Agricultural and Resource Economics Review (2025), **54**, 1–31
doi:10.1017/age.2025.1

RESEARCH ARTICLE

Pesticide use and the case for toxicity-based taxation: evidence from citrus greening in Florida

Audrey Rizk[1] and Ariel Singerman[2]

[1]Food and Resource Economics Department, University of Florida, Gainesville, FL, USA and [2]Food and Resource Economics Department, Citrus Research and Education Center, University of Florida, Gainesville, FL, USA
Corresponding author: Ariel Singerman; Email: singerman@ufl.edu

(Received 25 September 2024; revised 15 January 2025; accepted 17 January 2025; first published online 21 February 2025)

Abstract
Farmers make pest and disease management decisions without facing the social costs derived from their input choices. But given the sizable externalities involved, there is a rationale for government intervention. We model the profit-maximizing problem of a representative farmer by specifying a functional form for the damage function that incorporates the biological impact of the pathogen-vector system on yield as well as the abating impact of insecticides on the vector population. We use citrus greening disease in Florida as a case study because farmers there adopted an insecticide program that caused toxicity per acre to increase by 472%. Our simulation results show that a tax rate based on toxicity provides farmers with a strong incentive to substitute highly toxic chemicals with less toxic alternatives. Such a tax is also more efficient relative to a quantity-based tax that achieves a similar reduction in toxicity because it results in a significantly lower reduction in farmers' yield and profit.

Keywords: area-wide pest management; citrus greening; externalities; pest management

JEL Codes: D7; Q1; Q18

Introduction

Plant pests and diseases impose a significant constraint on agricultural productivity. Rossman (2009) estimated that invasive plant pathogens cause an estimated USD 21 billion in crop losses each year in the United States alone, while Bradshaw *et al.* (2016) estimated invasive insects to cost USD 70 billion annually worldwide. Therefore, pesticide applications are key for farmers to mitigate the impact of pests and diseases affecting their crops. Without the application of pesticides, the amount of harvested crops would be smaller and, *ceteris paribus*, prices would be higher. However, farmers do not face all of the costs associated with their pesticide input choices, they take private costs into consideration while ignoring the social costs. Therefore, farmers' pest and disease control decisions have consequences beyond their own farms.

The social costs that arise from pesticide use include adverse impact on human health of workers and consumers, the development of pesticide resistance, and potential ecological harm. The annual health costs derived from pesticide exposure in the U.S. are estimated at USD 1.5 billion (Bourguet and Guillemaud 2016). While the social cost generated by the development of pesticide resistance is on the rise due to the increasing reliance of agricultural producers worldwide on individual pesticide applications, global-scale cost estimates are lacking. But Carpenter and Gianessi (2010) estimate that increased chemical costs due to glyphosate resistance in the U.S are USD 10 billion annually.

As a consequence of the sizable externalities created by farmers' pesticide use, there is a strong case for government intervention because, as economic theory suggests, pesticides can be overused relative to the level preferred by society (Sexton, Lei, and Zilberman 2007). But using a command-and-control approach to regulate pesticides, which includes recommended dosages per application and maximum rates per season, leaves much to be desired (Zilberman and Millock 1997a). This is so because – other than bans, which would be unfeasible to implement on the grounds that farmers would not be able to control pests and diseases affecting their crops – direct controls such as restrictions on use (i.e., when, where, and how to use pesticides) or limits on the total quantity of chemical used do not provide any incentives for reducing pesticide use. Instead, when designed properly, market-based instruments are more cost-effective relative to command-and-control (OECD 2017).

The optimal level of pesticide use is obtained when the value of its marginal product is equal to the sum of the private cost and the marginal external costs. Therefore, the first-best policy would be that which achieves no deadweight loss. The most intuitive policy to try to capture the marginal external cost would then be the introduction of a Pigouvian tax that captures the cost of the externalities. In addition, an advantage of introducing a tax is that no monitoring is necessary because decision-making is decentralized at the farmer level. Importantly, however, the externalities generated from pesticide use are not directly observable, so taxing individuals based on the generation of those externalities is not feasible. Moreover, due to the complex nature of agricultural production, marginal external costs may be dependent on location, time, and application technology, making it virtually impossible to compute the tax level that leads to equating the social marginal benefits and costs associated with the use of pesticides; even when pesticides' externalities do not depend on location and use, it can be very challenging to determine such a tax (Sexton, Lei and Zilberman 2007). To complicate things further, typically, little data are available to accurately assess all the social costs of pesticide use.

Given the above-described challenges for computing the marginal external costs of pesticides, financial incentives such as taxes need to be applied to externality-causing inputs, whose use is observable, unlike externalities which are not. Since the relationship between the use of pesticides and the externalities they generate is not a direct one, the goal of a policy regulating the use of pesticides should be to minimize the deadweight loss derived from the market failure by inducing farmers to undertake levels of pesticide use that are closer to the social optimum (Waterfield and Zilberman 2012).[1] Thus, a second-best approach would consist of having policy makers choose a target level of pesticide use reduction, which can be attained introducing a pesticide tax (Baumol and Oates 1988).

[1]Sexton, Lei and Zilberman (2007) note that even if the relationship between pesticide-use levels and damage was a direct one, taxing inputs would still cause a deadweight loss because they distort farm-level decisions by reducing input use (without incentivizing other abatement efforts that may be less costly).

In practice, however, most environmentally related tax rates are not only significantly below marginal external costs but are also below levels that achieve significant behavioral changes (OECD 2017). Finger *et al.* (2017) argue that, in the context of pesticides, a tax should not be ad-valorem or per unit because pesticides vary widely with respect to their properties. Instead, the authors argue that the tax should be based on the risks each pesticide poses to reflect the social marginal costs associated with their use. A tax based on such a criterion would incentivize farmers to modify their pest management decisions by substituting the use of pesticides with higher external costs for those that have lower external costs. But, Skevas, Stefanou, and Lansink (2013) assessed the effectiveness of different fiscal measures in encouraging farmers to reduce pesticide use and their externalities and found that taxes based on the toxicity of pesticides did not result in the substitution of high- with low-toxicity pesticides. However, their study has some limitations. For example, the data the authors use on pesticides was based on expenditures and, therefore, they used a price index to infer quantities. Importantly, the authors only considered two tax categories in their analysis, one for high and one for low toxicity, which limited substitution possibilities. In fact, they mentioned that the absence of low-toxicity alternatives may explain their result.

In this study, we assess the effectiveness of imposing a tax on pesticide use based on two different criteria by using simulations at the farm-level in the context of the spread of citrus greening or Huanglongbing (HLB) disease on Florida's citrus industry. This is a highly relevant case study because the significant production challenge that such an invasive species has posed to citrus farmers in Florida encouraged them to adopt the use of significantly more toxic insecticides to try to control the vector of the disease and slow down the infection rate. Given that the current pesticide regulation in the U.S. – based on direct controls – does not penalize the decision of farmers to use chemicals that are more toxic in any way, it is a rational economic choice for farmers to adopt their use. Despite farmers' widespread adoption of such insecticides, the disease still decimated the state's citrus industry, eventually causing production to decrease by more than 90%. Such a devastating impact is evidence that the switch to more toxic chemicals by individual farmers may be futile,[2] calling into question the usefulness of the current regulation that allows them to apply pesticides without having to pay any of the social costs derived from their decisions.

Our contributions to the literature can be summarized as follows. First, we quantify the significant increase in toxicity derived from Florida orange farmers' decisions to adopt an intensive insecticide program to control the insect vector of HLB. Such an estimate should be useful to increase policymakers' awareness on the consequences of having no policies in place for restricting the use of pesticides that are highly toxic and, therefore, pose significant risks for human health and the environment. Second, we model the profit-maximizing problem of a representative farmer by specifying a functional form for the damage function that incorporates the biological impact of the pathogen-vector system on yield as well as the abating impact of different insecticides on the insect vector population based on previous entomological work.

Importantly, we also use estimates of the marginal benefit and toxicity for each pesticide based on multiple and detailed toxicity criteria. This allows us to compute a differentiated tax rate for each chemical, which arguably provides a better opportunity for

[2]A major fault of individual pest control is that the mobility of pests compromises its effectiveness (Hendrichs *et al.* 2007). The use of site-specific pest control does not consider that neighboring farmers share the pests. Therefore, individual actions within the farm have little impact on the pest density in future periods due to re-infestation from neighboring farms (Lazarus and Dixon 1984).

substitution patterns among them. In fact, our results show in detail how the substitution of high- with low-toxicity pesticides occurs under the different alternative policies we consider. To our knowledge, we are the first to model a functional form for the damage function of HLB to Florida citrus farmers that considers the underlying biological process that determines the relationship of the insect vector and the yield damage that the disease causes. By running simulations of such a farm-level model, we are able to quantify the differential impact of choosing a pesticide indicator that accounts for the heterogeneous properties of chemicals versus a quantity-based tax. The model is valuable because little empirical research has been conducted regarding the implementation of financial incentives in pesticide policy and their impact on pesticide use, farm income, and externalities at the farm level (exceptions include Falconer and Hodge (2001) and Skevas, Stefanou and Lansik (2013)). Third, this case study analysis helps renew attention to the significant inefficiency associated with the current command-and-control pesticide policy in the United States and makes a case for the need to complement it with an incentive system that would minimize the associated deadweight loss.

The rest of this article is organized as follows. In the next section, we provide an overview on the current pesticide policies in the U.S. and in Europe. We also discuss the impact of HLB in Florida and its relevance as a case study for the present analysis. In the following section, we present the theoretical model and the specification for tax policies based on two possible criteria. In the subsequent section, we show how we calibrate the model in terms of yield, prices, and the correlation between those two variables to run simulations of the model applied to the Florida citrus industry. In addition, we also specify a functional form to the damage function. We then summarize and discuss the results, and, in the last section, we offer some conclusions and make recommendations for the design of a more efficient pesticide policy in the United States.

Background

Pesticide policies in the U.S. and in Europe

The experience in OECD countries regarding the introduction of environmental taxes on agricultural production inputs, such as pesticides, is limited because only a small number of countries have implemented them (Nielsen *et al.* 2023). Instead, many governments have opted for a command-and-control approach to regulate pesticide use. Such a policy choice can largely be attributed to the challenges of assessing the damages derived from pesticide use and their variability caused by the spatial and temporal heterogeneity in applications.

In the United States, for example, the Environmental Protection Agency (EPA) regulates pesticides through their registration and labeling under the premise that their use "will not generally cause unreasonable adverse effects on the environment." By such a statement, the EPA means any unreasonable risk to man – including dietary risk from residues on foods that result from use of a pesticide – or the environment (EPA 2024a). Thus, the EPA requires that manufacturers test chemicals and mixtures for toxic effects prior to their approval, and monitors risks and side effects (EPA 2024b). Should a pesticide be found to have harmful effects on the environment or human health, they get banned. But there are no financial incentives for farmers to reduce the use of pesticides other than following the recommended application rates (Zilberman and Millock 1997b). Moreover, the command-and-control approach can sometimes be too lenient. The Environmental Protection Agency (EPA) is developing new guidelines for the use of pesticides to ensure improved compliance with the Endangered Species Act (ESA), which were brought about by lawsuits claiming that the EPA had failed to comply with the ESA when registering pesticides (EPA 2024c).

In Europe, there is a greater emphasis on financial incentives relative to the United States. National action plans are mandatory for all European Union member states since 2012. Pesticide policies in the different national action plans include subsidies for upgrading equipment, educating farmers, and increasing awareness regarding the introduction of pesticide taxes (Böcker and Finger 2016). The main stated goal of pesticide policies is to reduce the "risks and impacts of pesticide use on human health and the environment" (Remáč 2018, p.14). Taxes on pesticide use can contribute to achieve such a goal and a few countries have adopted such market-based policy based on different criteria.

Sweden was the first country to introduce a flat quantity tax on pesticides based on the volume sold in 1984 (Böcker and Finger 2016). Norway, on the other hand, introduced a tax on pesticides in 1988, which was designed as an ad-valorem tax but changed in 1999; it currently consists of a base rate per area plus an additional rate that is based on which of the seven possible categories the pesticide belongs to according to the risks it presents for human health and the environment. In 2009, France replaced a volume tax on pesticides with a 3-category tax by which products are charged a different fee based on the non-point agricultural pollution category to which they belong. Thus, mineral-based pesticide products are charged the lowest fee, products considered to be dangerous to the environment are charged approximately double the fee, and products that are carcinogenic or hazardous are charged the highest fee, which is approximately five times that of the lowest fee. Starting in 2013, Denmark implemented a pesticide tax by which each pesticide product receives a differentiated tax rate based on the environmental and health impacts of the product. Such a pesticide policy is considered to be the most sophisticated currently in place (OECD 2017) and makes the country a pioneer in implementing such an approach to curb the externalities associated with the application of pesticides in agriculture (Böcker and Finger 2016).

Citrus greening disease in Florida as a case study

Florida has historically been the largest orange- and citrus-producing state in the U.S. and a top global producer (USDA-NASS 2022). Orange production in Florida typically accounts for 90 percent of the state's annual citrus production.[3] Therefore, in our analysis we focus on such a crop. Since 2005, Florida citrus farmers have been facing the impact of HLB, a devastating bacterial disease transmitted by an insect vector (the Asian citrus psyllid) that has decimated the state's citrus industry (Singerman and Rogers 2020). As illustrated in Figure 1, orange production in Florida has decreased by more than 90% since the disease was first found. As a consequence, Florida has lost its status as the top citrus and orange-producing state in the United States (USDA-NASS 2022).

To try to mitigate the impact of the disease, Florida orange farmers have adopted several different practices, including an intensive insecticide program to control the propagation of the insect that transmits the disease (Shen *et al.* 2013).[4] Thus, farmers substituted the traditional insecticides they had been using (i.e., mainly petroleum or mineral oil) with significantly more toxic chemicals such as neonicotinoids. Figure 2 shows the toxicity measured in load (see appendix for a detailed explanation of how the load is computed) and quantity per acre of insecticide use for growing oranges in Florida from

[3]Also, approximately 90 percent of the oranges grown in Florida are processed into juice.

[4]The eradication of the disease or its vector is not practically nor economically feasible.

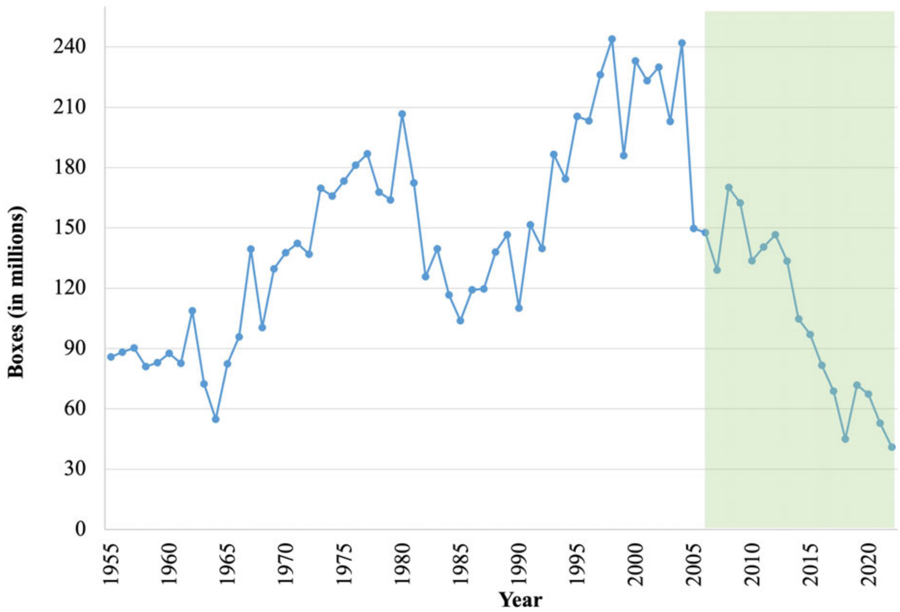

Figure 1. Orange production in Florida from 1955 to 2022, with shaded period (2005–2022) denoting citrus greening disease outbreak.

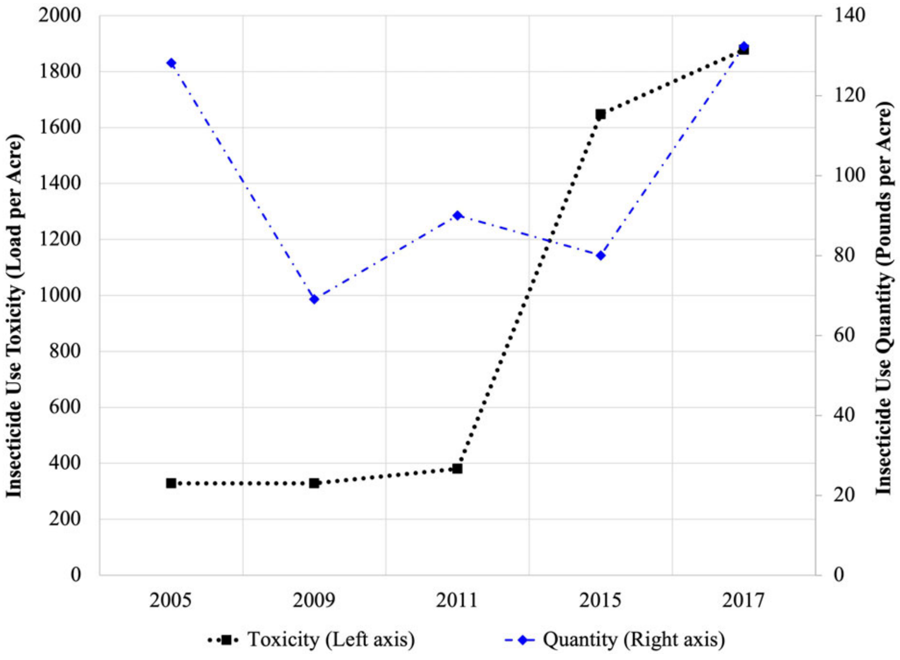

Figure 2. Insecticide use toxicity and quantity per acre for producing oranges in Florida from 2005 to 2017.

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

2005 to 2017. As illustrated by Figure 2, there is little difference, approximately 3%, in the quantity of insecticide used per acre from 2005 to 2017. However, such a figure also shows that the toxicity of insecticides used in orange production in Florida increased by 472% during that same period.

While the estimated increase in toxicity is very significant, to the extent that it only includes insecticides, it represents a lower bound on the total increase in toxicity of chemicals used by Florida citrus farmers to try to manage the impact of HLB. For example, the estimate does not include the toxicity and risks associated with citrus farmers' adoption of antibiotics as foliar sprays – following a decision of Florida policy makers to approve them in 2016.

The questionable approval of the use of antibiotics as foliar sprays (see Singerman and Lence 2023) is highly relevant because they can contribute to the development of antibiotic resistance with its consequent impact on public health. Given that the use of antibiotic foliar sprays was eventually found to be ineffective to enhance the health of HLB-infected trees (Li *et al.*, 2020), their use was short lived. However, the decision of farmers to substitute the use of insecticide sprays with antibiotics induced greater variability in the use of insecticides, which contributed not only to an increase in the population of the insect that transmits the disease, but also to an increase in resistance to insecticides (Chen *et al.*, 2018). The development of pesticide resistance can cause a further increase in their use to offset the lower susceptibility of the pest, which exacerbates the negative externalities generated (Dover and Croft 1986).

Given the drastic change in the toxicity of insecticides used by Florida orange farmers as a response to the exceptional challenge imposed by HLB, in this study, we use such a case to illustrate the change in outcomes derived from possible market-based interventions to capture, at least partially (as explained in the introduction), the external costs of pesticide use. In particular, we provide a conceptual and empirical framework to examine the change in farm-level outcomes (i.e., insecticide toxicity, profit, and yield per acre) from implementing a tax on insecticide use based on different pesticide indicators. The social cost mitigation achieved by lowering the use of pesticides through the implementation of a tax would make society better off (by decreasing the magnitude of the externalities and, thus, of the deadweight loss). In addition, given that producer surplus can be defined as revenue minus variable costs and, equivalently, as profit plus fixed costs, a tax based on the pesticide indicator that results in the greatest toxicity reduction at the lowest profit loss for producers will generate an outcome that is closer to the social optimum.

Model

We base our model on the damage control framework developed by Lichtenberg and Zilberman (1986), in which the farmer's use of pesticides is viewed as a damage control input. The premise of the model is that farmers apply pesticides to try to reduce the damage from pests and diseases and, thus, increase the proportion of potential output they can realize. The starting point of our model is the profit function for a representative farmer, which is given by $\Pi = TR - TC$, where Π, TR, and TC denote profit, total revenue, and total private cost, respectively; all three terms expressed in dollars per acre. For a representative Florida orange farmer, $TR = p \cdot q$, where p is the price of oranges per box and q is the quantity of oranges boxes produced per acre. Following Lichtenberg and Zilberman (1986), in our model, $q = y \cdot (1 - D(N_1))$, where y is the maximum potential yield per acre in the absence of disease, and $D(N_1)$ denotes the damage to yield caused by the density of the vector population, N_1, that spreads the disease. Therefore, $D(N_1)$ is between 0 and 1, and N_1 is a function, k, of the initial pest population N_0 and the quantity of insecticide I used per acre during the season, so that $N_1 = k(N_0, I)$.

Economic theory offers no guidance regarding the functional form that should be used to specify the damage function, so studies typically consider a variety of functional forms (Sexton, Lei and Zilberman 2007). Importantly, and in contrast to such an approach, in our model we use the findings of an entomological study on HLB to specify a functional form for the damage function that incorporates the underlying biological processes of the insect vector and the pathogen of the disease on yield. Thus, we model the damage to orange yield based on the study of Monzo and Stansly (2017). In their work, the authors used non-linear least-squares to model the relationship between yield losses and the cumulative number of psyllids in experiments they conducted in commercial groves of mature orange trees in Florida. They then fitted the data to a rectangular hyperbolic yield loss model by using the Newton-Raphson iterative estimation procedure. Thus, we define the yield damage function as follows:

$$D(N_1) = \left(\frac{\theta \cdot k(N_0,\ I)}{1 + \frac{\theta \cdot k(N_0,\ I)}{\eta}} \right) \cdot 100^{-1} \tag{1}$$

where θ denotes the slope of the curve at the origin – that is the rate of yield loss at low pest density – and η denotes the horizontal asymptote of the function, which denotes the maximum yield loss. Furthermore, based on feedback from entomologists at University of Florida Citrus Research and Education Center, we model the function $k(\cdot)$ in equation (1) as follows:

$$k(N_0,\ I) = N_0 \cdot \prod\nolimits_{i=1}^{n} (1 - x_i \cdot d_i \cdot I_i) \tag{2}$$

where x_i is the rate of reduction of the insect vector population from applying insecticide i, d_i is the duration of the effect of insecticide i in days expressed as a proportion of a year, I_i is the application rate of insecticide i, and n is the number of insecticides used.

For simplicity, in our model, we define the total private cost per acre as the sum of purchasing and applying inputs so that $TC(I, Z) = C(I) + \ W(Z)$, where $C(I)$ represents the private cost for pest control inputs I and $W(Z)$ represents the cost of all other grove caretaking inputs Z. Since we are particularly interested in the farmer's insecticide decisions, we assume that all other inputs are constant and given by $\overline{W(Z)}$.

Given that Florida citrus farmers typically spray insecticides mixed along with other chemicals, we assume that there is no additional cost of applying insecticides. Thus, the private cost of pest control inputs I is then given by the cost of the materials used. The total cost for a representative Florida orange farmer in the baseline scenario, which represents the current regulation, is then given by the following expression.

$$TC(I, Z) = \sum_{i=1}^{n} (r_i \cdot I_i) + \overline{W(Z)}$$

where r_i is the price of insecticide i and I_i is the annual application rate per acre of insecticide i. Importantly, insecticide use must be constrained so that each chemical application does not exceed its maximum recommended use $\overline{I_i}$, so that $I_i \le \overline{I_i}$. Therefore, the problem for the representative farmer whose objective is to maximize profit by choosing the level of each insecticide used can then be formalized as follows:

$$max_{I_i}\ E\left\{p\cdot y\left[1-\left(\frac{\theta\cdot N_0\cdot\prod_{i=1}^{n}(1-x_i\cdot d_i\cdot I_i)}{1+\frac{\theta\cdot N_0\cdot\prod_{i=1}^{n}(1-x_i\cdot d_i\cdot I_i)}{\eta}}\right)\cdot 100^{-1}\right]\right\}-\sum_{i=1}^{n}(r_i\ \cdot I_i\,)-\overline{W(Z)}$$

$$s.t. \tag{3}$$

$$I_i\ \le \overline{I_i}$$

Social planner and taxing

The setup in (3) can be modified to represent that of a social planner whose objective is to maximize social welfare, by subtracting an additional term denoting the net social costs of all insecticides used: $SC(\sum_{i=1}^{n} I_i\,)$. Thus, we assume such term represents all social benefits and costs of each insecticide used and that the latter are larger than the former. Such a setup, and in particular the estimate of the last term, would allow implementing a first-best policy that achieves no deadweight loss because all social costs are taken into account. However, as mentioned in the introduction, it would be virtually impossible to capture all social costs associated with pesticide use. Therefore, a second-best approach would consist of implementing of a tax policy that would reduce the size of the deadweight loss resulting from the market failure derived from farmers not internalizing the social costs of their input choices. A first tax policy we consider is based on adopting quantity indicator of insecticides used, whereas a second policy we consider is based on an indicator that accounts for the toxicity of insecticides.

If policy makers were to implement a tax on the quantity of insecticides used, the total cost to an orange farmer would be given by:

$$TC(I,Z)=\sum_{i=1}^{n}\left(\left(r_i\ +\ T_q\right)\cdot I_i\,\right)+\overline{W(Z)} \tag{4}$$

where T_q represents the rate for the quantity tax (in dollars per acre). If instead, policy makers were to implement a tax on the toxicity of insecticides (i.e., a load tax), the total cost to an orange farmer would be given by:

$$TC(I,Z)=\sum_{i=1}^{n}((r_i\ +\ L_i\cdot T_L\ )\cdot I_i\,)+\overline{W(Z)} \tag{5}$$

where L_i represents the load of insecticide i and T_L represents the rate for the load tax (in dollars per load).

Depending on whether a tax on quantity or on the toxicity of insecticides is implemented, the variable cost term in expression (3) needs to be modified according to equation (4) or (5), respectively. Thus, the simulations allow us to compare the outcomes in terms of yield, profit, and aggregate toxicity of insecticides in the baseline scenario to those obtained when implementing a tax to curb the social cost of insecticides.[5]

[5]The outcomes we obtain are for a single season. Evaluating the long-term impact is beyond the scope of this study but could be analyzed in future research.

Data and calibration

In this section, we describe the data we have available on insecticide use by Florida orange farmers, including active ingredients, cost, application rate, and cost-effectiveness. Then, we describe how we calibrate key variables (i.e., yield, prices, and the correlation between those two) for a representative Florida orange farmer to run our simulations. In the appendix we provide a detailed explanation of the procedure we followed to estimate the toxicity of each insecticide.

Insecticide data

USDA-NASS has collected data on the quantity of insecticide used for growing oranges in Florida from 2005 to 2017 by surveying farmers every odd year during that period, excluding 2013. According to the USDA-NASS data, eight different active ingredients – out of a total of 30 – account for over 90% of all insecticide use by Florida orange farmers. Our simulations and analysis are then based on the cost and traits of the most popular commercial products in the market that contain those active ingredients. To obtain estimates of the cost of insecticides, we collected quotes from chemical retailers and used their average. In addition, for each insecticide, we also gathered data regarding the rate of application per acre, the duration and magnitude of adult psyllid population reduction, and the proportion of active ingredients per product from the entomological literature available (Qureshi, Kostyk and Stansly 2014). Table 1 summarizes the data just described for each insecticide active ingredient and corresponding commercial product along with other relevant variables that we computed for each of them. Thus, the information in Table 1 is used for the variables defined in equation 2. Table 1 also includes the cost-effectiveness of each insecticide, which we obtained by using the prices and the duration of adult insect vector reduction listed in such table. The cost-effectiveness of insecticide i in dollars per acre per day is computed by multiplying the price of insecticide i by the application rate and dividing it by the duration of adult insect vector reduction in days multiplied by the magnitude of the insect vector reduction.

The main indicators used as a basis for taxing are the Quantity of Active Ingredients (QA) and the Load Index (LI), which measures the toxicity of a given pesticide on organisms other than the targeted one. While the QA indicator is simpler and, thus, often used in policy making, the LI indicator accounts not only for differences in dosage of pesticides but also for their environmental and health impacts at the product level (Kudsk, Jørgensen, and Ørum, 2018). Möhring *et al.* (2019) found that quantity-based pesticide indicators fail to identify important qualitative characteristics of pesticides, particularly for applications that have the highest values of the LI indicator.

Pesticides load

The load of a pesticide provides a measure of the toxicity from the use of such a chemical on human health and the environment. To estimate the load of insecticides used by Florida citrus farmers, we used data from the International Union of Pure and Applied Chemistry database regarding the properties of pesticides and bio-pesticides and follow the procedure established in the literature (Samsøe-Petersen *et al.*, 2012). The load of a pesticide has three

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 1. List of insecticide active ingredients (which account for over 90% of all insecticide use by Florida orange farmers) and corresponding most popular commercial product used to grow processed oranges in Florida along with their prices, application rates, proportion of active ingredient per product, duration, and magnitude of psyllids reduction, effective days of coverage, and cost-effectiveness

Insecticide active ingredient	Product name	Price ($/lb)	Product application Rate[1] (lb/acre)	Proportion of active ingredient per product[2]	Active ingredient application rate (lb/acre)	Duration of Adult psyllids reduction[1] (days)	Magnitude of psyllids reduction[1] (%)	Effective days of coverage[3] (days)	Cost-effectiveness[3] ($/acre per day)	Load (L/acre)
Chlorpyrifos	Lorsban	$4.56	5.000	44.9%	2.245	42	100	42	0.54	106.50
Dimethoate	Dimethoate	$5.44	1.000	44.7%	0.447	31	96	30	0.18	1.95
Imidacloprid	Admire Pro	$22.88	0.438	45.2%	0.198	67	88	59	0.17	3.09
Naled	Dibrom	$14.40	1.000	62.0%	0.620	42	91	38	0.38	288.97
Petroleum Oil	435 oil	$0.56	40.000	99.0%	39.600	38	76	29	0.78	51.48
Phosmet	Imidan	$11.04	1.500	70.0%	1.050	33	100	33	0.50	3.16
Spirotetramat	Movento	$41.60	1.000	22.4%	0.224	58	97	56	0.74	0.02
Zeta-Cypermethrin	Mustang Max	$20.64	0.269	18.1%	0.049	44	97	43	0.13	4.13

[1]Source: Qureshi, Kostyk and Stansly (2014). Note: In their study, the authors had two different application rates for each insecticide: low and high. Given the urgency of farmers to deal with the disease, we assume they applied the maximum rate possible (i.e., high).
[2]Source: Environmental Protection Agency (EPA) product labels.
[3]Source: Authors' calculations.

components: human health load, environmental fate load, and environmental toxicity load. We explain how we computed each of those components in detail in the appendix.[6]

Calibration

To calibrate our simulations, we use publicly available data from the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) regarding oranges' historical yield and prices in Florida. For cost estimates, we use publicly available data from the University of Florida. We calibrate our model to represent Valencia oranges because it is the variety with the highest proportion of planted acreage in the state, currently accounting for approximately 60% of the area. Importantly, the management practices and cost of production for non-Valencia oranges are identical to those of Valencia oranges.

To calibrate yield, we first estimate the trend for Valencia oranges yield data in Florida from 1955 to 2004, which we then use for obtaining two other estimates as explained next. Given that yield is a random variable in our model, we assume it follows a normal distribution. Using the estimated historical yield trend of Valencia oranges, we can obtain a sensible estimate for the mean of the yield distribution by computing the trend yield for year 2005. Thus, such an estimate represents the maximum potential yield of Valencia oranges per acre in the absence of HLB, which is reasonable because 2005 was the year in which HLB was first found in the state. In addition, we also use the trend to compute the de-trended yield for each year in our series so as to reflect 2005 technology but historical yield variability due to weather (i.e., weather draws). Thus, by estimating the variance of the resulting series, we obtain a sensible estimate for the variance of the yield distribution that we use as a basis for our simulations.

Regarding prices, we assume they follow a log normal distribution to avoid obtaining negative prices in our simulations. Given that the HLB outbreak was in 2005, we use the average of real prices in Florida for Valencia oranges from 1990 to 2004 as the mean of the distribution. The reason for choosing such a period is because in the 1980s there were several widespread freezes in Florida that caused orange trees and, therefore, orange supply to decrease and prices to increase significantly as a consequence. We obtained estimates of real prices by adjusting the nominal prices published by the USDA-NASS for inflation based on the annual Producer Price Index (PPI) for all U.S. citrus fruit (USDA-ERS 2019).

The final step in the calibration consisted of including an estimate of the negative correlation between prices and yield. Therefore, we computed the historical correlation between the two variables for Valencia oranges grown in Florida from 1955 to 2004, which we estimated at –0.33. We then used the Iman and Conover (1982) methodology – which only re-sorts the original yield and price draws – to impose such an observed correlation in our simulations.

In equation (1), we set parameters $\theta = 0.97$ and $\eta = 50.91$ following the work of Monzo and Stansly (2017), who obtained those estimates by pooling the data in the experiments they conducted in commercial groves of mature orange trees in Florida. Regarding the cost of inputs and applications for a representative orange farmer of processed oranges in Florida, we use farmer survey estimates provided by Singerman (2020), excluding the costs associated with the management of the insect vector of HLB (which we estimate in our

[6]The adverse effect of pesticides on the health of workers is included as part of the calculations of the load of a pesticide. However, the calculations for the load of a pesticide do not capture the potential externality on the health of consumers, which is a limitation of the load-based tax model.

simulations). Thus, our estimate for the cost of all other grove caretaking inputs denoted by $\overline{W(Z)}$ in expression (3) is \$1,600 per acre.

Results

We run simulations of the profit maximization problem for a representative Florida orange farmer denoted by expression (3) for the baseline scenario. We show results for population levels of the psyllid insect vector (N_0) from 0 to 80 because before 2012, when the significant increase in toxicity depicted in Figure 2 occurred, the average level of psyllids per orange block was less than 10, but it increased to a peak of 27 per orange block in 2017 (Singerman 2017). Thus, a level of psyllids that almost triples that count allows us to consider the likely further increase in psyllid population levels in following years.[7]

We then run simulations of the profit maximization problem for the cases in which a quantity-based tax and a load-based tax are implemented, which are denoted by the combination of expressions (3) and (4) for the former case and by the combination of expressions (3) and (5) for the latter case. The objective is to estimate the magnitude of the change in load, yield, and profit per acre when implementing each tax policy relative to the baseline.

For the load-based tax model, we run different tax rates per load (T_L) and found that, as the number of psyllids increases, a tax rate of \$2.50 makes the total load be asymptotic at a level of 29, which is the level of load in the baseline scenario when the number of psyllids is 20 (roughly representing a middle point in the spike of psyllid population between 2012 and 2017 described earlier). Therefore, we run the simulations using such a value as a "target load" because it arguably reflects a sensible maximum tax rate that would make sense implementing to reduce the toxicity of insecticides (i.e., higher tax rates would be futile in achieving a greater reduction in load).

In panel A of Table 2, we show the results of the simulations in levels for the baseline scenario, as well as for the scenario in which a load-based tax rate of \$2.50 per load is implemented. For comparison purposes, we also show the results for the scenario in which a quantity-based tax is implemented using the same rate. However, to make the comparison more meaningful between tax policies, in Table 2 we also show the results of a scenario for a quantity-based tax with a rate of \$12 because we found it yields a comparable target load level of 29 when the number of psyllids is 50. However, that quantity tax rate does not prevent toxicity from further increasing as the number of psyllids increases (as the load tax rate does). Hence, we also show the results for a quantity tax rate of \$20 that achieves a slightly lower but similar load to the load-based tax rate of \$2.50 when the psyllid number is 80.

In panel B of Table 2, we show the results of the simulations in panel A in percentage change relative to the baseline. The load-based tax rate of \$2.50 induces a significant reduction (74%) in the load of insecticides when the level of psyllids per acre is 10. The underlying substitution in insecticides causes a reduction in yield of 3% and of 16% in profit relative to the baseline. As expected, as the number of psyllids increases, both the percent reduction in load and profit increases significantly.[8] When the psyllids level is 60,

[7]In addition, profit becomes negative in the baseline scenario when the number of psyllids reaches a count of 120 but the additional psyllid levels show the same trends as those shown, so we omit them in the interest of space.

[8]The only exception in the pattern is for the percent load when the psyllid level increases from 10 to 20, which is driven by a relatively higher increase in load when the tax is applied but the load level is still lower compared to that of the baseline as seen in Panel A.

Table 2. Profit maximization simulation results showing change in load, yield, and profit per acre for the baseline, for a load-based tax of $2.50, as well as for a quantity-based tax of $2.50, $12, and $20 for different psyllid levels when the correlation between yield and prices is −0.33

	Baseline			Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)
A. Results in Levels															
0	0	335	369.89	0	335	369.89	0	335	369.89	0	335	369.89	0	335	369.89
10	25	325	266.63	6	316	223.98	22	324	251.33	4	312	216.08	0	308	209.95
20	29	320	222.07	19	312	155.70	27	318	201.55	17	311	140.53	5	298	111.05
30	108	314	184.12	26	310	112.04	45	313	161.72	22	307	92.20	12	294	47.83
40	243	310	150.52	28	307	75.91	135	309	127.05	25	303	51.95	15	290	0.23
50	343	306	120.93	29	302	43.11	237	304	96.07	29	298	16.09	17	285	−39.70
60	424	303	94.98	29	297	13.02	329	301	68.46	54	293	−16.01	19	282	−74.06
70	504	301	72.04	29	293	−14.69	407	298	43.97	93	290	−45.07	20	277	−105.47
80	581	300	51.82	29	289	−40.22	494	297	22.06	121	286	−71.39	25	274	−133.36

	% Change relative to baseline for											
	Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
B. Results in Percentage Change Relative to the Baseline												
0	0	0	0	0	0	0	0	0	0	0	0	0
10	−74%	−3.0%	−16%	−11%	−0.5%	−6%	−86%	−4.1%	−19%	−98%	−5.3%	−21%
20	−37%	−2.4%	−30%	−9%	−0.5%	−9%	−41%	−2.9%	−37%	−82%	−7.0%	−50%

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 2. (*Continued*)

	% Change relative to baseline for											
	Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
30	−76%	−1.2%	−39%	−59%	−0.3%	−12%	−79%	−2.3%	−50%	−89%	−6.4%	−74%
40	−88%	−0.9%	−50%	−44%	−0.3%	−16%	−90%	−2.2%	−65%	−94%	−6.3%	−100%
50	−92%	−1.3%	−64%	−31%	−0.5%	−21%	−92%	−2.7%	−87%	−95%	−6.8%	−133%
60	−93%	−2.1%	−86%	−22%	−0.7%	−28%	−87%	−3.3%	−117%	−96%	−7.2%	−178%
70	−94%	−2.9%	−120%	−19%	−1.0%	−39%	−82%	−3.9%	−163%	−96%	−8.0%	−246%
80	−95%	−3.6%	−178%	−15%	−1.2%	−57%	−79%	−4.7%	−238%	−96%	−8.7%	−357%

the load is reduced by 93% relative to the baseline, but the profit is also reduced significantly – to 86% – because the tax prevents farmers from using more toxic insecticides profitably. For higher levels of psyllid population, the profit under a load tax of $2.50 becomes negative.

The results of implementing a quantity-based tax model using a rate of $2.50 in Table 2 show that using such a tax type and rate initially induces a reduction in the load of insecticides. But as the number of psyllids increases, a farmer would find it profitable to use more toxic insecticides despite the tax and, therefore, the load increases. Thus, for levels of psyllids greater than 30, the percent change in load relative to the baseline starts decreasing (in absolute value). When the psyllids level is 60, the load is reduced by only 22% (versus 93% with the load-based tax). The percent reduction in profit is increasing due to the effect of the tax combined with the increase in the number of psyllids. Even though a quantity tax of $12 is more effective at reducing the load relative to the rate of $2.50, the pattern in load reduction is similar; it starts decreasing for levels of psyllids greater than 50. Only when the quantity-based tax is $20, the percent reduction in load remains steady at more than 90% when the number of psyllids is 40 or more. Importantly, however, the percent reduction in profit using the $20 quantity-based tax rate roughly doubles that obtained when using a load-based tax of $2.50 for a number of psyllids of 40 or more.

Table 3 shows the prevalence and pattern of insecticide use in each of the scenarios included in Table 2 and for each level of psyllid population. The table illustrates, for example, that in the baseline scenario the criterion used to choose the level of use of each insecticide is based on the cost-effectiveness (which is shown in Table 1). In addition, Table 3 also shows the pattern of substitution that takes place when a tax on load is implemented; the most toxic insecticides such as Naled and Chlorpyrifos are no longer used because they are taxed more heavily. Interestingly, when the quantity tax is $20, Naled is still used (albeit at a very low level) when the psyllid level is 80.

Sensitivity analysis

Our model hinges on the correlation imposed between prices and yield of processed Valencia oranges that we estimated based on historical values. However, such a value may no longer hold under current market conditions. Thus, we conduct a sensitivity analysis for different correlation values to examine whether and to what extent the simulation results change. We run the simulations for correlation values between the two variables of −0.50 and −0.75. When the (absolute) value of the correlation between prices and yield increases, yield draws that have lower values are matched more often with the price draws that have higher values to reach the target correlation (as described in the calibration section when referring to the Iman and Conover (1982) methodology).

The simulation results for the correlation values of −0.50 and −0.75 are shown in Tables 4 and 5, respectively. The results in Tables 2, 4, and 5 show that as the (absolute) value of the correlation increases, profit in all scenarios decreases for all psyllids levels. This is because a higher correlation value implies that a change in yield is offset more often by a change in prices in the opposite direction. As the absolute value of the correlation between yield and prices increases, the choice of insecticides used changes slightly in the baseline and quantity tax-based scenarios as denoted by the change in load. Nevertheless, for the load-based tax case the load and yield change only marginally. Thus, an additional advantage to implementing a load-based policy to curb the social costs of insecticide use is that such a tax would be more stable should the correlation between price and yield change.

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 3. Prevalence of insecticide use (as percentage of maximum possible application) by scenario for each psyllid population level

Psyllid Level	Chlorpyrifos	Dimethoate	Imidacloprid	Naled	Petroleum Oil	Phosmet	Spirotetramat	Zeta-Cypermethrin	Ending Psyllid Level
Use in Baseline Scenario									
0	0%	0%	0%	0%	0%	0%	0%	0%	0
10	0%	15%	93%	0%	0%	0%	0%	100%	3
20	0%	96%	100%	0%	0%	0%	0%	100%	5
30	0%	100%	100%	19%	0%	0%	0%	100%	7
40	0%	100%	100%	51%	0%	2%	0%	100%	9
50	2%	100%	100%	73%	0%	11%	0%	100%	11
60	9%	100%	100%	86%	0%	20%	0%	100%	12
70	20%	100%	100%	95%	0%	26%	0%	100%	13
80	40%	100%	100%	97%	0%	28%	0%	100%	14
Use in Load-based Tax Scenario ($2.50)									
0	0%	0%	0%	0%	0%	0%	0%	0%	0
10	0%	5%	78%	0%	0%	0%	0%	1%	7
20	0%	31%	100%	0%	0%	0%	0%	55%	8
30	0%	64%	100%	0%	0%	0%	0%	90%	9
40	0%	85%	100%	0%	0%	0%	0%	100%	10
50	0%	97%	100%	0%	0%	0%	0%	100%	13
60	0%	100%	100%	0%	0%	0%	2%	100%	15
70	0%	100%	100%	0%	0%	2%	5%	100%	17

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 3. (*Continued*)

Psyllid Level	Chlorpyrifos	Dimethoate	Imidacloprid	Naled	Petroleum Oil	Phosmet	Spirotetramat	Zeta-Cypermethrin	Ending Psyllid Level
80	0%	100%	100%	0%	0%	4%	18%	100%	19
Use in Quantity-based Tax Scenario ($2.50)									
0	0%	0%	0%	0%	0%	0%	0%	0%	0
10	0%	0%	68%	0%	0%	0%	0%	100%	4
20	0%	44%	100%	0%	0%	0%	0%	100%	6
30	0%	90%	100%	4%	0%	0%	0%	100%	8
40	0%	100%	100%	25%	0%	0%	0%	100%	10
50	0%	100%	100%	49%	0%	2%	0%	100%	12
60	6%	100%	100%	67%	0%	5%	0%	100%	13
70	14%	100%	100%	78%	0%	7%	0%	100%	14
80	28%	100%	100%	87%	0%	5%	0%	100%	15
Use in Quantity-based Tax Scenario ($12)									
0	0%	0%	0%	0%	0%	0%	0%	0%	0
10	0%	0%	45%	0%	0%	0%	0%	0%	8
20	0%	0%	97%	0%	0%	0%	0%	57%	9
30	0%	0%	100%	0%	0%	0%	0%	86%	10
40	0%	8%	100%	0%	0%	0%	0%	98%	12
50	0%	24%	100%	1%	0%	0%	0%	99%	15
60	0%	39%	100%	7%	0%	0%	0%	100%	17

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 3. (*Continued*)

Psyllid Level	Chlorpyrifos	Dimethoate	Imidacloprid	Naled	Petroleum Oil	Phosmet	Spirotetramat	Zeta-Cypermethrin	Ending Psyllid Level
70	0%	50%	100%	16%	0%	0%	0%	100%	19
80	2%	57%	100%	21%	0%	0%	0%	100%	21
Use in Quantity-based Tax Scenario ($20)									
0	0%	0%	0%	0%	0%	0%	0%	0%	0
10	0%	0%	6%	0%	0%	0%	0%	0%	10
20	0%	0%	59%	0%	0%	0%	0%	4%	15
30	0%	0%	80%	0%	0%	0%	0%	33%	17
40	0%	0%	88%	0%	0%	0%	0%	51%	19
50	0%	0%	92%	0%	0%	0%	0%	59%	22
60	0%	0%	93%	0%	0%	0%	0%	69%	25
70	0%	3%	93%	0%	0%	0%	0%	73%	28
80	0%	7%	92%	1%	0%	0%	0%	80%	30

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 4. Profit maximization simulation results showing change in load, yield, and profit per acre for the baseline, for a load-based tax of $2.50, as well as for a quantity-based tax of $2.50, $12, and $20 for different psyllid levels when the correlation between yield and prices is −0.50

A. Results in Levels

Psyllid level	Baseline			Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)
0	0	335	362.53	0	335	362.53	0	335	362.53	0	335	362.53	0	335	362.53
10	25	326	259.35	6	316	216.74	22	324	244.02	4	312	208.81	0	308	202.96
20	30	320	215.03	18	312	148.24	27	318	194.43	18	311	133.26	5	298	103.81
30	101	314	177.12	26	311	105.12	38	313	154.77	23	308	85.26	12	294	40.26
40	241	309	143.57	29	307	69.05	130	308	120.13	25	303	45.31	16	290	−7.01
50	344	306	113.85	29	302	36.45	239	304	89.18	28	298	9.39	18	286	−46.42
60	430	303	87.80	29	297	6.48	321	301	61.41	41	293	−22.76	19	282	−80.77
70	511	301	64.79	29	292	−21.21	409	298	36.73	84	290	−51.85	20	278	−112.21
80	590	300	44.46	29	289	−46.85	503	297	14.80	116	286	−78.20	24	275	−139.60

B. Results in Percentage Change Relative to the Baseline

% Change relative to baseline for

Psyllid level	Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
0	0	0	0	0	0	0	0	0	0	0	0	0
10	−74%	−3.0%	−16%	−11%	−0.6%	−6%	−86%	−4.1%	−19%	−99%	−5.4%	−22%
20	−38%	−2.5%	−31%	−9%	−0.5%	−10%	−41%	−2.8%	−38%	−83%	−7.0%	−52%

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 4. (*Continued*)

B. Results in Percentage Change Relative to the Baseline

% Change relative to baseline for

	Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
30	−74%	−1.0%	−41%	−63%	−0.2%	−13%	−77%	−2.1%	−52%	−88%	−6.3%	−77%
40	−88%	−0.8%	−52%	−46%	−0.3%	−16%	−90%	−2.2%	−68%	−94%	−6.2%	−105%
50	−92%	−1.2%	−68%	−30%	−0.5%	−22%	−92%	−2.7%	−92%	−95%	−6.4%	−141%
60	−93%	−2.1%	−93%	−25%	−0.8%	−30%	−90%	−3.3%	−126%	−96%	−6.9%	−192%
70	−94%	−2.9%	−133%	−20%	−1.0%	−43%	−84%	−3.9%	−180%	−96%	−7.8%	−273%
80	−95%	−3.7%	−205%	−15%	−1.2%	−67%	−80%	−4.8%	−276%	−96%	−8.5%	−414%

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 5. Profit maximization simulation results showing change in load, yield, and profit per acre for the baseline, for a load-based tax of $2.50, as well as for a quantity-based tax of $2.50, $12, and $20 for different psyllid levels when the correlation between yield and prices is −0.75

A. Results in Levels

	Baseline			Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)	Load	Yield (boxes)	Profit ($)
0	0	335	351.71	0	335	351.71	0	335	351.71	0	335	351.71	0	335	351.71
10	25	326	248.77	7	316	206.36	23	324	233.11	3	312	197.78	0	308	192.87
20	29	320	204.69	19	313	137.28	27	318	183.89	18	312	122.17	5	298	93.10
30	72	314	166.88	27	311	94.88	35	313	144.59	24	308	75.36	12	295	29.31
40	236	309	133.26	29	307	59.02	102	308	109.98	25	303	35.51	16	291	−17.94
50	373	306	103.60	29	302	26.68	234	304	78.98	25	297	−0.50	18	288	−56.60
60	435	303	77.31	29	297	−3.12	337	301	51.21	36	293	−32.76	21	284	−90.07
70	487	301	54.02	29	292	−30.72	419	298	26.24	54	289	−61.84	21	280	−120.66
80	580	300	33.48	29	289	−56.33	511	296	4.10	85	286	−88.25	23	277	−147.76

B. Results in Percentage Change Relative to the Baseline

% Change relative to baseline for

	Load tax $2.50			Quantity tax $2.50			Quantity tax $12			Quantity tax $20		
Psyllid level	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
0	0	0	0	0	0	0	0	0	0	0	0	0
10	−72%	−2.8%	−17%	−9%	−0.5%	−6%	−87%	−4.2%	−20%	−99%	−5.4%	−22%
20	−36%	−2.3%	−33%	−8%	−0.5%	−10%	−39%	−2.7%	−40%	−82%	−6.9%	−55%

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table 5. (*Continued*)

B. Results in Percentage Change Relative to the Baseline												
% Change relative to baseline for												
	Load tax \$2.50			Quantity tax \$2.50			Quantity tax \$12			Quantity tax \$20		
Psyllid level	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit	Load	Yield	Profit
30	−63%	−0.8%	−43%	−51%	−0.1%	−13%	−67%	−1.8%	−55%	−84%	−6.1%	−82%
40	−88%	−0.7%	−56%	−57%	−0.4%	−17%	−89%	−2.2%	−73%	−93%	−5.9%	−113%
50	−92%	−1.2%	−74%	−37%	−0.5%	−24%	−93%	−2.8%	−100%	−95%	−6.0%	−155%
60	−93%	−1.9%	−104%	−23%	−0.7%	−34%	−92%	−3.2%	−142%	−95%	−6.1%	−217%
70	−94%	−2.8%	−157%	−14%	−0.9%	−51%	−89%	−3.8%	−214%	−96%	−6.8%	−323%
80	−95%	−3.7%	−268%	−12%	−1.1%	−88%	−85%	−4.7%	−364%	−96%	−7.5%	−541%

Conclusions and policy implications

Applications of pesticides are critical for farmers to manage pests and diseases affecting their crops. But when farmers apply pesticides, they ignore the social costs associated with their use. In the United States, pesticides are regulated only through their registration and labeling; there are no financial incentives for farmers to reduce the use of pesticides other than following the recommended application rates. Given the sizable externalities generated by pesticide use, there is a rationale for further government intervention. As argued by Zilberman and Millock (1997a), the role of economists in assessing pesticide policies is to expose the inefficiency associated with existing regulations and propose alternatives. Thus, using citrus greening disease in Florida as a case study – where farmers adopted the use of highly toxic insecticides to try to control the spread of the insect that transmits the disease – we use simulations to compare the outcomes of implementing a tax on insecticide use based on different criteria to curb the social costs associated with their use.

Our simulations' results show that taxing farmers using a load-based tax would provide them with a strong incentive to reduce the use of pesticides that are more toxic and substitute them with less toxic chemicals. Instead, a policy using a quantity-based tax would need to have a significantly higher rate to achieve a similar effect but the percentage reduction in profit and yield would be significantly higher in such a case. Thus, a load-based tax would be more effective to help correct the market failure derived from farmers not internalizing the social costs of their input choices.

A significant proportion of the crop damage that pesticides aim to prevent is caused by invasive species such as HLB. Economics can not only be helpful in informing pesticide policy, but it can also aid in the design of policies that would minimize and mitigate the effects of invasive species (Sexton, Lei and Zilberman 2007). In this regard, since our results show that a load-based tax would significantly increase the cost of using insecticides to combat pests and diseases – which would in turn cause loss of yield and profit – policy makers could, for instance, exempt farmers from paying the tax under certain circumstances.

Invasive species like HLB pose a collective-action problem (see, for example, Perrings *et al.* 2002; Florec *et al.* 2013; Singerman and Rogers 2020). Hence, the ability of individual farmers to effectively control mobile pests in the long run depends critically on the actions of neighboring farmers (Lazarus and Dixon 1984), which creates a public-good dilemma. It is, therefore, key for policy makers to realize that the lack of policies restricting the toxicity of pesticides being used may not even be beneficial for farmers in the long run – as it has been the case of citrus farmers in Florida – because farmers (incorrectly) view pesticides as a guarantee to achieve fewer production losses (Deguine *et al.* 2021), which promotes a false belief in the possibility of self-reliance for controlling pests that require instead collective action (Bagavathiannan *et al.* 2019).

Policy makers could achieve multiple desirable societal objectives by designing a policy that would minimize the deadweight loss derived from farmers ignoring the social costs of their input choices and simultaneously mitigate the impact of invasive species as exemplified next. Spraying insecticides as part of a regional pest and disease control such as an Area-wide Pest Management program (AWPM) has been shown to be superior to site-specific control when pests and disease vectors are mobile (Faust 2008; Singerman, Lence and Useche 2017). The underlying premise for AWPM is that coordinating sprays allows neighboring farmers to control the pests and diseases at a lower (social) cost by increasing the productivity of their inputs. However, due to its voluntary character, an AWPM program can suffer from low farmer participation (Hendrichs *et al.*, 2007; Singerman and

Useche, 2019). A policy combining a load-based tax and a potential exemption from it when neighboring farmers coordinate sprays could contribute to reduce pesticide use and therefore the externalities associated with it because farmers could choose to either apply insecticides individually (and be subject to the tax) or in coordination with neighbors (and be exempt from the tax). Thus, farmers would not necessarily be worse off by the introduction of the tax policy but they would unequivocally reduce the externalities associated with their pesticide choices.[9]

Last, but not least, there is evidence that the introduction of a load-based tax targeting the externalities of pesticide use in Denmark has been effective in inducing behavioral change on farmers and has resulted in an overall reduction of pesticide toxicity by 18% (Nielsen *et al.* 2023). Given that global warming will likely contribute to increase the vulnerability of crops to pests and diseases and, thus, lead farmers to increase chemical use (Lyall, Suk and Tait 2006), policy makers in the United States could consider complementing the current pesticide regulatory system with financial incentives, such as a load-based tax, to reduce the risks for human health and the environment derived from the toxicity of pesticide use.

Data availability statement. The authors confirm that the data supporting the findings of this study will be available within the article.

Competing interests. The author(s) declare none.

References

Bagavathiannan, M.V., S. Graham, Z. Ma, J.N. Barney, S.R. Coutts, A.L. Caicedo, R. De Clerck-Floate, N.M. West, L. Blank, A.L. Metcalf, M. Lacoste, C.R. Moreno, J.A. Evans, I. Burke, and H. Beckie. 2019. "Considering Weed Management as a Social Dilemma Bridges Individual and Collective Interests." *Nature Plants* **5**: 343–351.

Baumol, W.J. and W.E. Oates. 1988. *The Theory of Environmental Policy*. 2nd ed. New York, NY: Cambridge University Press.

Böcker, T. and R. Finger. 2016. "European Pesticide Tax Schemes in Comparison: An Analysis of Experiences and Developments." *Sustainability* **8**(4): 378.

Bourguet, D. and T. Guillemaud. 2016. "The Hidden and External Costs of Pesticide Use." *Sustainable Agriculture Review* **16**: 35–120.

Bradshaw, C.J., B. Leroy, C. Bellard, D. Roiz, C. Albert, A. Fournier, M. Barbet-Massin, J.M. Salles, F. Simard, and F. Courchamp. 2016. "Massive Yet Grossly Underestimated Global Costs of Invasive Insects." *Nature Communications* **7**: 12986.

Carpenter, J.E. and L.P. Gianessi. 2010. "Economic Impact of Glyphosate-Resistant Weeds." In Vijay K. Nandula ed., *Glyphosate Resistance in Crops and Weeds*, pp. 297–312. New York: John Wiley & Sons, Inc.

Chen, X. D., T. A. Gill, M. Ashfaq, K. Pelz-Stelinski, and L. Stelinski. 2018. "Resistance to Commonly used Insecticides in Asian Citrus Psyllid: Stability and Relationship to Gene Expression." *Journal of Applied Entomology* **142**(10): 967–977.

Deguine, J.P., J.N. Aubertot, R.J. Flor, F. Lescourret, K.A.G. Wyckhuys, and A. Ratnadass. 2021. "Integrated Pest Management: Good Intentions, Hard Realities. A Review." *Agronomy for Sustainble Devevelopment.* **41**: 38.

Devillers, J., S. Bintein, and D. Domine. 1996. "Comparison of BCF Models Based on Log P." *Chemosphere* **33**(6): 1047–1065.

Dover, M.J. and B.A. Croft. 1986. "Pesticide Resistance and Public Policy." *Bioscience* **36**(2): 78–85.

[9]"By reducing insecticide use, the implementation of a load-tax may cause the psyllid population to be higher in the following period relative to the baseline. However, should the tax act as a large enough incentive for farmers to coordinate sprays, that may not need to be the case."

Environmental Protection Agency (EPA). 2016. *Sci-Grow Description*. Washington DC: Environmental Protection Agency.

Environmental Protection Agency (EPA). 2024a. *Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA) and Federal Facilities*. Washington DC: Environmental Protection Agency.

Environmental Protection Agency (EPA). 2024b. *Toxic Substances Control Act (TSCA) and Federal Facilities*. Washington DC: Environmental Protection Agency.

Environmental Protection Agency (EPA). 2024c. *Endangered Species Litigation and Associated Pesticide Limitations*. Washington DC: Environmental Protection Agency.

Falconer, K. and I. Hodge. 2001. "Pesticide Taxation and Multi-objective Policy-making: Farm Modelling to Evaluate Profit/Environment Trade-offs." *Ecological Economics* **36**(2): 263–279.

Faust, R.M. 2008. "General Introduction to Areawide Pest Management." In O. Koul, G.W. Cuperus, and N. Elliott (eds.), *Areawide Pest Management Theory and Implementation*, pp. 1–14. Cambridge, MA: CAB International.

Finger, R., N. Möhring, T. Dalhaus, and T. Böcker. 2017. "Revisiting Pesticide Taxation Schemes." *Ecological Economics* **134**(2017): 263–266.

Florec, V., R.J. Sadler, B. White, and B.C. Dominiak. 2013. "Choosing the Battles: The Economics of Area Wide Pest Management for Queensland Fruit Fly." *Food Policy* **38**: 203–213.

Hendrichs, J., P. Kenmore, A.S. Robinson, and M.J.B. Vreysen. 2007. "Area-Wide Integrated Pest Management (AW-IPM): Principles, Practice and Prospects." In Vreysen, M.J.B., A.S. Robinson, and J. Hendrichs (eds.), *Area-Wide Control of Insect Pests: From Research to Field Implementation*, pp. 3–31. AA Dordrecht, The Netherlands: Springer.

Iman, R. L. and W. J. Conover. 1982. "A Distribution-Free Approach to Inducing Rank Correlation Among Input Variables." *Communication in Statistics: Simulation and Computation* **11**(3): 311–334.

Kudsk, P., L.N. Jørgensen, and J.E. Ørum. 2018. "Pesticide Load—a New Danish Pesticide Risk Indicator with Multiple Applications." *Land Use Policy* **70**: 384–393.

Lazarus, W. F. and B. L. Dixon. 1984. "Agricultural pests as common property: control of the corn rootworm." *Am. J. Agric. Econ.* **66**: 456–465.

Li, S., F. Wu, Y. Duan, A. Singerman, and Z. Guan. 2020. "Citrus Greening: Management Strategies and Their Economic Impact." *HortScience* **55**(5): 604–612.

Lichtenberg, E. and D. Zilberman. 1986. "The Econometrics of Damage Control: Why Specification Matters." *American Journal of Agricultural Economics* **68**(2): 261–273.

Lyall, C., J. Suk, and J. Tait. 2006. "T3: risk evaluation work package. Results from expert survey. Office of Science and Innovation Foresight: Detection and Identification of Infectious Diseases." Available at: http://www.foresight.gov.uk/Infectious%20Diseases/T3.pdf

Möhring, N., S. Gaba, and Finger, R. 2019. "Quantity Based Indicators Fail to Identify Extreme Pesticide Risks." *Science of The Total Environment* **646**: 503–523.

Monzo, C. and P.A. Stansly. 2017. "Economic Injury Levels for Asian Citrus Psyllid Control in Process Oranges from Mature Trees with High Incidence of Huanglongbing." *PLoS ONE* **12**(4): 1–25.

Nielsen, H.Ø., M.T. Hedegaard Konrad, A.B. Pedersen, and S. Gyldenkærne. 2023. "Ex-post Evaluation of the Danish Pesticide Tax: A Novel and Effective Tax Design." *Land Use Policy* **126**: 106549.

Organization for Economic Development Co-operation and Development (OECD). 2017. "Environmental Fiscal Reform – Progress, Prospects and Pitfalls. Working Document." Available at: https://www.oecd.org/tax/environmental-fiscal-reform-progress-prospects-and-pitfalls.htm

Perrings, C., M. Williamson, E.B. Barbier, D. Delfino, S. Dalmazzone, J. Shogren, P. Simmons, and A. Watkinson. 2002. "Biological Invasion Risks and the Public Good: An Economic Perspective." *Conservation Ecology* **6**(1): 1.

Qureshi, J., B. Kostyk, and P. Stansly. 2014. "Insecticidal Suppression of Asian Citrus Psyllid Diaphorina citri (Hemiptera: Liviidae) Vector of Huanglongbing Pathogens." *PLoS ONE* **9**(12): 1–22.

Remáč, M. 2018. *Directive 2009/128/EC on the Sustainable use of Pesticides*. Brussels, Belgium: European Parliament, European Parliamentary Research Service.

Rossman, A. 2009. "The impact of invasive fungi on agricultural ecosystems in the United States." *Biological Invasions* **11**: 97–107.

Samsøe-Petersen, L., C. Bøje, L.F. Hansen, J. Kjølholt, L.N. Jørgensen, P. Kudsk, and J.E. Ørum. 2012. *The Agricultural Pesticide Load in Denmark 2007–2010*. Odense, Denmark: The Danish Environmental Protection Agency.

Sexton, S.E, Z. Lei and D. Zilberman. 2007. "The Economics of Pesticides and Pest Control." *International Review of Environmental and Resource Economics* **1**(3): 271–326.

Singerman, A. and S.H. Lence. 2023. "The Source of Uncertainty Influences Technology Adoption." *European Review of Agricultural Economics* **50**(2): 591–623

Singerman, A. 2020. *Cost of Producing Processed Oranges in Southwest Florida in 2018/19*. Gainesville, FL: University of Florida.

Singerman, A. 2017. "Results in After Citrus Bactericides Put to the Test. Growing Produce magazine." Available at: https://www.growingproduce.com/citrus/insect-disease-update/results-in-after-citrus-bactericides-put-to-the-test/

Singerman, A., S.H. Lence, and P. Useche. 2017. "Is Area-wide Pest Management Useful? The Case of Citrus Greening." *Applied Economic Perspectives and Policy* **39**(4): 609–634.

Singerman, A. and M. Rogers. 2020. "The Economics Challenges of Dealing with Citrus Greening: The Case of Florida." *Journal of Integrated Pest Management* **11**(1): 1–7.

Singerman, A. and P. Useche. 2019. "The Role of Strategic Uncertainty in Area-wide Pest Management Decisions of Florida Citrus Growers." *American Journal of Agricultural Economics* **101**(4): 991–1011.

Shen, W., J. Cevallos-Cevallos, U. Nunes da Rocha, H.A. Arevalo, P.A. Stansly, P. Roberts, and A.H.C. van Bruggen. 2013. "Relation between Plant Nutrition, Hormones, Insecticide Applications, Bacterial Endophytes, and *Candidatus* Liberibacter asiaticus Ct Values in Citrus Trees Infected with Huanglongbing." *European Journal of Plant Pathology* **137**: 727–742.

Skevas, T., S.E. Stefanou, and A.O. Lansink. 2013. "Do Farmers Internalise Environmental Spillovers of Pesticides in Production?" *Journal of Agricultural Economics* **64**(3): 624–640

U.S. Department of Agriculture, Economic Research Service. 2019. *Producer Price Indexes*. Washington DC: United States Department of Agriculture, Economic Research Service.

U.S. Department of Agriculture, Economic Research Service. 2022. *Florida Citrus Statistics 2020–2021*. Washington DC: United States Department of Agriculture, National Agricultural Statistics Service.

Wang, W.-X. 2016. "Bioaccumulation and Biomonitoring." In *Marine Ecotoxicology: Current Knowledge and Future Issues*, eds. J. Blasco, P. Chapman, O. Campana, and M. Hampel, 1st edition, 99–119. Cambridge, MA: Academic Press.

Waterfield, G. and D. Zilberman. 2012. "Pest Management in Food Systems: An Economic Perspective." *Annual Review of Environment and Resources* **37**: 223–245.

Zilberman, D. and K. Millock. 1997a. "Pesticide Use and Regulation: Making Economic Sense Out of an Externality and Regulation Nightmare." *Journal of Agricultural and Resource Economics* **22**(2):321–332

Zilberman, D. and K. Millock. 1997b. "Financial Incentives and Pesticide Use." *Food Policy* **22**(2): 133–144.

Appendix: pesticide load calculation

The first component of a pesticide load is the human health load, which measures the risk of exposure that an insecticide poses to human health when handling and applying the pesticide. The load of each pesticide is calculated based on the hazard statements that appear on the label of the product; each statement is assigned risk points, and then those points are converted to a load per pound of product by multiplying the points by a load factor. Table A1 shows the risk points and corresponding load on human health for the different hazard statements that appear on the pesticides' labels. As an example, Table A2 summarizes the sum of risk points from the hazard statement and the Human Health Load for eight insecticide active ingredients – out of a total of 30 – that account for over 90% of all insecticide use by Florida orange farmers. The conversion from risk points to load per lb. of product involves dividing the total by a reference value of 300. We then convert the Human Health Load per lb. of product to Load per lb. of active ingredient.

The second component of a pesticide load is the environmental fate load, which measures three distinct characteristics of a pesticide: degradation, bioaccumulation, and leaching. Degradation measures how long an insecticide persists in the environment and is calculated using the following expression:

Table A1. Risk points and load on human health associated with the different hazard statements found on pesticides' labels

Hazard statements with respect to human health	Risk points	Load (L per lb product)
Repeated exposure may cause skin dryness or cracking	10	0.0728
Harmful if swallowed	10	0.0728
may be fatal if swallowed and enters airways	10	0.0728
Causes skin irritation	10	0.0728
May cause respiratory irritation	10	0.0728
Harmful in contact with skin	15	0.1102
Causes serious eye irritation	15	0.1102
Harmful if inhaled	15	0.1102
May cause an allergic skin reaction.	20	0.1455
May cause drowsiness or dizziness	30	0.2205
Toxic if swallowed	50	0.3660
May cause allergy or asthma symptoms or breathing difficulties if inhaled	50	0.3660
May cause harm to breast-fed children	50	0.3660
Fatal if swallowed	70	0.5137
Toxic in contact with skin	70	0.5137
Causes severe skin burns and eye damage	70	0.5137
Causes serious eye damage	70	0.5137
Toxic if inhaled	70	0.5137
Suspected of causing genetic defects (possible route of exposure)	70	0.5137
Suspected of causing cancer (possible route of exposure)	70	0.5137
Suspected of damaging fertility or the unborn child (possible specific effect/exposure route)	70	0.5137
May cause damage to organs (possible specific organs/route of exposure)	70	0.5137
May cause damage to organs through prolonged or repeated exposure (possible specific organs/route of exposure)	70	0.5137
Fatal if swallowed	85	0.6239
Fatal in contact with skin	85	0.6239
Fatal if inhaled	85	0.6239
Fatal in contact with skin	100	0.7275
Causes severe skin burns and eye damage	100	0.7275
Fatal if inhaled	100	0.7275
May cause genetic defects (possible route of exposure)	100	0.7275

(*Continued*)

https://doi.org/10.1017/age.2025.1 Published online by Cambridge University Press

Table A1. (*Continued*)

Hazard statements with respect to human health	Risk points	Load (L per lb product)
May cause cancer (possible route of exposure)	100	0.7275
May damage fertility or the unborn child (possible specific effect/route of exposure)	100	0.7275
Causes damage to organs (possible specific organs/route of exposure)	100	0.7275
Causes damage to organs through prolonged or repeated exposure (possible specific organs/route of exposure)	100	0.7275

Source: Samsøe-Petersen *et al.*, 2012, p. 17.

Table A2. Sum of risk points and human health Load for the top eight insecticides' active ingredients used to grow processed oranges in Florida

Insecticide active ingredient	Sum of the risk points	Human health load (L a.i./lbs)
Chlorpyrifos	50	0.03394
Dimethoate	25	0.01691
Imidacloprid	10	0.00647
Naled	50	0.04687
Petroleum Oil	175	0.26195
Phosmet	90	0.09525
Spirotetramat	115	0.03895
Zeta-Cypermethrin	45	0.01232

$$D_i = \frac{DT_i^{50} \cdot D_{Ref}^{LF}}{DT_{Ref}^{50}}$$

where D_i denotes insecticide i's degradation in Load per pounds of active ingredient (L/lbs a.i.), DT_i^{50} is the half-life (in days) of insecticide i's active ingredient in the soil, and D_{Ref}^{LF} and DT_{Ref}^{50} represent the values for the load factor (in L/lb a.i.) and the half-life (in days) of the active ingredient of a reference substance, respectively (Samsøe-Petersen *et al.* 2012). The reference substance is an approved active ingredient with the worst value for load.

Bioaccumulation is the second characteristic that defines the environmental fate load of an insecticide and it refers to the progressive accumulation over time of a contaminant in an organism relative to its level in the ambient medium. The bioconcentration factor (BCF) is an indicator measuring the ability of a chemical to be assimilated by organisms from the water and it is used to calculate bioaccumulation (Wang, 2016). When the BCF of an insecticide was not available in the database, following the literature, we estimated it by using the so-called log Pow model, which correlates laboratory bioconcentration factors determined in fish and n-octanol/water partition coefficients. The relationship between the two variables was studied by Devillers *et al.* (1996), and the formula linking them that we used is the following:

Table A3. Parameters of reference substances to be used in the environmental toxicity load calculation

Short term	Unit for reference value	Reference value	Load factor
Birds	LD50 mg per kg body weight	49	1.00
Mammals	LD50 mg per kg body weight	20	1.00
Fish	LC50 mg per liter water	0.00021	30.00
Daphnia	EC50 mg per liter water	0.0003	30.00
Algae	EC50 mg per liter water	0.000025	3.00
Aquatic Plants	EC50 mg per liter water	0.00036	3.00
Earthworms	LC50 mg per kg soil	3.4	2.00
Bees	LD50 microgram per bee	0.02	100.00
Long Term	Unit for reference value	Reference Value	Load Factor
Fish	NOEC mg per liter water	0.000115	3.00
Daphnia	NOEC mg per liter water	0.000115	3.00
Earthworms	NOEC mg per kg soil	0.2	2.00

Source: Samsøe-Petersen *et al*., 2012, p. 20.

$$BCF_i = 10^{0.85 \cdot \log(Pow_i) - 0.7}$$

where BCF_i denotes insecticide i's bioconcentration factor and Pow_i is the octanol/water partition of insecticide i. Bioaccumulation, denoted by B_i, is then computed using the following expression:

$$B_i = \frac{BCF_i \cdot BCF_{Ref}^{LF}}{BCF_{Ref}}$$

where BCF_{Ref}^{LF} and BCF_{Ref} represent the coefficients for the bioconcentration factor load (in L/lb a.i.) and bioconcentration factor for a reference substance, respectively.

Leaching is the third characteristic that defines the environmental fate load of an insecticide. It measures the mobility of pesticides in soil, which indicates their potential for migrating to groundwater. This factor is calculated by using the Screening Concentration in GroundWater (SCI-GROW) model – a screening model used to estimate insecticide concentrations in groundwater (EPA, 2016). Leaching is calculated using the formula:

$$Le_i = \frac{SCI_{GROW_i} \cdot Le_{Ref}^{LF}}{Le_{Ref}}$$

where Le_i denotes insecticide i's leaching in Load per pounds of active ingredient (L/lbs a.i.), SCI_{GROW_i} is the SCI-GROW index of insecticide i, and Le_{Ref}^{LF} and Le_{Ref} represent the coefficients for the leaching load factor (in L/lb a.i.) and the SCI-GROW index of a reference substance, respectively. Thus, to compute the environmental fate load of each insecticide active ingredient, we simply added the values we obtained for each of its three sub-components: degradation, bioaccumulation, and leaching.

The third and last component of the load of a pesticide is the environmental toxicity load, which measures the load of an insecticide on different organisms other than the targeted one. This measure is composed of the short-term effects on birds, mammals, fish daphnia, algae, aquatic plants, earthworms, and bees, and the long-term effects on fish daphnia, and earthworms (Samsøe-Petersen *et al.* 2012). Table A3 shows the different reference values and load factors for each component of the environmental toxicity load. Each of the components is multiplied by a reference value and divided by a reference load:

Table A4. Toxicity (load) components and total load per pound and per acre for the top eight insecticides' active ingredients that are used to grow processed oranges in Florida

Insecticide active ingredient	Human health (L/lb)	Environmental fate (L/lb)	Environmental toxicity (L/lb)	Load (L/lb)	Load[1] (L/acre)
Chlorpyrifos	0.03	1.55	45.85	47.44	106.50
Dimethoate	0.02	0.02	4.31	4.35	1.95
Imidacloprid	0.01	1.33	14.30	15.63	3.09
Naled	0.05	0.14	465.89	466.07	288.97
Petroleum Oil	0.26	1.00	0.04	1.30	51.48
Phosmet	0.10	0.03	2.88	3.01	3.16
Spirotetramat	0.04	0.01	0.03	0.08	0.02
Zeta-Cypermethrin	0.01	0.24	84.71	84.96	4.13

[1]Those values were obtained by multiplying the total load by the rate of application per acre.

$$E_{i_n} = \frac{RV_n}{v_{i_n}} \cdot RL_n$$

where E_{i_n} is insecticide i's effect on organism n in Load per pounds of active ingredients (L/lb a.i.), RV_n is the value for the reference substance on organism n, RL_n is the reference load of the reference substance on organism n in Load per pounds of active ingredients (L/lbs a.i.), and v_{i_n} is the effect/value of insecticide i on organism n. Short- and long-term effects are then added up to obtain the total environmental toxicity load of a pesticide.

We obtain the total load for each of the eight insecticides we consider by simply summing up the values we obtained for each of its three components: the human health load, the environmental fate load, and the environmental toxicity (see Table A4). In the last column of Table A4, we also show the area load for each insecticide. Calculating the load of each insecticide per acre allows us to compare the load of insecticides used by Florida orange farmers for a standard measure of unit area. Thus, we obtain the total area load of insecticide i at the maximum yearly recommended use (AL_i) in L/acre, as follows:

$$AL_i = (H_i + EF_i + ET_i) \cdot U_i \tag{1}$$

where is H_i represents the Human Health Load of insecticide i, EF_i is insecticide i's environmental fate load, ET_i is the environmental toxicity load of insecticide i – all in L/lb a.i. – and U_i is the actual use of insecticide i on Florida oranges in lb a.i./acre.

In contrast to the calculations above, the Quantity of Active Ingredients index simply measures insecticide use so that $QA_i = U_i$, where QA_i is the quantity of active ingredients in lb a.i./acre.

Cite this article: Rizk, A. and A. Singerman (2025). "Pesticide use and the case for toxicity-based taxation: evidence from citrus greening in Florida." *Agricultural and Resource Economics Review* **54**, 1–31. https://doi.org/10.1017/age.2025.1