overusing farms/farmers

While measuring overuse of pesticides is an evolving area of research, there are numerous studies examining the factors affecting pesticide use in agriculture but fewer studies assessing the determinants of pesticide overuse. In this review, we therefore examine previous research on determinants of pesticide use and overuse based on both agronomic and economic considerations in order to develop a robust set of potential determinants. Factors that increase pesticide quantity/expenditure may be potential determinants of overuse since they positively affect the amount of pesticides used in the agronomic approach or decrease the VMP as an economic criterion of overuse. The following review integrates all these perspectives to develop potential determinants of pesticide overuse (Table 1).

Several sociodemographic characteristics such as gender, age, education, household size and household income may have impacts on overuse of pesticides in agriculture. The effect of gender is not clear; for example, Wang et al. (2018) found men are less likely to overuse pesticides than women because most female farmers are less experienced in developing countries such as China. This result is contrary to the finding of Schreinemachers et al. (2020) for female farmers in Southeast Asia. Rahman and Chima (2018) also suggest that female-headed households have lower access to modern inputs such as pesticides than male ones in Nigeria.

The effect of age is fairly clear in pesticide overuse studies. Older farmers tend to overapply pesticides compared with younger farmers because they do not follow the standard dosage (Dasgupta, Meisner, & Wheeler, 2007; Dasgupta, Meisner, Wheeler, Xuyen, et al., 2007) or they do not easily change their habits regarding pesticide application (Huang et al., 2020). This may relate to older farmers in general making farming decisions based on their experience rather than regulations or economic efficiency. However, experienced farmers may have knowledge about how to control pests without heavy reliance on pesticides, ensuring a high VMP of pesticides, and less overuse (Jallow et al., 2017; Wang et al., 2018).

More educated farmers are less likely to overuse pesticides, which is expected because they tend to follow the instructions on pesticide labels or given by agronomic experts (Jallow et al., 2017; Khan et al., 2015). However, the effect of educational programmes such as integrated pest management or good agricultural practices training on pesticide overuse is indeterminant (Jallow et al., 2017; Wang et al., 2018).

The effects of household size and income on pesticide overuse are not clear. Family farms in Vietnam with more members working in the fields tend to have use of pesticides, possibly implying a lower probability of pesticide overuse (Migheli, 2017). However, this has not been directly examined in pesticide overuse studies yet. Higher income households can afford to buy more pesticides (quantity and type), leading to higher probability of pesticide overuse (Huang et al., 2020). This may contradict the result of Migheli (2017) who suggests higher income can reduce pesticide use and enable more expensive solutions such as organic or biological controls. On the contrary, off-farm income, as a percentage of total income, represents both affordability and farm labour substitution, and negatively affects the use of pesticides (Migheli, 2017), potentially implying lower probability of pesticide overuse for higher off-farm income due to the substitution effect. Reliance on farm income to meet household expenses may encourage farmers to use more pesticides, especially when the latter are viewed as risk-reducing inputs (Skevas et al., 2014), all else equal.

Farmer/farm attributes such as risk aversion, farm size, crop and location have been introduced as potential determinants of pesticide overuse. A risk-averse farmer mostly uses pesticides for crop protection. The literature shows that they tend to use more pesticides than required, leading to higher probability of pesticide overuse (Jallow et al., 2017; Qin & Lü, 2020). In China, risk-averse subsistence farmers were likely to have higher pesticide use than risk-neutral farmers (Gong et al., 2016).

TABLE 1 Factors affecting pesticide use (quantities/overuse) in agricultural production.

No.	Determinants	Quantity/Expenditure of pesticides: Effect	Quantity/Expenditure of pesticides: Articles	Overuse of pesticides by agronomic/Legal definition: Effect	Overuse of pesticides by agronomic/Legal definition: Articles	Overuse of pesticides by economic criteria: Effect	Overuse of pesticides by economic criteria: Articles
Demographic characteristics							
1	Male[a]	+	Rahman and Chima (2018)			− +	Wang et al. (2018), Schreinemachers et al. (2020)
2	Age	+/−	Huang et al. (2000), Migheli (2017), Zheng et al. (2020)	+	Dasgupta, Meisner, and Wheeler (2007)	+	Huang et al. (2020)
3	Farming experience	+	Rahman and Chima (2018)	−	Jallow et al. (2017)	+ −	Huang et al. (2020), Wang et al. (2018)
4	Education			−	Khan et al. (2015), Jallow et al. (2017)		
5	IPM training[a]			+	Khan et al. (2015), Jallow et al. (2017)	−	Wang et al. (2018)
6	Household size (working on farm)	−	Migheli (2017)				
7	Income	−	Migheli (2017)			+	Huang et al. (2020)
8	Off-farm income	−	Migheli (2017)				
Farmer/farm characteristics							
9	Risk-averse[a]	+	Huang et al. (2000), Mariyono et al. (2018)	+	Qin and Lü (2020); Jallow et al. (2017)		
10	Farm/land ownership[a]	+	Migheli (2017)	+	Dasgupta, Meisner, and Wheeler (2007)		
11	Farm size			+/−	Qin and Lü (2020); Wu et al. (2018)	− +	Huang et al. (2020), Schreinemachers et al. (2020)

(Continues)

TABLE 1 (Continued)

		Quantity/Expenditure of pesticides		Overuse of pesticides by agronomic/Legal definition		Overuse of pesticides by economic criteria	
No.	**Determinants**	**Effect**	**Articles**	**Effect**	**Articles**	**Effect**	**Articles**
12	Crop	+/−	Douglas and Tooker (2015), Migheli (2017)	+/−	Dasgupta, Meisner, and Wheeler (2007)		
13	Location (e.g. climate and pest population)			+/−	Dasgupta, Meisner, and Wheeler (2007) (Shetty (2004)		
14	Debt[a]	+	Migheli (2017)				
15	Retailer's information[a]			+	Jallow et al. (2017)	+	Schreinemachers et al. (2020)
16	Joining cooperatives[a]			−	Qin and Lü (2020)	−	Huang et al. (2020)
17	Extension accessibility[a]			−	Jallow et al. (2017)	−	Schreinemachers et al. (2020)

Abbreviation: IPM, integrated pest management.

All effects are statistically significant at least at the 10% level. The plus (+) sign means the effect is positive; the minus (−) sign means the effect is negative; the plus/minus (+/−) means the direction of the effect is indeterminate (i.e. some studies have found a positive effect and others have found a negative effect).

[a]The determinants are binary (dummy) variables.

The effect of farm size on overuse in general is indeterminant. In the paper by Wu et al. (2018), small farms in China, typically about 0.1 ha for each parcel, were strongly related to overuse of pesticides because of lack of farming knowledge and management skills. In contrast, Qin and Lü (2020) found large-scale rice farms tend to overuse pesticides compared with small-scale rice farms because of differences in market orientation of these farms. In particular, the probability of pesticide overuse among small farms is lower than that among large farms when the rice eaten by households is a large proportion of their yield.

Empirical studies have shown crop and locational factors as significant determinants of pesticide overuse (e.g. Dasgupta, Meisner, & Wheeler, 2007; Migheli, 2017; Shetty, 2004). Different crops require different use of pesticides, since there is a range of pests and diseases associated with each crop. For example, rice versus fruit (apples, peaches and strawberries) production is often faced with different kinds of insects and diseases. Moreover, fruit crops often require a considerable number of preventive applications to produce acceptable fruit quality (Skevas et al., 2016). Locational factors relate to climate, rainfall (drought), temperature and pest population, as well as pesticide availability, which affect the use and overuse of pesticides.

Additional socio-economic factors such as debt, access to information from retailers, membership in agricultural cooperatives and extension availability are also possible determinants of pesticide overuse. Migheli (2017) showed farmers who have informal debt are more likely to increase the quantity of pesticides used than those who have formal debt (given the same total debt) because formal institutions have more credit constraints. This empirical result may imply a relationship between debt and affordability; farms without debt are more able to buy pesticides, leading to a higher probability of pesticide overuse.

Farmers who have easier access to information from retailers tend to apply pesticides at more than the recommended dosage (Jallow et al., 2017) or more than the optimal use (Schreinemachers et al., 2020). Retailers have an incentive to sell more inputs to farmers. In contrast, farmers who are members of a cooperative and have more access to extension are less likely to overuse pesticides (Jallow et al., 2017; Qin & Lü, 2020) and are able to improve VMPs of pesticides (Huang et al., 2020; Schreinemachers et al., 2020).

Although numerous studies indicate the presence of pesticide overuse in developing countries, there is little research on determinants of overuse. By merging the literature on studies determining the overuse of pesticides and studies quantifying the amount of pesticides used in agricultural production, the paper contributes to the literature of determinants of pesticide overuse by extracting hypotheses about potential determinants from demographic characteristics and farmer/farm attributes. Demographic variables such as age and household income are more likely to relate to pesticide overuse while education is less likely to be associated with pesticide overuse. Farmer/farm attributes such as risk aversion, crop and location are potentially significant factors leading to the overuse of pesticides. There are thus gaps in the literature regarding possible determinants of overuse that can be fruitfully examined.

3 | METHODOLOGY

3.1 | Measuring pesticide overuse

This study employs the economic approach to measuring pesticide overuse. Following other studies in the literature, pesticide overuse is defined as the amount of pesticides that exceeds an economically defined optimal level (Cai et al., 2021; Grovermann et al., 2013; Zhang et al., 2015). Assuming that farmers are profit maximisers, one can compute a privately optimal level of pesticides as the point at which the marginal returns or revenues of using pesticides equal the marginal costs of those pesticides (i.e. the market price of pesticides). When this equality holds, farmers maximise their profit.

The marginal returns of pesticide use can be calculated using a crop production function relating outputs produced to inputs used. An appropriate crop production function would distinguish between inputs that directly increase output (e.g. land and fertiliser) and those that increase output indirectly by reducing losses to crop pests and diseases (e.g. pesticides) (Lansink & Carpentier, 2001; Lichtenberg & Zilberman, 1986; Skevas et al., 2013). The former are typically called productive inputs, while the latter are referred to as damage abatement inputs. Lichtenberg and Zilberman (1986) were the first to propose crop production functions that treat damage abatement inputs and productive inputs asymmetrically. Following these authors, a production function that explicitly accounts for the role of damage abatement inputs in the production process can be written as follows:

$$y = F(x)D(z) \tag{1}$$

where y is a single output, x denotes productive inputs and z denotes pesticides. $F(x)$ is referred to as the production function, while function $D(z)$, which takes values between zero and unity, is called the damage abatement function. $D(z)$ determines the extent of any damage and pesticides' effectiveness in reducing this damage. The asymmetric specification in (1) implies that actual output is scaled by the damage abatement (Skevas et al., 2013). It further implies that damage is independent of potential output ($F(x)$); that is, the marginal rate of substitution between any pair of productive inputs (x) is independent of damage abatement inputs (z) (Saha et al., 1997).

Using information on output (p) and input prices (w and s for productive inputs and pesticides, respectively), the farm-level profit function is written as:

$$\Pi = py - wx - sz \tag{2}$$

Maximising Equation (2) with respect to pesticides results in the private economically optimal level of pesticides as the point at which the marginal returns of using pesticides equal the marginal cost of those pesticides (Grovermann et al., 2013):

$$\frac{\partial \Pi}{\partial z} = \frac{\partial (py - wx - sz)}{\partial z} = \frac{\partial (pF(x)D(z) - wx - sz)}{\partial z} = 0 \tag{3}$$

$$\frac{\partial (pF(x)D(z))}{\partial z} = s$$

3.2 | Specification and econometric estimation issues

Estimating Equation (1) empirically requires the specification of functional forms for the production function, $F(x)$, and the damage abatement function, $D(z)$. The Cobb–Douglas (C–D) specification is used to empirically approximate $F(x)$. This specification has a long tradition in the analysis of agricultural production functions in general, and for pesticide impact assessment in particular (Carpentier & Weaver, 1997; Carrasco-Tauber & Moffitt, 1992; Cai et al., 2021; Grovermann et al., 2013; Huang et al., 2002; Saha et al., 1997; Schreinemachers et al., 2020; Skevas et al., 2012, 2013; Zhang et al., 2015). For $D(z)$, alternative specifications have been used in the literature, including the exponential, logistic, Pareto and Weibull. The exponential specification is chosen here because it clearly allows for decreasing marginal returns to pesticide use (thus reducing the likelihood that pesticide productivity is overestimated) (Schreinemachers et al., 2020). It is also the most commonly used damage abatement specification in the literature and has been shown to produce robust results (Grovermann et al., 2013; Lansink & Carpentier, 2001; Pemsl et al., 2005; Schreinemachers et al., 2020; Skevas et al., 2012). After defining $F(x)$ and $D(z)$, Equation (1) can be written as:

$$y_i = e^{\alpha} \prod_{j=1}^{J} x_{ij}^{\beta_j} (1 - e^{-\gamma_1 z_i}) \tag{4}$$

where i denotes farm i, j is the number of productive inputs used, α, β and γ are the parameters to be estimated and all other terms are as previously defined. Calculating the first-order partial derivative of z, the marginal product (MP) of pesticides is obtained:

$$\mathrm{MP}_i = \frac{\partial y_i}{\partial z} = \gamma_1 e^{\alpha} \prod_{j=1}^{J} x_{ij}^{\beta_j} e^{-\gamma_1 z_i} \tag{5}$$

Since in this study both the pesticide input and output variables are measured in monetary rather than physical units (see the Data section), the MP_i in Equation (5) is essentially the VMP or shadow value of pesticides (i.e. the Vietnamese Dong [VND] benefit of a VND spent on pesticides). As explained earlier, the privately optimal level of pesticide use happens at the point where the VMP of pesticides equals their market price. Like in Grovermann et al. (2013) and Singbo et al. (2015), the pesticide price was set to unity here because pesticides are expressed in monetary units. Therefore, setting Equation (5) to unity and solving for z_i results in the privately optimal level of pesticides, z_i^*:

$$z_i^* = \frac{\log\left(\gamma_1 e^{\alpha} \prod_{j=1}^{J} x_{ij}^{\beta_j}\right)}{\gamma_1} \tag{6}$$

Note that z_i^* is farm-specific because it depends on the level at which all other inputs (x_{ij}) are applied. In line with previous studies (Cai et al., 2021; Schreinemachers et al., 2020), the difference between actual (z_i) and optimal (z_i^*) pesticide use is employed to define pesticide overuse. If this difference is positive (negative), then pesticides are overused (underused).

To facilitate the estimation of the coefficients in Equation (6), we take the natural logarithm of both sides of Equation (4) and estimate this equation using non-linear least squares. We also perform an F-test to test the C–D specification against a flexible translog function, which nests the C–D specification.

Endogeneity is often a problem when modelling crop output and damage abatement, since the unobserved factors that cause output damage are relegated to the error term (e.g. level of pest infestation) and also lead producers to decide to apply certain amounts of pesticides (Horna et al., 2008). The endogeneity problem can be solved using an instrumental variable approach (see Horna et al., 2008; Huang et al., 2002). Unfortunately, we do not have valid instruments to implement such an approach (e.g. farm- or region-specific pesticide prices). Consequently, we make the untestable assumption that pesticide use is exogenous (i.e. is uncorrelated with the error term) and recognise it as a limitation of our approach.

3.3 | Assessing the factors that affect pesticide over- or underuse

Farmer overuse/underuse of pesticides was modelled as a two-step process whereby the decision to overuse/underuse pesticides was first modelled using probit regression. Then, for those overusing pesticides, the intensity of overuse was modelled using a truncated regression (truncated to take into account that only farmers who overuse pesticides are examined). A similar approach to the one used here has been used by Schreinemachers et al. (2020) and

Cai et al. (2021) to assess the determinants of pesticide overuse in vegetable production in Southeast Asia and apple production in China, respectively.

In the first step, a probit model was estimated to understand what factors or farm/farmer characteristics might be associated with overuse versus underuse of pesticides. The dependent variable in this model is a dummy variable that takes the value of 1 if the farmer under investigation overuses pesticides and zero if he/she underuses pesticides.[1] The specification of the probit model is as follows:

$$\Pr\left(D_i = 1 \mid h_i\right) = \Phi\left(\frac{\delta_k * h_i'}{\sigma_k}\right) \tag{7}$$

where Pr denotes probability, D is the binary variable of farmer i over (1) or underusing pesticides (0), Φ is the normal cumulative distribution function, h is a vector of explanatory variables, δ_k is a vector of parameters to be estimated and σ_k is the standard deviation for the overuse model. Equation (7) is estimated using the maximum likelihood estimation approach.

In the second step, the following truncated regression model is estimated:

$$A_i = \rho h_i' + \epsilon_i \tag{8}$$

where A is the amount of overuse of pesticides (i.e. $A_i = z_i - z_i^*$) for farmers overusing pesticides (i.e. $z_i > z_i^*$), ρ the vector of coefficients, h the explanatory variables and ϵ_i an error term that is independently and normally distributed with mean zero and variance σ.[2] Using this model, the results are interpreted as the impact of a variable h on the quantity of overuse conditional on the farmer overusing pesticides.

4 | DATA

The data used in this study come from the 2016 Vietnamese Household Living Standard Survey (GSO, 2017). The survey data set includes 5552 farm households, which were randomly sampled from a list of 33,480 active Vietnamese farms in 2016. All agricultural crops produced in Vietnam are included in the data set, grouped in the survey instrument as rice, fruit trees, industrial crops, staple, nonstaple food crops and others.

According to the data set, 70% of sample farms produced multiple crops at the same time, which means these farms produced more than two out of the six category crops in 2016. With the intention of focussing on farms engaged primarily in rice and fruit production, we selected farms for the analysis whose revenues from sales of rice and fruit, respectively, comprise at least 80% of their total annual revenues.[3] After imposing these requirements, excluding all missing and zero[4] observations, as well as outliers (i.e. observations greater than three stan-

[1]As will become clear in the Section 5, no sample farmer used pesticides at the optimal level.

[2]Underuse models are not presented because of the small number of observations leading to nonsignificant models (fruit) or lack of significant variables (rice).

[3]This is necessary because the data on input use are not separated by crop.

[4]We exclude observations that report zero values for output and principal inputs (e.g. land and labour) because no farm can be assumed to be in operation without reporting positive values for such measures. Furthermore, from a theoretical standpoint, farms that can produce the given output from zero values of some inputs use a different production technology than those that use at least some amounts of those inputs to produce the same output. To assure that all sample farms use a single homogeneous production technology, as required by the conventional production function approach, farms that report zero values for inputs are excluded from the analysis.

TABLE 2 Data description.

	Rice farms		Fruit farms	
Variable (units)	**Mean**	**SD**	**Mean**	**SD**
Farm revenue (10^6 VND[a])	29.87	38.03	76.75	76.51
Input variables				
Capital (10^6 VND)	0.232	0.278	0.799	2.423
Labour (Man-years)	0.425	0.290	0.732	0.451
Land (ha)	0.476	0.595	0.492	0.529
Intermediate inputs (10^6 VND)	5.798	7.787	8.764	11.11
Pesticides (10^6 VND)	2.168	4.449	3.790	4.898
Farm/farmer characteristics				
Female gender (base: Male)	0.167	0.009	0.189	0.030
Age (years)	51.00	12.68	53.60	12.40
Education				
No qualified (base)	0.213	0.010	0.223	0.031
Primary school	0.258	0.011	0.251	0.033
Middle school	0.395	0.012	0.377	0.037
High school and above	0.134	0.009	0.149	0.027
Household size (persons)	3.922	1.435	4.080	1.487
Poverty status (base: No[b])	0.110	0.008	0.046	0.016
Off-farm income (10^6 VND)	95.25	257.9	78.48	135.7
Farm income as per cent of total (points)	38.18	27.07	55.46	31.81
Debt (base: No debt)	0.240	0.011	0.183	0.029
Contract agricultural work (base: No)	0.025	0.004	0.011	0.008
Region				
Mekong Delta (base)	0.201	0.010	0.463	0.038
Red River Delta	0.315	0.012	0.120	0.025
Northern Mountainous Areas	0.172	0.009	0.177	0.029
Northern and Coastal Centre Areas	0.288	0.011	0.194	0.030
Others	0.024	0.004	0.046	0.016
Sample size	1579		175	

[a]1 USD = 22,361 VND (dong) in 2016.

[b]The Vietnamese Government assigned poverty status to households those lived in rural and had monthly average income per capita $<0.7\times10^6$ VND or those lived in urban or city and had monthly average income per capita $<0.9\times10^6$ VND.

dard deviations from the mean), the final data set used in this study consists of 1579 rice farms and 175 fruit tree farms.

Summary statistics for the data used in our study and for each group of farms (i.e. rice and fruit farms) can be found in Table 2. For the farm-level profit maximisation framework, one output and five categories of inputs are distinguished. Output or farm revenue (y) is defined as the revenue in VND (1 USD = 23,500 VND = 1.5 AUD) from the sales of all crop products. Inputs are categorised into two groups: productive inputs (x) and damage abatement inputs such as pesticides (z). The productive category includes capital, labour, land and intermediate inputs. Capital represents the value of tools and machinery. Labour represents the working time of farm household members and hired workers and is measured in man-year units. Land represents the total area used for all crop production and is measured in hectares (ha).

Intermediate inputs (excluding pesticides) include the cost of seeds, fertiliser, seedlings, energy, irrigation, and hired cattle traction. Pesticides are defined as the amount of money a farm spent on herbicides, insecticides and fungicides.

The determinants of pesticide over or underuse include nine variables: gender, age, educational attainment, household size, off-farm income, farm income as a percentage of total income, poverty status, contract agricultural work, debt and region. Gender is a dummy variable with male as the base. Age is defined as the age in years of the head of the household. Educational attainment is operationalised to match Vietnam education in the past, consisting of four possible categories: no qualified (base category), primary school, middle school, high school and above. Household size is the number of household members, including children. Off-farm income includes all money received from nonagricultural wage employment. The farm income percentage is defined as the ratio of farm income to total household income. Poverty is a dummy variable that takes the value 1 if a farm household is considered 'poor' under the Vietnamese standard, and 0 if above that level. Contract agricultural work is a dummy variable that takes the value 1 if a farmer provides agricultural services to other farmers and 0 otherwise. Providing contract agricultural work may be related to farming experience, a variable that is not in the data set. Debt is a dummy variable that takes the value 1 if a farmer holds private debt, and 0 otherwise. Region is a dummy variable indicating the region where the farm household operates. These regions include the Mekong Delta (base), Red River Delta, Northern Mountainous areas, and Northern and Coastal central areas.

Table 2 indicates that the mean sales of fruit farms in 2016 were more than double those of rice farms. Concerning input use, fruit farms spent more on pesticides and intermediate inputs and were more capital and labour-intensive than rice farms. There were no substantial differences in terms of farm or farmer characteristics between these groups of farms. Most specialised fruit farms were located in the Mekong Delta, while most specialised rice farms operated in the Red River Delta, and Northern and Coastal Centre areas.

5 | RESULTS

5.1 | Pesticide overuse and underuse results

We report production function estimates after having applied an F-test to decide between the C–D and translog specifications. Based on this test, the use of the C–D specification could not be rejected (F-statistic = 1.7 [p-value = 0.53] for rice, and F-statistic = 0.41 [p-value = 0.83] for fruit).[5] Table 3 presents the coefficients of the preferred C–D production function for the two types of crops.[6] The R^2 was 0.92 for rice and 0.78 for fruit crops, which is significantly higher than those reported by previous studies in Southeast Asian countries and China that used the same functional form (Cai et al., 2021; Grovermann et al., 2013; Schreinemachers et al., 2020). For the logged productive inputs, the coefficients can be interpreted directly as elasticities (the percentage change in output resulting from a 1 per cent increase in input). For both crops, most of the productive inputs have a significant impact on production at the 1% or 5% significance level. For rice farms, land exerts the highest impact on output followed by intermediate inputs. For fruit farms, intermediate inputs have the most important impact on production followed by labour. The regression coefficient for

[5]See Table S1 for the F-test of C–D against translog specification for the production function used in the study.

[6]We examined potential multicollinearity of the production inputs by calculation of the variance inflation factor (VIF) for each production input. The VIF scores range from 1 to 5, indicating multicollinearity is not a problem.

TABLE 3 Production function estimates.

		Rice farms		Fruit farms	
Variable	**Symbol**	**Estimate**	***p*-Value**	**Estimate**	***p*-Value**
Constant	β_0	1.999	0.000	1.899	0.000
Capital	β_3	0.041	0.000	0.194	0.000
Labour	β_1	−0.024	0.017	0.271	0.000
Land	β_2	0.485	0.000	0.150	0.016
Intermediate inputs	β_4	0.478	0.000	0.542	0.000
Pesticides	γ_1	0.066	0.000	0.053	0.423
N	–	1579	–	175	–
Pseudo R^2	–	0.923	–	0.782	–

Note: The pseudo R^2 is provided for non-linear least squares estimation of Equation (4) as an alternative goodness-of-fit measure. This value is not directly comparable to the R^2 for OLS models as it cannot be interpreted as the proportion of the variability in the dependent variable that is explained by model. Instead, the pseudo R^2 would be a relative measure among similar models indicating how well the model explains the data (Mangiafico, 2016).

TABLE 4 Average value of marginal product of pesticides, average optimal, and over-/underexpenditures on pesticides, and per cent of farmers over-/underusing pesticides.

	Rice farms	**Fruit farms**
Average VMP of pesticides	0.9	1.1
Average optimal pesticide expenditure (in 10^6 VND)	0.107	0.146
Percent of farmers overusing pesticides (%)	94.9	95.4
Percent of farmers underusing pesticides (%)	5.1	4.6
Average overexpenditure (in 10^6 VND)	2.282	3.968
Average underexpenditure (in 10^6 VND)	0.063	0.081

pesticides (which is not directly interpretable) was positive for both crops and similar in terms of magnitude, and significant for rice. The VMP of pesticides was calculated for each sample farmer. As noted above, the VMP of pesticides is the value of output resulting from an additional VND spent on pesticides. The average VMP of pesticides was 0.9 VND and 1.1 VND for rice and fruit farms, respectively (Table 4).[7]

For each farmer in the sample, the optimal or profit-maximising level of pesticide expenditure was calculated based on the estimated regression coefficients and observed productive input use. This optimal value was then compared with the actual pesticide expenditure of the producer to determine overuse/underuse. Table 4 shows that the average optimal value of pesticide expenditure was 0.107 million dong for rice and 0.146 million dong for fruit farms. About 94.9% and 95.4% of the sample rice and fruit farmers, respectively, overused pesticides. These results are in line with Wang et al. (2018) and Schreinemachers et al. (2020), despite differences in terms of the country and crops studied. Sample rice and fruit farmers who overused pesticides overspent, on average, about 2.282 and 3.968 million dong on pesticides, respectively. Pesticide expenditures below the economic optimum for rice and fruit farms underusing pesticides were, on average, 63 and 81 thousand dong, respectively (Table 4).

[7]While up to the third quartile, the VMP was close to 1, the mean VMP was greater at 0.9 and 1.1 for rice and fruit farms, respectively, due to a few values well above 1.

5.2 | Analysis of determinants of pesticide overuse

Next, we turn to investigating the determinants of overuse of pesticides in rice and fruit farming systems in Vietnam. Note that the investigation is implemented in two stages: identifying factors affecting pesticide overuse versus underuse (Stage 1) and analysing the intensity of overuse for those farms/ farmers who overused pesticides (Stage 2). The same explanatory variables are examined in the probit models (Stage 1) and the truncated regressions (Stage 2). Before conducting the regressions, pair-wise correlations among the explanatory variables were examined. We also obtained variance inflation factors (VIF) of the independent variables to check for multicollinearity in the probit model. In general, the correlation coefficients were less than 0.26, and the VIF scores were less than 2.5, and thus acceptable for the model estimation.[8]

The first stage is used to characterise the farms/farmers overusing versus underusing pesticides. Tables 5 and 6 report results, by crop, of the probit model and relevant statistics in the 'stage 1' column.[9] In terms of goodness of fit, the McFadden pseudo R^2 values of the probit models for rice and fruit crops are 13.3% and 45.0%,[10] respectively. Such values of pseudo R^2 are acceptable for empirical studies of determinants (e.g. Wang et al., 2018). Moreover, the likelihood ratio tests for the models are significant, α-level = 1% and 5% for rice and fruit farms, respectively, confirming that the two models significantly predict the likelihood of pesticide overuse versus underuse. We report average marginal effects of the determinants on pesticide overuse in the probit model over all farms in the sample rice and fruit farms, respectively. Only statistically significant results are discussed.

Table 5 shows that for rice farms, age, household size, farm income as a per cent of total income and region have significant effects on the likelihood that a farm overused versus underused pesticides. The effect of age is positive in previous studies determining pesticide overuse, but indeterminant in studies of pesticide quantity. We find the marginal effect of age is positive for rice farms. The results imply older farmers tend to overuse pesticides in rice production, although on average the effect is very small, 0.1% for a 1-year increase in age. The positive effect of age for rice farms in this study is in line with Huang et al.'s (2020) study that showed older rice farmers tend to overuse pesticides due to their habits or experience.

The literature suggests a household with more members working in the fields may result in fewer pesticides used due to the substitution effect of labour (Migheli, 2017). Interestingly, we find a positive effect of household size for rice, implying family farms with more household members are more likely to overuse pesticides. However, the average effect is small: an increase of 1.0% for rice in the probability of overuse given one more family member. One possible reason for the positive effect of household size may be higher expenses due to larger family size and greater reliance on farm income. It is a common perception of many Vietnamese farmers that pesticides are productive factors that increase crop profits or food security (Hoi et al., 2013), implying that poorer farmers are more encouraged or likely to overuse pesticides.

Farm income as a per cent of total income is an income measurement that represents the family's reliance on farm income. We find a positive effect of farm income proportion on the

[8]See Table S2 for the correlation coefficients, and Table S3 for the VIF scores.

[9]We also implemented the probit model using a dummy variable for crop (pooled data case), but the results had higher Akaike information criteria (AIC) and Bayesian information criteria (BIC) and lower pseudo R^2, implying multicollinearity because of crop and region as indicated by the literature (See Table S4).

[10]The high pseudo R^2 that indicates overfitting of the model for the fruit sample was obtained due to a data issue where only a few fruit farms underused pesticides. When we recoded the 'education' and 'region' variables that require mode observations to pass the issue, the new pseudo R^2 is 27.9% (See Table S5).

TABLE 5 Model estimates of determinants of pesticide overuse in rice (Standard errors in parentheses).

	Stage 1: Pesticide overuse versus underuse		Stage 2: Intensity of pesticide overuse (10^6 VND)
Independent variables (factors)	**Coefficients**	**M. Effects**[a]	**Coefficients**
Female gender (base: Male)	−0.230 (0.154)	−0.024 (0.018)	−8.953 (3.831)**
Age (years)	0.009* (0.005)	0.001* (0.001)	−0.052 (0.095)
Education (base: No qualified)			
Primary school	0.042 (0.178)	0.004 (0.017)	3.495 (2.826)
Middle school	0.044 (0.170)	0.004 (0.016)	3.886 (3.254)
High school and above	0.004 (0.214)	0.000 (0.021)	5.206 (4.072)
Household size (persons)	0.107** (0.045)	0.010** (0.004)	4.154*** (1.009)
Poverty status (base: No)	−0.225 (0.168)	−0.021 (0.016)	−40.28*** (12.52)
Off-farm income (10^6 dong)	0.001 (0.000)	0.000 (0.000)	0.008*** (0.002)
Farm income as per cent of total (points)	0.014*** (0.003)	0.001*** (0.000)	0.477*** (0.083)
Debt (base: No debt)	−0.162 (0.134)	−0.015 (0.012)	−0.165 (2.296)
Contract agricultural work (base: No)	−0.356 (0.314)	−0.033 (0.029)	13.14** (5.64)
Region (base: Mekong Delta)			
Red River	−0.234 (0.304)	−0.010 (0.011)	−125.12*** (25.84)
Northern Mountainous Areas	−0.966*** (0.292)	−0.082*** (0.019)	−252.61*** (54.15)
Northern and Coastal Centre	−0.773*** (0.287)	−0.055*** (0.014)	−178.10*** (37.04)
Others	−0.723 (0.442)	−0.049 (0.041)	−36.91*** (10.87)
Intercept	0.979** (0.488)	–	−50.68*** (12.34)
No. of observations	1579		1498
LR chi-square (df)	85 (15)		2235 (15)
Pr(>chi-square)	0.000***		0.000***
AIC	586		3162
BIC	672		3252
R^2	13.3%[b]		34.0%
Sigma	–		10.86***

[a]We report average marginal effects.

[b]McFadden pseudo R^2 are reported for probit models.

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

likelihood of overusing pesticides in rice farming; that is, the probability that a rice farmer overused pesticides would increase 1.0% on average as his farm income proportion increases by 10%. Deriving more income from farming may be an indication of a higher commitment to agricultural activities. Full-time farmers may overuse pesticides to secure their main source of income, particularly if they are risk-averse (Gong et al., 2016).

The region variables, representing locational factors, are found to have important effects on overuse on rice farms. In this study, we find farmers in most areas (except Red River Delta) are significantly less likely to overuse pesticides on rice relative to the base of the Mekong Delta. In other words, pesticide overuse is more likely in the Mekong Delta region, which is widely known as having the highest density of rice farms. The difference in the likelihood of pesticide overuse ranges from 5.5% to 8.2% across farms located in the Northern and Coastal Centre and Northern Mountainous areas. This is in line with findings of earlier studies reporting excessive

TABLE 6 Model estimates of determinants of pesticide overuse in fruit (standard errors in parentheses).

	Stage 1: Pesticide overuse versus underuse		Stage 2: Intensity of pesticide overuse (10^6 VND)
Independent variables (factors)	**Coefficients**	**M. Effects**[a]	**Coefficients**
Female gender (base: Male)	0.415 (1.018)	0.020 (0.043)	−5.747 (12.24)
Age (years)	−0.064** (0.026)	−0.004** (0.001)	−0.607 (0.532)
Education (base: No qualified)			
Primary school	−10.34 (521.8)	−0.085 (1.296)	5.462 (12.12)
Middle school	−9.996 (521.8)	−0.055 (2.197)	14.81 (13.60)
High school and above	−10.23 (521.8)	−0.071 (1.656)	−6.019 (14.92)
Household size (persons)	0.412** (0.209)	0.023** (0.011)	3.709 (3.592)
Poverty status (base: No)	5.233 (1681)	0.290 (93.38)	−38.14 (45.34)
Off-farm income (10^6 dong)	−0.004 (0.003)	−0.000 (0.000)	0.096 (0.070)
Farm income as per cent of total (points)	−0.003 (0.012)	−0.000 (0.000)	0.944 (0.750)
Debt (base: No debt)	0.042 (0.841)	0.002 (0.047)	3.648 (8.405)
Contract agricultural work (base: No)	−2.824 (1790)	−0.157 (99.41)	−15.96 (58.12)
Region (base: Mekong Delta)			
Red River	−0.766 (0.733)	−0.050 (1.429)	−81.89 (88.00)
Northern Mountainous Areas	4.788 (890.1)	−0.029 (2.579)	4.49 (9.24)
Northern and Coastal Centre	−0.509 (0.711)	−0.029 (1.111)	5.68 (8.97)
Others	−1.218 (0.867)	0.099 (1.171)	−73.97 (65.76)
Intercept	14.84 (521.8)	–	−94.86 (89.17)
No. of observations	175		167
LR chi-square (df)	29(15)		94(15)
Pr(>chi-square)	0.015**		0.000***
AIC	68		726
BIC	118		779
R^2	45.0%[b]		22.8%
Sigma	–		12.28**

[a]We report average marginal effects.

[b]McFadden pseudo R^2 are reported for probit models.

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

use of pesticides on farms in the Mekong Delta (Berg, 2001; Klemick & Lichtenberg, 2008; Migheli, 2017). It is intuitive and reasonable that there is little difference between the Mekong Delta and the Red River Delta, which is the second most dense area of rice production. While we do not have data on the availability of inputs, we also expect the density of input suppliers in these areas to be higher.

The second stage is to analyse the intensity of pesticide overuse for overusing farms. In the 'stage 2' column of Table 5, gender, household size, poverty status, off-farm income, farm income proportion, contract agricultural work and region have significant effects on the extent of pesticide overuse in the truncated regression for rice farms. Age is no longer significant at the 10% level. As expected, female farmers tend to have lower intensity of pesticide overuse than male farmers in this study: the extent of overuse for women is 8.953 million dong less than for men. Household size has a positive effect on the likelihood of overuse but also a positive effect on the intensity of pesticide overuse, by 4.154 million dong for one more member in the family.

Three income measurements: poverty status, off-farm income and farm income proportion all have positive effects on the extent of pesticide overuse in rice. The intensity of overuse for 'poor' farmers is 40.28 million dong less than for nonpoor farmers. This can be explained by the income effect where households designated as 'poor' by the Vietnamese Government standard would probably be less able to afford intensive use of pesticides. We find a small effect of off-farm income: the intensity increases by VND 8000 for an increase of 1 million VND in off-farm income. Those with more off-farm income may be more able to afford pesticides but may also be substituting pesticides for labour. Similar to household size, farm income proportion among rice farmers also has a positive effect on the intensity of pesticide overuse: for a one percentage point increase in the farm income proportion, the intensity of overuse increases by VND 477,000.

Rice farmers who provide contract agricultural work have a higher level of pesticide overuse, by 13.136 million VND, than those who do not. Farmers doing contract work may work on larger farms that overuse pesticides to protect yields from pests and diseases and to reduce labour costs. This may in turn influence the contract workers' practices on their own farms. Another potential explanation is that farmers engaging in contract work may get their input recommendations from chemical companies that want to sell a higher volume of products, leading to higher applications of pesticides. However, these explanations are merely speculations and require further scrutiny when relevant data are available.

The effect of region on the intensity of pesticide overuse in rice is clearer than the results from the probit model. Farmers in every region have lower intensity of overuse, from 36.9 to 252.6 million VND less, than those located in the Mekong Delta area. The result confirms the heavy dependence on pesticides in this region in terms of pesticide overuse and intensity of overuse.

For fruit crop production (Table 6), age and household size significantly affect the probability of overuse. While the effect of age was positive for rice farms, it is negative for fruit farms. The effect for fruit farms is significant at the 5% level, and the magnitude of the effect was larger, but still small (0.004). The negative effect of age for fruit farms may be explained by the fact that older farmers tend to use less pesticides than young farmers given the same application frequency (Huang et al., 2000). Another reason is older farmers probably have more farming experience, which tends to be positively associated with higher efficiency of specific inputs such as pesticides for fruit crops. It may also be the case that their trees are older and less susceptible to pest damage. Interestingly, we find a positive effect of household size for both rice and fruit production, and, similar to rice, the average effect is small: an increase of 2.3% for fruit farms in the probability of overuse given one more member in the family. There are no significant factors in the truncated regression on the intensity of overuse of pesticides for fruit farms in the 'stage 2' column.

6 | CONCLUSIONS

Understanding pesticide overuse is crucial to farmers' profits, health status and the environment. We focus on rice and fruit farms since government data indicate 80% of farms grow rice, and these farms use more than 60% of total pesticides while fruit farms are the biggest consumers in terms of average expenditure. This study represents the first assessment of pesticide overuse in rice and fruit production at the farm level in Vietnam. The results are important for farmers and policymakers in Vietnam as well as other developing countries.

Using a 2016 national data set of 1579 rice farms and 175 fruit farms, we find about 95% of rice and fruit farms were overusing pesticides, while no rice or fruit farm was found to use pesticides optimally. These results suggest that policies need to be designed to address overuse of pesticides in agricultural production, especially in the developing country context. Another implication is that reduction in pesticide use is feasible for farmers and would lead to substantial reductions in terms of both input costs and environmental impacts.

The study also analyses the determinants of those farms or farmers that overused versus underused pesticides, and for overusing farmers, the intensity of overuse. While a variety of factors affect the decision to overuse pesticides and the intensity of overuse in our sample, based on the magnitude of the effects, the region where farms are located is the most important determinant of pesticide overuse in rice production. Rice farmers more intensively overusing pesticides are more likely to be located in the Mekong Delta. This result is in line with findings of earlier studies reporting excessive use of pesticides on farms in the Mekong Delta (Berg, 2001; Klemick & Lichtenberg, 2008; Migheli, 2017). Results also show that female and poorer rice farmers have lower intensity of overuse while those who have higher off-farm income, higher farm income proportion or participate in contract agricultural employment have higher levels of pesticide overuse. The fact that multiple income factors affect the decision to overuse or the intensity of overuse implies the important link between income and pesticide overuse. Pesticide overuse may relate to the perception in Vietnam that pesticides increase yields, rather than reducing damages. One important implication is that the government needs to take multiple factors into account when designing pro-environmental policies, especially in regions where pesticide overuse is prevalent, such as the Mekong Delta and Red River Delta. In addition, improving education and delivering knowledge and information regarding pesticide use to farmers are needed to avoid misconceptions about pesticides as productive inputs or their on- and off-farm impacts. The intensity of overuse is an important factor both for farmer profitability and for environmental and health impacts compared to results from a simple probit model.

This research used existing data that were not specifically designed to study pesticide use. Further research could collect data to examine the effect of income on pesticide use accounting for the impacts of education, experience, crop characteristics and regional factors. The impact of accessibility could also be examined in more detail since pesticides may be less available in some remote areas than in the Mekong Delta. The role of pesticide information sources could potentially be important. Data that separated pesticide inputs by crop would enable the study of pesticide efficiency in multicrop farms, controlling for farmer characteristics. Separating different types of pesticides, versus combining insecticides, herbicides and fungicides, may also lead to more detailed recommendations.

ACKNOWLEDGEMENTS

This work was supported by the USDA National Institute of Food and Agriculture, Hatch projects 1025527 and 00081458. We would also like to thank the editors, Tihomir Ancev and Moriah Bostian, as well as two anonymous reviewers for their helpful suggestions.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are from the Government of Vietnam. Restrictions apply to the availability of these data. The code used in the paper is available from the authors upon request.

ORCID

Laura McCann https://orcid.org/0000-0002-8781-7130

REFERENCES

Aniah, P., Kaunza-Nu-Dem, M.K., Dong-Uuro, P.P., Ayembilla, J.A. & Osumanu, I.K. (2021) Vegetable farmers' knowledge on pesticides use in Northwest Ghana. *Environment, Development and Sustainability*, 23(5), 7273–7288.

Antle, J.M. & Pingali, P.H. (1994) Pesticides, productivity, and farmer health: a Philippine case study. *American Journal of Agricultural Economics, Agricultural and Applied Economics Association*, 76(3), 418–430.

Belbase, K. & Grabowski, R. (1985) Technical efficiency in Nepalese agricuture. *Journal of Development Areas*, 19(4), 515–525.

Berg, H. (2001) Pesticide use in rice and rice-fish farms in the Mekong Delta, Vietnam. *Crop Protection*, 20(10), 897–905. Available from: https://doi.org/10.1016/S0261-2194(01)00039-4

Bravo-Ureta, B. & Pinheiro, A. (1993) Efficiency analysis of developing country agriculture: a review of the Frontier function literature. *Agricultural and Resource Economics Review*, 22(1), 88–101. Available from: https://doi.org/10.1017/S1068280500000320

Cai, J., Xiong, J., Hong, Y. & Hu, R. (2021) Pesticide overuse in apple production and its socioeconomic determinants: evidence from Shaanxi and Shandong provinces, China. *Journal of Cleaner Production*, 315, 128179.

Carpentier, A. & Weaver, R.D. (1997) Damage control productivity: why econometrics matters. *American Journal of Agricultural Economics*, 79(1), 47–61.

Carrasco-Tauber, C., & Moffitt, L.J. (1992) Damage control econometrics: functional specification and pesticide productivity. *American Journal of Agricultural Economics*, 74, 158–162.

Dang, V.H., Nguyen, T.H., Choi, K.C. & Jeung, E.B. (2007) Unexpected estrogenicity of endocrine disruptors may evoke a failure of pregnancy derived from uterine function: overview of their possible mechanism(s) through steroid receptors. *Journal of Embryo Transfer*, 22(4), 199–208.

Dasgupta, S., Meisner, C. & Wheeler, D. (2007) Is environmentally friendly agriculture less profitable for farmers? Evidence on integratedpest management in Bangladesh. *Review of Agricultural Economics*, 29(1), 103–118. Available from: https://doi.org/10.1111/j.1467-9353.2006.00332.x

Dasgupta, S., Meisner, C., Wheeler, D., Xuyen, K. & Lam, N.T. (2007) Pesticide poisoning of farm workers–implications of blood test results from Vietnam. *International Journal of Hygiene and Environmental Health*, 210, 121–132.

Douglas, M.R., & Tooker, J.F. (2015) Large-scale deployment of seed treatments has driven rapid increase in use of neonicotinoid insecticides and preemptive pest management in US field crops. *Environmental Science & Technology*, 49(8), 5088–5097.

Ecobichon, D.J. (2001) Pesticide use in developing countries. *Toxicology*, 160(1–3), 27–33. Available from: https://doi.org/10.1016/s0300-483x(00)00452-2

Fan, M., Shen, J., Yuan, L., Jiang, R., Chen, X., Davies, W.J. et al. (2012) Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China. *Journal of Experimental Botany*, 63(1), 13–24. Available from: https://doi.org/10.1093/jxb/err248

FAOSTAT. (2019). Available from: http://www.fao.org/faostat/en/#data/RP

General Statistics Office of Vietnam. (2017) *Vietnam household living standard survey 2016*. Hanoi: Statistical Publishing House.

General Statistics Office of Vietnam. (2018) *Statistical yearbook of Vietnam 2017*. Hanoi: Statistical Publishing House.

Gong, Y., Baylis, K., Kozak, R. & Bull, G. (2016) Farmers' risk preferences and pesticide use decisions: evidence from field experiments in China. *Agricultural Economics*, 47(4), 411–421.

Grovermann, C., Schreinemachers, P. & Berger, T. (2013) Quantifying pesticide overuse from farmer and societal points of view: an application to Thailand. *Crop Protection*, 53, 161–168.

Hoai, P.M., Ngoc, N.T., Minh, N.H., Viet, P.H., Berg, M., Alder, A.C. et al. (2010) Recent levels of organochlorine pesticides and polychlorinated biphenyls in sediments of the sewer system in Hanoi, Vietnam. *Environmental Pollution*, 158, 913–920. Available from: https://doi.org/10.1016/j.envpol.2009.09.018

Hoi, P.V., Mol, A. & Oosterveer, P. (2013) State governance of pesticide use and trade in Vietnam. *Wageningen Journal of Life Sciences*, 67, 19–26. Available from: https://doi.org/10.1016/j.njas.2013.09.001

Horna, D., Smale, M., Al-Hassan, R., Falck-Zepeda, J. & Timpo, S.E. (2008) Insecticide use on vegetables in Ghana. In: Institute, I.F.P.R. (Ed.), IFPRI discussion paper. Washington.

Huang, J., Hu, R., Rozelle, S., Qiao, F. & Pray, C.E. (2002) Transgenic varieties and productivity of smallholder cotton farmers in China. *Australian Journal of Agricultural and Resource Economics*, 46(3), 367–387.

Huang, J., Qiao, F., Zhang, L. & Rozelle, S. (2000) *Farm pesticide, rice production, and human health*. CCAP's Project Report, 11. Ottawa, Canada: International Development Research Centre.

Huang, Y., Luo, X., Tang, L. & Yu, W. (2020) The power of habit: does production experience lead to pesticide overuse? *Environmental Science and Pollution Research*, 27, 25287–25296.

Jallow, M.F., Awadh, D.G., Albaho, M., Devi, V. & Thomas, B. (2017) Pesticide risk behaviors and factors influencing pesticide use among farmers in Kuwait. *The Science of the Total Environment*, 574, 490–498.

Khan, M., Mahmood, H.Z. & Damalas, C.A. (2015) Pesticide use and risk perceptions among farmers in the cotton belt of Punjab, Pakistan. *Crop Protection*, 67, 184–190.

Klemick, H. & Lichtenberg, E. (2008) Pesticide use and fish harvests in Vietnamese rice agroecosystems. *American Journal of Agricultural Economics*, 90, 1–14. Available from: https://doi.org/10.1111/j.1467-8276.2007.01059.x

Lamers, M., Schreinemachers, P., Ingwersen, J., Sangchan, W., Grovermann, C. & Berger, T. (2013) Agricultural pesticide use in mountainous areas of Thailand and Vietnam: towards reducing exposure and rationalizing use. In: Fröhlich, H.L. & Schreinemachers, P. (Eds.) *Sustainable land use and rural development in Southeast Asia: innovations and policies for mountainous areas*. Springer Berlin, Heidelberg: Springer Environmental Science and Engineering. Available from: https://doi.org/10.1007/978-3-642-33377-4_4

Lansink, A.O. & Carpentier, A. (2001) Damage control productivity: an input damage abatement approach. *Journal of Agricultural Economics*, 52(3), 11–22.

Lansink, A.O. & Silva, E. (2004) Non-parametric production analysis of pesticides use in The Netherlands. *Journal of Productivity Analysis*, 21, 49–65. Available from: https://doi.org/10.1023/B:PROD.0000012452.97645.30

Lichtenberg, E. & Zilberman, D. (1986) The econometrics of damage control: why specification matters. *American Journal of Agricultural Economics*, 68(2), 261–273.

Mangiafico, S.S. (2016) *Summary and analysis of extension program evaluation in R*, version 1.20.01. Available from: rcompanion.org/handbook/

Mariyono, J., Kuntariningsih, A., & Kompas, T. (2018) Pesticide use in Indonesian intensive farming and its determinants. *Management of Environmental Quality: An International Journal*, 29(2), 305–323. Available from: https://doi.org/10.1108/MEQ-12-2016-0088

Meisner, C. (2005) *Poverty-environment report: pesticide use in the Mekong Delta, Vietnam*. Washington, DC: World Bank.

Migheli, M. (2017) Land ownership and use of pesticides. Evidence from the Mekong Delta. *Journal of Cleaner Production*, 145, 188–198. Available from: https://doi.org/10.1016/j.jclepro.2017.01.045

Minh, T.B., Iwata, H., Takahashi, S., Viet, P.H., Tuyen, B.C. & Tanabe, S. (2008) Persistent organic pollutants in Vietnam: environmental contamination and human exposure. *Reviews of Environmental Contamination and Toxicology*, 193, 213–290. Available from: https://doi.org/10.1007/978-0-387-73163-6_4

Murphy, H.H., Hoan, N.P., Matteson, P. & Abubakar, A.L. (2002) Farmers' self-surveillance of pesticide poisoning: a 12-month pilot in northern Vietnam. *International Journal of Occupational and Environmental Health*, 8(3), 201–211. Available from: https://doi.org/10.1179/107735202800338894

Pemsl, D., Waibel, H. & Gutierrez, A.P. (2005) Why do some Bt-cotton farmers in China continue to use high levels of pesticides? *International Journal of Agricultural Sustainability*, 3(1), 44–56.

Pimentel, D. (2005) Environmental and economic costs of the application of pesticides primarily in the United States. *Environment, Development and Sustainability*, 7, 229–252.

Pingali, P.L. (2004) Environmental consequences of agricultural commercialization in Asia. *Environment and Development Economics*, 6(4), 483–502. Available from: https://doi.org/10.1017/S1355770X01000274

Qin, S. & Lü, X. (2020) Do large-scale farmers use more pesticides? Empirical evidence from rice farmers in five Chinese provinces. *Journal of Integrative Agriculture*, 19, 590–599.

Rahman, S. & Chima, C.D. (2018) Determinants of pesticide use in food crop production in southeastern Nigeria. *Agriculture*, 8, 1–14.

Saha, A., Shumway, C.R. & Havenner, A. (1997) The economics and econometrics of damage control. *American Journal of Agricultural Economics*, 79(3), 773–785.

Sarkar, S., Gil, J., Keeley, J. & Jansen, K. (2021) *The use of pesticides in developing countries and their impact on health and the right to food*. Brussels: European Union. Available from: https://doi.org/10.2861/28995

Schreinemachers, P., Grovermann, C., Praneetvatakul, S., Heng, P., Nguyen, T.T., Buntong, B. et al. (2020) How much is too much? Quantifying pesticide overuse in vegetable production in Southeast Asia. *Journal of Cleaner Production*, 244(1), 118738. Available from: https://doi.org/10.1016/j.jclepro.2019.118738

Schreinemachers, P. & Tipraqsa, P. (2012) Agricultural pesticides and land use intensification in high, middle and low income countries. *Food Policy*, 37(6), 616–626. Available from: https://doi.org/10.1016/j.foodpol.2012.06.003

Sharma, A., Kumar, V., Shahzad, B., Tanveer, M., Sidhu, G.P.S., Handa, N. et al. (2019) Worldwide pesticide usage and its impacts on ecosystem. *SN Applied Sciences*, 1, 1446.

Shetty, P.K. (2004) Socio-ecological implications of pesticide use in India. *Economic and Political Weekly*, 39(49), 5261–5267.

Singbo, A.G., Lansink, A.O. & Emvalomatis, G. (2015) Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production. *European Journal of Operational Research*, 245(1), 265–272.

Skevas, T., Guan, Z. & Peres, N.A. (2016) Economic performance and comparative riskiness of different management practices for control of botrytis fruit rot in Florida strawberry. *Crop Protection*, 82, 82–90.

Skevas, T., Lansink, A.O. & Stefanou, S.E. (2012) Measuring technical efficiency in the presence of pesticide spillovers and production uncertainty: the case of Dutch arable farms. *European Journal of Operational Research*, 223(2), 550–559.

Skevas, T., Stefanou, S. & Lansink, A.O. (2013) Do farmers internalise environmental spillovers of pesticides in production. *Journal of Agricultural Economics*, 64, 624–640.

Skevas, T., Stefanou, S.E. & Lansink, A.O. (2014) Pesticide use, environmental spillovers and efficiency: a DEA risk-adjusted efficiency approach applied to Dutch arable farming. *European Journal of Operational Research*, 237(2), 658–664.

Sun, S., Zhang, C. & Hu, R. (2020) Determinants and overuse of pesticides in grain production: a comparison of rice, maize and wheat in China. *China Agricultural Economic Review*, 12(2), 367–379. Available from: https://doi.org/10.1108/CAER-07-2018-0152

Tam, N.T., Berg, H., Hang, N. & Cong, N. (2015) Effects of chlorpyrifos ethyl on acetylcholinesterase activity in climbing perch cultured in rice fields in the Mekong Delta, Vietnam. *Ecotoxicology and Environmental Safety*, 117, 34–40. Available from: https://doi.org/10.1016/j.ecoenv.2015.03.020

Teklu, B.M., Haileslassie, A. & Mekuria, W. (2022) Pesticides as water pollutants and level of risks to environment and people: an example from Central Rift Valley of Ethiopia. *Environment, Development and Sustainability*, 24(4), 5275–5294. Available from: https://doi.org/10.1007/s10668-021-01658-9

Toan, P.V., Sebesvari, Z., Bl¨asing, M., Rosendahl, I. & Renaud, F.G. (2013) Pesticide management and their residues in sediments and surface and drinking water in the Mekong Delta, Vietnam. *The Science of the Total Environment*, 452–453, 28–39. Available from: https://doi.org/10.1016/j.scitotenv.2013.02.026

Veettil, P.C., Krishna, V.V. & Qaim, M. (2017) Ecosystem impacts of pesticide reductions through Bt cotton adoption. *Australian Journal of Agricultural and Resource Economics*, 61(1), 115–134.

Wang, J., Chu, M. & Ma, Y. (2018) Measuring rice farmer's pesticide overuse practice and the determinants: a statistical analysis based on data collected in Jiangsu and Anhui provinces of China. *Sustainability*, 10(3), 1–17.

WHO-FAO. (2019) *Global situation of pesticide management in agriculture and public health*. Geneva: Licence: CC BY-NC-SA 3.0 IGO.

Wu, Y., Xi, X., Tang, X., Luo, D., Gu, B., Lam, S. et al. (2018) Policy distortions, farm size, and the overuse of agricultural chemicals in China. *Proceedings of the National Academy of Sciences of the United States of America*, 115(27), 7010–7015.

Zhang, C., Guanming, S., Shen, J. & Hu, R. (2015) Productivity effect and overuse of pesticide in crop production in China. *Journal of Integrative Agriculture*, 14, 1903–1910.

Zheng, W., Luo, B., & Hu, X. (2020) The determinants of farmers' fertilizers and pesticides use behavior in China: An explanation based on label effect. *Journal of Cleaner Production*, 272, 123054. Available from: https://doi.org/10.1016/j.jclepro.2020.123054

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Tran, L., Skevas, T. & McCann, L. (2023) Measuring pesticide overuse and its determinants: Evidence from Vietnamese rice and fruit farms. *Australian Journal of Agricultural and Resource Economics*, 67, 417–437. Available from: https://doi.org/10.1111/1467-8489.12521