Pesticide use reductions at landscape level: efficient allocation of land uses

Abstract

There is an increasing conflict of interest between food security and environmental and health issues that may be caused by pesticide use. Biological control of pests by natural predators could provide a substitute for pesticides, but it is intimately related to the ecological dynamics of pests and predators at landscape level. There is, however, a potentially efficient composition of the landscape into cropland and grassland, that would leave the production constant, while reducing the use of pesticides. In this paper, we aim at identifying this efficient allocation of land and at computing the reduction in the amount of pesticides. To do so, we use data at landscape level simulated from an ecological-economic model and nonparametric frontier techniques that allow us to identify the pesticide-efficient landscape composition. Moreover, we analyze the effect of some agronomic characteristics and economic incentives on the efficiency in pesticide use. Our results show that pesticides could be reduced by 7% on average without affecting the agricultural output. Dispersed grasslands within the landscape and a tax on pesticide use are the variables that reduce pesticide use at landscape level.

Keywords: Environmental Efficiency; Pesticide Minimization; Land Use Allocation; Data Envelopment Analysis; Trade-offs Analysis; Bootstrapping.

1 Introduction

Pests (insects, diseases and weeds) have always been a major concern in agriculture, as they may result in important production losses (Walker, 1983), which are undesirable in the current context of increasing food security concerns. Over the last decades, crop protection measures have mainly relied on chemical products (Maddy, 1983; Settle, 1983), which may have a positive impact on the agricultural production by reducing pest damage. However, pesticides also generate adverse effects on the environment and human health. Moreover, the virulence of pests may increase due to the destruction of predators caused by pesticides (Boussemart et al., 2011). As a consequence, there exists an increasing legislation to promote prudent use of pesticides (Labite et al., 2011) and a call for the development of alternative pest control methods (Bunyan and Stanley, 1983). Particularly, in 2009 the European Union put into place the Directive 2009/128/EC to establish "a framework to achieve a sustainable use of pesticides by reducing risks and impacts of pesticide use on human health and the environment and promoting the use of Integrated Pest Management and of alternative approaches or techniques such as non-chemical alternatives to pesticides". This Directive indicates that each EU member state must develop and adopt a National Action Plan to reduce pesticide use. For instance, the National Action Plan in France has led to the development of the Ecophyto program to reduce the use of phytopharmaceutical products by 50%. Several institutions have undertaken a number of initiatives to reduce the use of pesticides in agricultural production within this plan between 2009 and 2014, and results from a farm pilot project (so-called DEPHY network[1]) have supported the possibility of combining a reduction in the use of phytopharmacautical products while meeting the economics objectives. However, at the French national level, the use of these products have increased by 5% in the period 2009-2013 (Ecophyto, 2015).

In this context, biological control of pests by their natural predators is presented as a solution (Landis et al., 2000). Such agro-ecological solutions depend on the ecological prey-predator dynamics of the pest (the prey) and their predators at the landscape scale (Bianchi et al., 2006). Implementing these solutions requires modifying the landscape (e.g., favoring wildlife friendly farming practices or predators habitats), which may cause reductions in the agricultural output since the land uses that favor natural predators are less productive. At the same time, the potential benefits of these measures, which mainly consist in a reduction of the environmental pollution at the landscape level, are difficult to assess. Therefore, an important research agenda is to determine the extent to which these agro-ecological solutions could effectively result in a reduction of pesticide use while maintaining the level of agricultural output. To do so, one needs to identify landscapes with a high level of natural

[1]See `http://agriculture.gouv.fr/dephy-expe` for detailed information about the DEPHY farm pilot project.

pest control, which make it possible to reduce pesticide use without reducing agricultural production.

In light of the foregoing, the objective of this paper is to provide a measure of the pesticide-efficient landscape composition and to analyze the impacts of agronomic and economic factors on the efficiency.

Unfortunately, there is no reliable data to be analyzed to assess the efficiency of different landscapes with respect to pesticide use. On going experiments on agroecological practices are conducted at small scales (field-level and surrounding areas), with a focus on the agronomic and ecological phenomena at hand, without considering the economic aspects of the issue. No data set provides information on the links between the landscape composition (ecological habitat types), the pest and their predators densities, the effect on agricultural yields (damages) and economic data on pesticide use. These links depend on quite complex ecological dynamics. To assess the relationships between agricultural production and pest control at a landscape scale, one can use ecological models (spatially-explicit, dynamic prey predators models) and encompass them in an economic analysis. Landscape simulation can be used to assess at the same time ecological and economic aspects of pest control, accounting for both natural predation and the effect of pesticides on the pest population.

Models have another advantage. They can be used to explore the performance of a system under various scenarios (potential landscapes in our case) which are not observed. This is a relevant tool for analyzing potential policy instruments. For example, the trade-offs between economic and ecological outcomes are often studied with spatially explicit models of land use. Polasky et al. (2008) used spatially explicit ecological economic models to explore various land use scenarios and represent the trade-offs between biodiversity and economic returns. They use *efficiency frontiers* to represent these trade-offs, emphasizing that past and current land uses are not on the efficiency frontier. However, they do not analyze the efficiency of the landscape.

In this paper, we aim at developing a method to identify pesticide-efficient allocations of land uses in different production contexts, as well as the factors that promote efficiency. In particular, we aim at analyzing the trade-offs between agricultural production and environmental performance in terms of pesticide use at landscape level. To do so, we analyze data obtained through simulations in an agent-based model in which landscapes are generated by individual (field) land use decisions, depending on the economic (prices and costs, monetary incentives), agronomic (soil quality) and ecological (pests and predators densities at the field level) contexts. Using simulated data allows us to explore a large variety of landscape types, going from low-productive, extensive agricultural landscapes to highly productive, intensive landscape. Each landscape is composed of 100 agricultural fields and, for each field, there are four potential land uses: land can either be allocated to extensive grassland (which are favorable to pest's natural predators) or to cropland with three levels of pesticide intensity: none, medium and high. Ecological dynamics at the field and landscape levels determine global and local populations of pests and their predators (metapopulation models), which generate damages and agricultural losses. Moreover, the model includes a set of public policies that promote reductions in pesticide use and/or implementation of land uses favorable to predators. The public policies are taxes on pesticide use, subsidies on grassland, as well as a price bonus for production without pesticides. Thus, landscapes in the data set are composed by fields allocated according to the farmers' expectations on yields (according to their anticipation of damages, which depends on the ecological dynamics and the pesticide treatment) and the implemented public policies.

The problem of how much pesticides could be reduced can be reformulated as a question about how efficiently fields are allocated within the landscape in terms of pesticide use. In this sense, we propose a linear program that determines the optimal proportions of land use to obtain the minimum pesticide use. Thus, we use Data Envelopment Analysis (DEA) to construct a nonparametric frontier that identifies the most efficient landscapes in terms of pesticide use.

Moreover, the effect of economic and agronomic factors on the level of efficiency in pesticide use is analyzed using the methodology proposed by Simar and Wilson (2007). Specifically, we implement the Algorithm #2 which consists on a truncated regression and a double bootstrap.

Our results show that efficiency in pesticide use can be increased by strongly reducing the proportion of land allocated to the most pesticide-intensive cropland and increasing the number of fields devoted to medium-treated cropland along with grassland. Over all the simulated landscapes, grassland has a positive, indirect effect on the level of output as it serves as a substitute for pesticides. Moreover, the Gini Indices computed for the actual and the efficient proportions of land uses indicate that wildlife-friendly farming is the most efficient land management strategy for reducing pesticide use. Regarding the determinant of the level of efficiency, landscapes where fields devoted to grassland are more dispersed seem to be more efficient in pesticide use. Furthermore, a tax on pesticide use has a positive and significant effect on the level of efficiency, whereas subsidies to promote grassland and a bonus price for crops produced without using pesticides have significantly negative effects on this measure.

The contribution of the paper is two-fold. First, we develop an approach to compare landscapes in terms of pesticide use. This approach is based on efficiency analysis tools applied to simulated data obtained from an ecological-economic model of agricultural land use and pest (and their natural predators) dynamics. This allows us to examine the eco-efficiency of agricultural production at a landscape scale, focusing on the role of the ecological phenomena (pest predation) taking place at this scale. Second, we use this approach to determine the (theoretical, model-based) drivers of pesticide use efficiency at the landscape scale. This allows us to exhibit the levers that public policies could use to trigger a pesticide use reduction.

The paper is organized as follows. In Section 2 we briefly explain the ecological-economic model used to generate the data and we describe the relevant variables for the study. In Section 3 we discuss the concept of efficiency in pesticide use and the methodologies applied for its analysis. The results are presented in Section 4, and in Section 5 we conclude with a discussion in which we summarize the main results and provide some policy implications.

2 Simulated landscape production and pesticide use data

We aim at analyzing the trade-offs between agricultural production and environmental performance in terms of pesticide use at landscape level. For this purpose, we develop a three-stage approach.

First, we frame a spatially explicit ecological-economic model of agricultural land use and pesticide use, and simulate the production of several agricultural landscapes. Landscapes vary in terms of composition and spatial organization of different land uses and pesticide intensity. Each landscape is associated to two outcomes: the agricultural production and the level of pesticide use.

Second, we use the simulation outputs in an efficiency analysis to determine the efficient landscape composition that minimizes the level of pesticide use while maintaining constant the level of production. We perform a descriptive analysis of the efficient landscape compositions addressing the question of the pesticide-efficient agricultural land management strategy.

Last, using the computed efficiency scores and the features used in the model and data generation, we analyze the impact of public policies and spatial factors on the efficiency in pesticide use at landscape level. This last stage may provide useful information for the design of policy measures intended to reduce pesticide use.

In this section, we describe the model used to generate the data, as well as some descriptive statistics on the data set to be used in the efficiency analysis of next sections.

2.1 Land uses, agricultural production and pesticide pollution

We consider (simulated) areas with similar production possibilities, i.e., with identical potential agricultural production (agronomic context) and facing the same pest issue. Each area is composed by 100 plots of different quality with a given distribution representing the area's heterogeneity. Fig. 1 describes an example of soil quality distribution (potential yield of a plot) randomly generated from a truncated normal law. Mean and variance are parameters which can vary to represent particular contexts, for example the agricultural potential of a country, region or county in terms of mean productivity and soil heterogeneity.

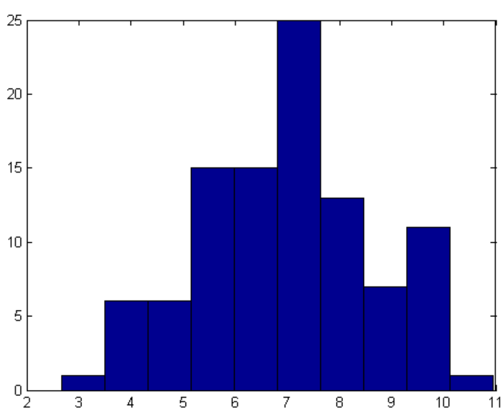

Figure 1: Soil quality distribution

Simulated areas differ only in the spatial distribution of agricultural quality. We consider a range of spatial aggregation of soil quality to obtain a variety of landscape structures. Fig. 1 presents three examples with different spatial arrangement for plots.

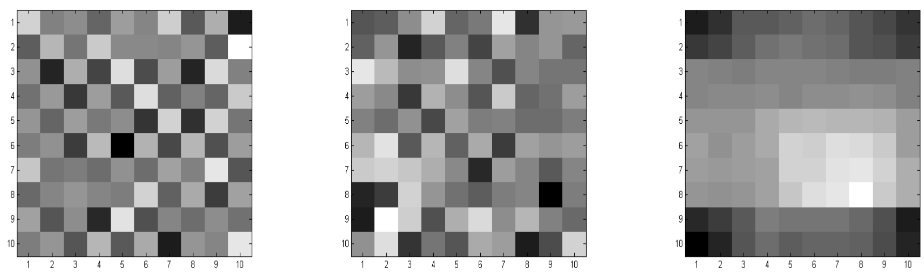

Figure 2: Examples of soil quality maps with 3 different levels of spatial correlation between soil quality

We consider two types of land allocation: grassland and cropland, and three levels of pesticide intensity for cropland: no pesticide, intermediate and high use of pesticides. This offers a choice set of four land uses for each plot: grassland (*Grassland*), cropland without pesticides (*Cropland 0*), cropland with a medium level of pesticides (*Cropland 1*), crop with a high level of pesticides (*Cropland 2*). Each land use generates a profit, which is the difference between the benefits obtained from selling the agricultural products at exogenously given prices and potential subsidies on the one hand, and production costs and taxes on the other hand.

Each plot is allocated to one of the land uses. Technically, we use a microeconomics-based optimization program to determine the land use maximizing the profit at the plot scale (Ricardian rent maximization) given the economic context (price, economic incentives), the agronomic context (potential yield), and the ecological context (anticipated pest population). The model thus mimics, in a very stylized and simplified way, the behavior of individual farmers within a landscape. The general idea is to obtain landscapes generated by incentive-sensitive decision processes, which endogenously account for pest dynamics.[2]

[2]In the model, grasslands provide a fixed profit, which does not depend on soil quality or pest density. Cropland production depends on soil quality and on pest abundance (which influence yield through damages). Cropland profit is thus heterogeneous over space and time. Farmers form anticipations on pest density, compute anticipated profit for the four land uses, and allocate their plot to the land use with the highest return. The optimization program is annual-based, with asymmetric conversion costs for switches between grassland and cropland (see Barraquand and Martinet, 2011, for a description of this type of asym-

As the purpose of this paper is to focus on the efficiency of agricultural production at a landscape level, we emphasize that other inputs (in particular fertilizers) are used efficiently at the field level. The only source of inefficiency is thus related to pests and predators, which have the dimension of common pool resources (respectively bad and good) with spatial externalities. Grasslands generate positive externalities on cropland plots by favoring the dynamics of pest's predators. Pesticides affect both pest and predators dynamics, with spatial externalities too. Pesticide is also a public bad, with benefits at the individual scale diverging from global interest. These externalities result in collective, landscape-scale inefficiencies. They can be partially corrected by means of incentives, e.g., by favoring grassland with subsidies, or reducing incentives for pesticide use through taxes or a higher price for pesticide free products.

2.2 Data generation and description

We generate a set of 864 landscapes, which differ in terms of composition and disposition of land uses.

The composition of landscapes is varied using incentives modifying land use choices. To examine a diversity of agricultural production configurations, we explore a range of values for three *ad hoc* monetary incentives: (i) a tax on pesticide use, which takes four different levels from 0 to 30 Euro per TFI unit[3], (ii) a subsidy on grassland, which takes six different levels from 0 to 500 euros per ha[4] and (iii) a bonus price for cropland output produced without pesticides (either 0% or 20% bonus[5]). The tax and bonus price influence the intensity of production in terms of pesticides for cropland. The subsidy favors grassland over cropland. As a result, the composition of the landscape varies, with different proportions of grassland and cropland with different pesticide use level. By combining these three instruments, we obtain 48 *incentive contexts* ($6 \times 4 \times 2$), leading to different landscape compositions. This gives us a range of landscapes, from extensive agriculture landscapes dominated by grassland with a relatively low level of production to intensive agricultural landscapes dominated by

metric conversion costs). As usual in this type of land-use share models, plots with low quality are more likely allocated to grassland and plots with higher quality to cropland (Lichtenberg, 1989; Feng and Babcock, 2010; Lankoski et al., 2010; Lankoski and Ollikainen, 2011).

[3]The average cost of pesticide expressed in TFI unit for the main croplands in France is 33 Euro (**?**). The highest tax level thus correspond to something close to a 100% *ad valorem* tax.

[4]This range corresponds to subsidies levels within the European Common Agricultural Policy

[5]This level of price bonus could represent a specific market such as organic food.

cropland with pesticide use.

The spatial organization of landscapes is varied by considering different land quality maps generated from the same quality distribution. These maps are obtained by varying the spatial correlation of qualities across space, according to 9 different values for an aggregation index (see Figure 2 for an illustration with three levels of aggregation), with 2 generated maps for each aggregation value. We apply the 48 incentive contexts to the 18 maps, generating 864 landscapes (48×18). Note that, in the absence of pests, the 18 landscapes in a given incentive context would give the same production as the economic model has no other spatial interactions than the ecological dynamics.

Table 3 shows some descriptive statistics of the proportion of land uses. The type of land use with the highest average proportion is *Cropland 1* – moderately treated field (an average of 59 fields per landscape), followed by *Grassland* (in average 21 fields with grassland per landscape). The two remaining types of land uses, *Cropland 0* – untreated fields, and *Cropland 2* – heavily treated fields, represent, in average, only 10% of the fields per landscape each.

	Mean	Std. Dev	Min	Max
Grassland	0.21	0.17	0.01	0.57
Cropland 0	0.10	0.11	0.00	0.42
Cropland 1	0.59	0.26	0.13	0.98
Cropland 2	0.10	0.11	0.00	0.42

Table 1: Descriptive Statistics of the land uses proportions

All landscapes face the same pest invasion. The pest is introduced in the landscape at 20% of its carrying capacity, and the temporal dynamics of the landscape are simulated. For each landscape, we compute the production level, the quantity of pesticide over the landscape and the density of pests and predators. To smooth the oscillations due to the prey-predator dynamics, we average the production and pollution over time, from the invasion time to the end of the planning horizon. Each landscape is thus characterized by two outputs: a production level and a pollution level.

This gives us a data set composed of production-pollution outcomes. On average, the *Profit* is 585.23 €/ha, the *Production* is 5.62 tons/ha and the level of *Pollution* or pesticide, expressed using the Treatment Frequency Index (TFI), is 2.36 TFI.

	Mean	Std. Dev	Min	Max
Profit	585.23	37.35	470.29	659.01
Production	5.62	0.90	3.52	6.86
Pollution	2.36	0.60	0.88	3.23

Table 2: Descriptive Statistics of the production variables

Figure 3 depicts the combinations of production and pollution obtained for the different simulated landscapes. It can be seen that, for low levels of production, there is high heterogeneity in terms of pollution. There exist landscapes that produce the same level of output using a lower level of pesticides. Therefore, the amount of pesticides could be reduced while keeping production constant. However, the potential for reductions in terms of pollution is smaller for higher production levels.

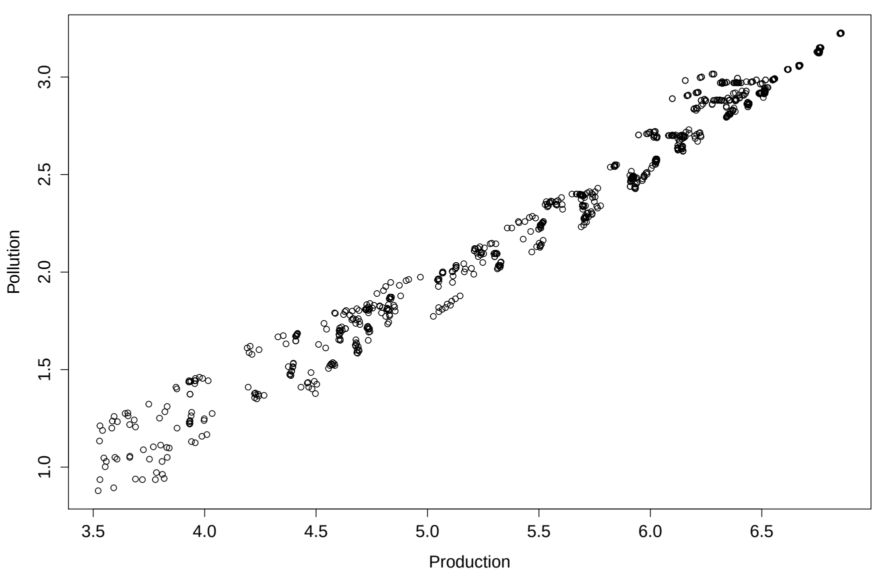

Figure 3: Production vs Actual Pollution

As indicated above, land use is determined by maximizing the profit given the economic context, the agronomic context and the ecological context. Thus, there are several environmental factors that may affect the level of pesticide use for given output quantities. These variables can be categorized into two types, namely spatial (agronomic) factors and public policies.

Among the spatial (agronomic) factors, we consider two aggregation indices that quantify landscape spatial patterns of grassland (*Grassland Agg*) and pesticide use (*Pesticide Intensity*). Regarding the public policies that may affect environmental performance, we consider the economic incentives described above. That is, a variable that captures the level of taxes on pesticide use (*Pesticide tax*), the subsidies promoting grassland (*Grassland subsidy*) and an indicator of the bonus price for crops produced without using pesticides.

	Mean	Std. Dev	Min	Max
Grassland Agg	0.38	0.44	0.00	1.00
Pesticide Intensity	0.84	0.12	0.56	0.99
Pesticide tax	15	11.19	0.00	30
Grassland subsidy	250	170.88	0.00	500
Price bonus	0.10	0.10	0.00	0.20

Table 3: Descriptive Statistics of the environmental factors

3 Efficiency in pesticide use: background, concept and methodologies

3.1 Measuring efficiency in pesticide use

In the last decades, there has been an increasing concern about the environmental impacts of agricultural activity (OECD, 2008). In this context, the assessment of environmental performance in the agricultural sector has become central to policy makers (Lansink and Wall, 2014). Production frontier models seem a natural tool for measuring environmental performance as the objective of minimizing the environmental impact of agricultural activity can be thought of as an efficiency problem. Thus, a vast literature has used different frontier techniques to measure environmental efficiency in the agricultural sector since the late 1980's. Tyteca (1996) distinguishes two approaches to measure environmental performance depending on how environmental effects are included into frontier models. In the first type, known as " environmentally adjusted production efficiency" (EAPE), efficiency models are estimated using Stochastic Frontier Analysis (SFA) or Data Envelopment Analysis (DEA) including for environmental pressures either as an undesirable output or as an environmentally detrimental input. Several studies have assessed the level of efficiency of pesticides using this approach. Lansink and Silva (2004) analyzes the productivity of pesticides using DEA on specialized Dutch cash crop farms, and the results show a substantial under-utilization of pesticides. Wossink and Denaux (2006) compare the level of efficiency in pesticide use in for producers of transgenic cotton and conventional cotton using data from a survey of cotton growers in North Carolina, USA. Efficiency scores are computed by means of DEA and then, efficiency determinants are investigated using a Tobit model. Skevas et al. (2012) include pesticides as an input and, the impact of pesticides on water organisms and biological controllers as outputs to measure technical efficiency controlling for pesticides' dynamic effects and production uncertainty. To do so, a dynamic DEA is applied to data on Dutch specialized arable farms covering the period 2002-2007.

The second approach, labeled as "frontier eco-efficiency" (FEE), analyzes the relation between ecological outcomes and economic outcomes rather than conventional inputs and outputs. Pesticide use has also been included as a pollutant in Eco-efficiency analysis. For instance, Picazo-Tadeo et al. (2011) aim at analyzing agricultural sustainability for a sample of Spanish farmers operating in a rain/fed agricultural system. Among the five relevant environmental indicators related to pressures generated jointly with agricultural production, they include pesticide risk as an important environmental indicator that informs about the overall toxicity generated through the pesticide used. They compute eco-efficiency at farm level but also pressure-specific potential reductions that could be still possible after attaining the equiproportional reduction of all pressures, that allow them to calculate a pressure-specific eco-efficiency measures following the approach by Koopmans (1951). Beltrán-Esteve et al. (2014) also analyze eco-efficiency including pesticide risk as an environmental pressure, for different types of olive producers. They use a metafrontier approach to differentiate between traditional mountain and traditional plain growing systems. This methodology allows one to assess technical efficiency and technological gaps between different production systems. Moreover, directional distance functions are used to compute eco-efficiency at pressure level for each type of production system, so that it is possible to evaluate the advantages and disadvantages of the two different production technologies regarding the level of eco-efficiency related to a specific environmental pressure.

A third approach, which incorporates the materials balance principle into environmental efficiency analysis, is increasingly used (Coelli et al., 2007; Lauwers, 2009; Hoang and Coelli, 2011). In this type of models, the pollutant is considered as a materials balance outcome rather than being treated as an additional variable. The goal is to identify the combination of inputs that would result in the lowest possible quantity of pollution for a given level of output, that is, the environmentally optimal allocation of inputs (Reinhard and Thijssen, 2000). This methodology has been used to study the effects of nutrients in agricultural production, but it has not been yet applied to analyze the effects of pesticides.

As indicated above, we aim at measuring the efficiency in pesticide use of a landscape unit relative to a sample of N comparable landscapes (those with the same biological context). Therefore, we consider a set of landscapes simulated using the ecological-economic model explained in Section 2.1, that produce agricultural output y using land x that can be allocated to different uses $j = 1, ..., J$. The technology set T that represents all feasible combinations of land and agricultural output is:

$$T = \left\{(y, x) \ \epsilon \ \Re_{+}^{J} | \text{ x can produce y}\right\} \tag{1}$$

As explained in Section 2.1, each type of land use has an implicit pesticide content. Therefore, since a given level of agricultural output is to be produced[6], efficiency in pesticide can be computed answering the question: what is the combination of land uses that would use the lowest quantity of pesticides for a given level of agricultural output. This problem can be solved in an analogous manner to a cost minimization problem. Note that the efficiency in pesticide use measure, as in the case of cost efficiency, could be decomposed into two components: technical efficiency and allocative efficiency (Coelli et al., 2007). However, as discussed above, the simulated landscapes in the analysis are technically efficient, so in this case we can only measure allocative efficiency.

[6] In the current context of increasing food security concerns, reductions in pesticide use must not lead to crop losses caused by pests (Popp et al., 2012; Godfray et al., 2010). Therefore, we are interested here in the reduction of pesticide use that maintains output steady.

The pollution due to allocative inefficiency is generated by a non-optimal choice of land uses. In Figure 4 we illustrate the concept of allocative inefficiency assuming that land can be allocated into land use x_1 and land use x_2 to produce a certain level of crop y. Landscapes are assumed to minimize the pollution given the pesticide content of land use p_1 and p_2.

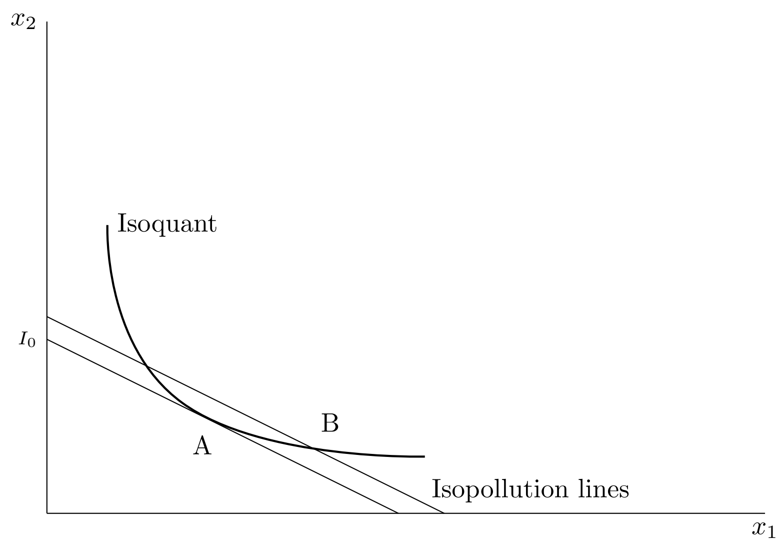

Figure 4: Allocative efficiency

The isoquant represents the possible minimum combinations of land uses x_1 and x_2 that can produce the level of crop y, therefore, for that level of production, a landscape is technically efficient if it chooses a land use mix on the isoquant. The isopollution line depicts all combinations of land uses which generate the same level of pollution. The slope of the isopollution line is given by the ratio p_1/p_2. In this figure we can see that landscape B is technically efficient as it is on the isoquant line, but it is allocative inefficient as the same output level could be produced generating less pollution as its actual land use mix is not optimal. However, landscape A is both technically and allocative efficient.

The pesticide function P indicates the level of pesticides needed to produce output y by allocating land to different land uses x given a vector of pesticide content of each type of land use $p = (p_1, ..., p_j)$. The pesticide minimization function for all technically feasible land use-output combinations can be written as:

$$P(p, y) = \min_x p'x \text{ such that } T(y, x) = 0 \tag{2}$$

The pesticide function satisfies the following properties:

- Nonnegativity: $P(p, y) \geq 0$
- Nondecreasing in p: if $p' \geq p$, then $P(p', y) \geq P(p, y)$
- Nondecreasing in y: if $y' \geq y$, then $P(p, y') \geq P(p, y)$
- Homogeneity of degree one in pesticide content p: $P(\alpha p, y) = \alpha P(p, y)$ for $\alpha > 0$
- Concave in p: $P(\alpha p_1 + (1 - \alpha)p_2, y) \geq \alpha P(p_1, y) + (1 - \alpha)P(p_2, y)$ for $0 \leq \alpha 1$

In order to measure the trade-offs between agricultural production and environmental damage caused by the use of pesticides, we use Data Envelopment Analysis to construct a nonparametric frontier that identifies the most efficient landscapes in terms of pesticide use. The objective is to allocate land to certain uses for the purpose of minimizing the pesticide use at landscape level. Therefore, the following linear program determines the optimal proportions of land use within landscapes for landscape$_0$ by minimizing the pesticide function:

$$\begin{aligned} &\min_{\lambda_i x_{ij}} \sum_{j=1}^{4} p_j x_{ij} \\ &s.t. \sum_{i=1}^{n} \lambda_i x_{ij} - x^*_{0j} \leq 0 \\ &\sum_{i=1}^{n} \lambda_i Y_i - Y_0 \geq 0; \sum_{i=1}^{n} \lambda_i = 1 \end{aligned} \tag{3}$$

where x_{ij} is the proportion of fields devoted to each j land use for landscape i, p_j is the pesticide content of each j land use, Y_i is the output for landscape i and λ_i is the non-negative weights for landscape i.

Efficiency in pesticide use is then calculated as the ratio of the pesticide use associated with the efficient proportions of land use x^*_{ij} to the pesticide use associated to landscape i x_{ij}:

$$PE_i = \frac{\sum_{j=1}^{4} p_j x_{ij}^*}{\sum_{j=1}^{4} p_j x_{ij}} \tag{4}$$

The efficiency in pesticide use score ranges between 0 and 1, where value 1 indicates full efficiency. As indicated above, in our case, we are only observing allocative efficiency as all landscapes in our sample produce the agricultural output using the same number of fields. However, if the number of fields used to produce the agricultural output could be also reduced, the efficiency in pesticide use measure could be decomposed into technical and allocative efficiency.

3.2 Explaining efficiency in pesticide use: truncated regression

Measuring efficiency in pesticide use may be insufficient on its own as a basis for policy making. In this sense, further analysis is needed to understand the links between agricultural production and environmental damage, the driving forces of change, and the psychological and ethical motives of producer and consumer behavior (OECD, 1998). However, as noted by Lansink and Wall (2014), the determinants of environmental efficiency have received much less attention than the measurement of this indicator.

There are few studies analyzing the efficiency determinants for environmentally adjusted production efficiency models. Reinhard et al. (2002) use a two-stage approach to analyse differences in environmental efficiency for Dutch dairy farms. Technical and environmental efficiency are estimated in the first stage using stochastic frontier analysis and, in the second stage, the estimated environmental efficiency scores are regressed against several factors such as physical environment, technology and management indicators. Galdeano-Gómez et al. (2006) study environmental performance in the Spanish horticultural sector over the period 1994-2002 by estimating an environmental productivity index applying stochastic frontier analysis. In a second stage, improvements in labor quality and productivity, growth of capital intensity and environmental spillovers have a positive effect on the environmental performance in this sector.

The determinants of efficiency have been also examined in environmentally adjusted production efficiency models implementing nonparametric methods. For instance, Wossink and Denaux (2006) investigate the determinants of environmental efficiency scores previously obtained using a Tobit regression. However, this approach may be inappropriate because the serial correlation of the first stage DEA efficiency estimates is not taken into account, as shown by Simar and Wilson (2007).

Therefore, this serial correlation of DEA efficiency scores should be taken into account in a second stage analysis of efficiency determinants. Therefore, we apply the methodology proposed by Simar and Wilson (2007). Specifically, we implement the Algorithm #2 which consists on a truncated regression and a double bootstrap.

In order to apply the methodology proposed by Simar and Wilson (2007), it is necessary that the dependent variable follows a distribution with left-truncation at 1, so we transform the efficiency estimates obtained using equation (4) by taking its inverse so that the transformed efficiency scores range from 1 to infinity. Once the transformation is performed, the truncated regression of the efficiency in pesticide use scores on a set of explanatory variables can be written as:

$$\varepsilon_i = z_i\beta + \epsilon_i \geq 1 \tag{5}$$

where ε_i represents (the inverse of) the efficiency scores and z_i is a vector of efficiency determinants (in this case, the agronomic and economic factors). The estimates are included in a bootstrap procedure that generates bias-corrected efficiency scores. Then, this bias-corrected scores are used in a truncated maximum likelihood estimation. Finally, a second bootstrap is applied to construct confidence intervals for the coefficients estimated in the last truncated regression. For further details about the bootstrap procedure, see Appendix A.

4 Results

4.1 Efficiency analysis

Using the linear program in Equation (3) we obtain the optimal proportions of different land uses that minimize the level of pesticides while maintaining the output constant. The mean proportions for each land use and a test of mean differences between the proportions in actual and optimal land uses is shown in Table 4.

On average, there is a significant difference between the optimal and the actual proportions of the four types of land uses. The mean optimal proportions of *Grassland* and *Cropland 1* are significantly higher than the actual mean values. However, this difference is negative and significant for *Cropland 0* and *Cropland 2*, which is the land use that receives the most intensive application of pesticide.

	Actual Mean	Efficient Mean	Change	T-statistic	p-value
Grassland	0.21	0.22	0.06	1.59	0.11
Cropland 0	0.10	0.07	-0.31	-7.35	0.00
Cropland 1	0.59	0.68	0.14	8.04	0.00
Cropland 2	0.10	0.03	-0.67	-16.50	0.00

Table 4: Mean differences in actual and optimal Land use

These preliminary results can be interpreted as follows. Over all the simulated landscapes, efficiency in pesticide use could be increased (i.e., pesticides can be reduced while maintaining constant the level of production) by strongly reducing the most intensive cropland (*Cropland 2* is reduced by 67% in mean) and cropland without pesticides (*Cropland 0* is reduced by 31%) while increasing medium-treated cropland (*Cropland 1*).The average proportion of *Grassland* also increases, however the change is not significant at conventional levels. This is probably due to the fact that, in spite of *Grassland* having a positive, indirect effect on production and serving as a substitute for pesticides, this land use may only increase for high production levels. Therefore, it is important to describe these land use changes for different production levels to uncover the efficient land use composition.

Thus, these results can be examined in further details by considering the optimal land allocation for different production configurations. We divide the landscapes of our sample in four groups according to their production level. Table 5 and Figure 5 show the changes in terms of land uses for the four production quartiles.

Q1: The descriptive statistics indicate that landscapes within the first production quartile have a higher proportion of *Grassland* in average (0.45), followed by *Cropland 1* (0.39), *Cropland 0* (0.11) and *Cropland 2* (0.06). This corresponds to more extensive agricultural landscapes, with a large proportion of grassland and a relatively low grain production level. In order to minimize pesticide use for landscapes in this first quartile while keeping the level of production constant, it is necessary to reduce pesticide intensity on croplands, which requires an increase of the cultivated area (i.e., decreasing grassland area) to compensate for the yield loss. The proportion of the most intensive cropland is reduce to 0 (*Cropland 2* decreases by 100%) while there is an increase of cropland without pesticides (*Cropland 0*) by 36%. The proportion of *Cropland 1* is influenced by two patterns. On the one hand, the reduction of intensity on plots formerly used as *Cropland 2* should benefit to *Cropland 1* (reduced intensity on plots using pesticides). On the other hand, some of the plots formerly used as *Cropland 1* should cease to use pesticides to back up the increase in *Cropland 0*. The net effect on *Cropland 1* appears to be positive and the share of this land use increases by 8%. The potential efficiency gains for low production landscapes would thus be obtained by lowering yields (due to the reduction of pesticide use) while increasing cultivated area. This somehow recalls the land-sharing strategy proposed to maintain agricultural production while preserving biodiversity (Green et al., 2005). In some ecological contexts, producing less intensively on a larger area has a positive effect on an environmental objective, keeping the production unchanged.

Q2: Landscapes in the second production quartile have a fewer proportion of grassland and overall more intensive cropland than in the previous quartile. *Cropland 1* (moderate pesticide use) is the land use with the highest average proportion (0.53), *Grassland* occupying 26% of these landscapes on average. This corresponds to balanced landscapes, with significant production and a good deal of grassland. Here again, efficiency improvements would come from a strong decrease of the most intensive land use (*Cropland 2* decreases by 90%). The induced reduction of production is compensated by an increase of the cultivated area (*Grassland* area decreases by 12%), which benefit to cropland with a moderate pesticide use (*Cropland 1* area increases by 26%). At the same time, the proportion of *Cropland 0* (initially at 0.11) decreases by 18%.

Q3: Concerning the third production quartile, the highest average land use proportion is also *Cropland 1* (0.61), followed by the two other types of cropland (*Cropland 0* at 0.14 and *Cropland 2* at 0.15). *Grassland* occupies only a tenth of the landscape in this quartile, on average. This corresponds to quite intensive landscapes, dominated by cropland of various pesticide intensity. In order to improve the efficiency in these landscapes, the area of the most intensive cropland (*Cropland 2*) is reduced by 73%, while that of *Cropland 1* increases by 30%. The area of cropland without pesticides diminishes (*Cropland 0* decreases by 40%). The cultivated area decreases as the *Grassland* area increases by 40%. This type of strategy at a landscape level somehow recalls the land-sparing strategy proposed to maintain agricultural production while preserving biodiversity (Green et al., 2005). In some ecological contexts, improving an environmental or ecological outcome while maintaining agricultural production at the landscape level can be achieved by reducing the cultivated area while intensifying production.

Q4: In the fourth production quartile, the average proportion of *Cropland 1* is equal to 0.84, that is, this type of land use is much higher than the remaining uses. Regarding the other land uses, grassland and cropland without pesticide (*C*ropland 0) represent a small proportion of the total land (4% each, on average). However, pesticide intensive croplands (*C*ropland 2) are on average 8% of the total land. Landscapes belonging to this production quartile are very intensive agricultural landscapes, dominated by croplands with pesticide use, allowing a high production. Our efficiency analysis results suggest that pesticide efficiency could be improved by reducing the number of cropland without pesticides in favor of grasslands. This corresponds to a reduction of the cultivated area, leaving the most intensive cropland (almost) untouched. This is possible only if yield increases on the remaining area. This is made possible in the context of our ecological economic model only if pest damage decreases due to a positive effect of grassland. Note, however, that the potential efficiency gains are lower in these high production landscapes, with only a small reduction in pesticide use at optimum. Here again, this recalls land-sparing strategies.

Production quantile	Land use	Actual Mean	Efficient Mean	Change	T-statistic	p-value
Q1	*Grassland*	0.45	0.43	-0.04	-2.92	0
	Cropland 0	0.11	0.15	0.36	9.8	0
	Cropland 1	0.39	0.42	0.08	2.99	0
	Cropland 2	0.06	0	-1	-12.55	0
Q2	*Grassland*	0.26	0.23	-0.12	-4.74	0
	Cropland 0	0.11	0.09	-0.18	-2.8	0.01
	Cropland 1	0.53	0.67	0.26	10.17	0
	Cropland 2	0.1	0.01	-0.9	-14.12	0
Q3	*Grassland*	0.1	0.14	0.4	10.84	0
	Cropland 0	0.14	0.03	-0.79	-12.4	0
	Cropland 1	0.61	0.79	0.3	10.66	0
	Cropland 2	0.15	0.04	-0.73	-11.84	0
Q4	*Grassland*	0.04	0.08	1	13.99	0
	Cropland 0	0.04	0.01	-0.75	-3.74	0
	Cropland 1	0.84	0.83	-0.01	-0.9	0.37
	Cropland 2	0.08	0.08	0	-0.13	0.9

Table 5: Mean differences in actual and optimal Land use

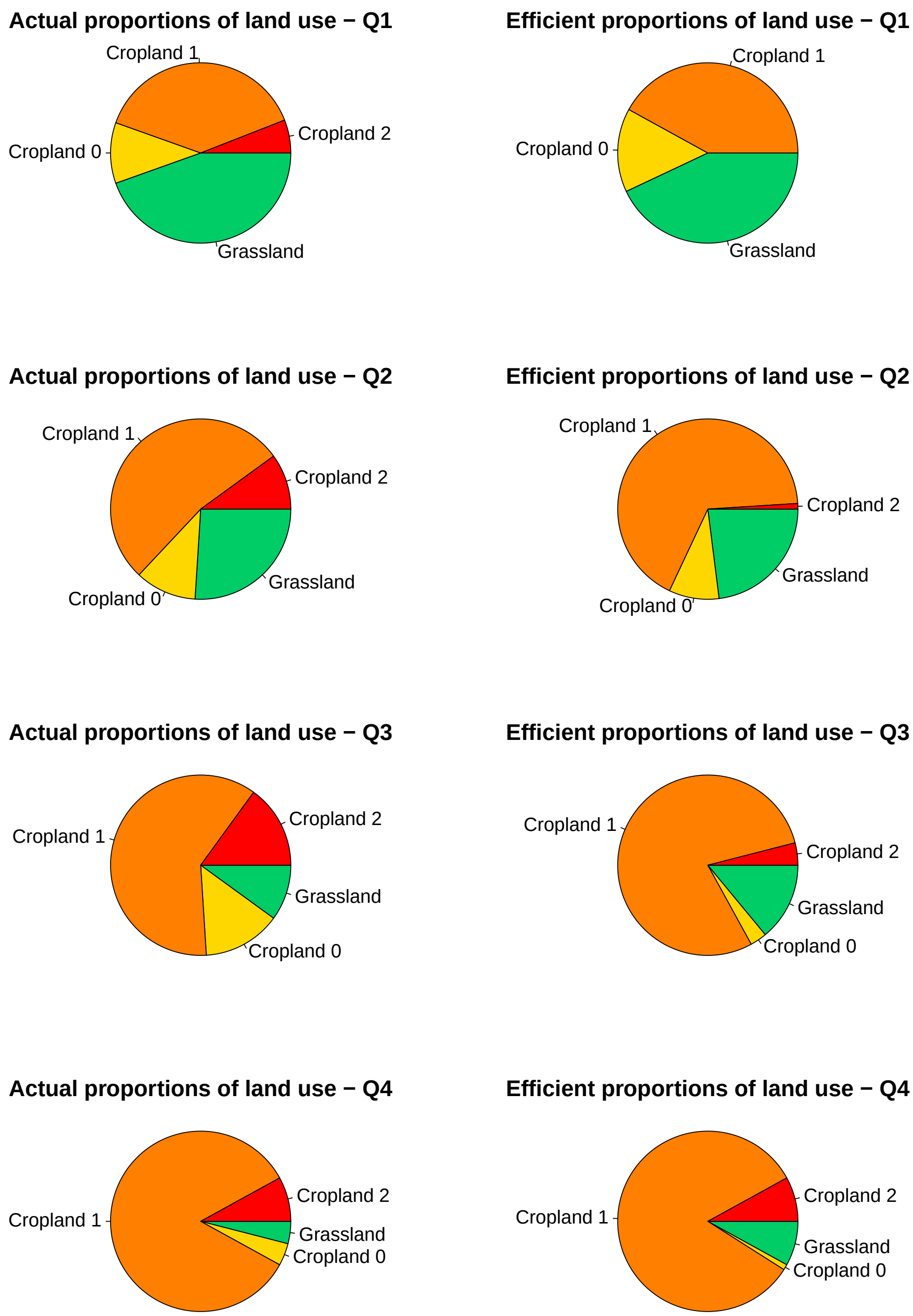

Figure 5: Mean proportions of land use

As indicated above, these changes in the proportions of land use would lead to minimizing the pesticides used to produce a given level of output. In order to compute how much pesticides could be reduced, the efficiency in pesticides use measure is calculated using Equation (4). These scores, presented in Table 6, represent the potential radial reduction in pesticide use. The mean efficiency score is 0.93, that is, pesticides could be reduced by an average of around 7% while maintaining the level of production by optimally allocate land to certain uses. The most inefficient landscape could reduce its pesticide use by 31%, as it has an efficiency score of 0.69, however the number of landscapes that are fully efficient, that is, whose efficiency score is equal to 1, represents only 2.73% of the landscapes. These results are in line with those obtained by the farm pilot project DEPHY. They found that pesticides could be reduced in average by 12% without affecting the level of production (Pillet et al., 2014). Despite the fact that this reduction in pesticide use is slightly larger than the average reduction that we have compared, it is still within our range of potential decreases in pesticide use. It is worthy to note that their results refer to reductions in pesticide use at farm level, rather than landscape level.

Mean	Min	1^{st} Q	Median	3^{rd} Q	Max
0.93	0.69	0.90	0.95	0.98	1.00

Table 6: Descriptive Statistics of Efficiency in Pesticide Use

Figure 6 shows box-plots for each quartile of the *Production* variable. Each box-plot shows the distributional characteristics of each quartile. The median efficiency score increases with the production level, while the dispersion decreases, that is, the level of efficiency is higher for high production levels and there is less room for pesticide reductions. This result is consistent with the intuition which builds on Figure 3.

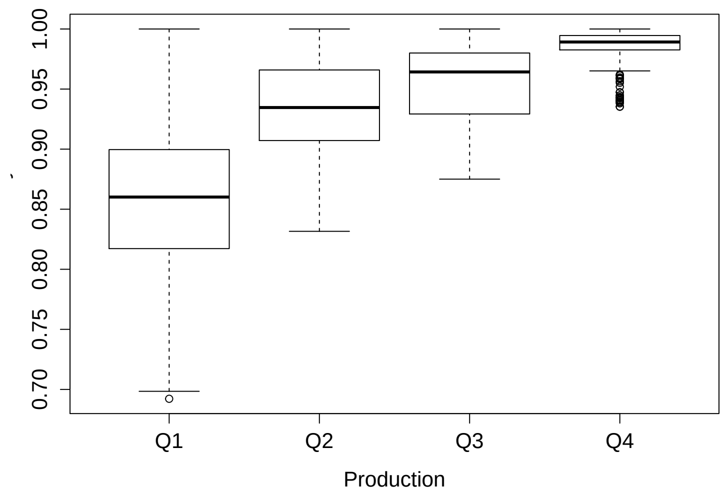

Figure 6: Boxplot

4.2 Efficiency determinants analysis

As indicated above, once the efficiency in pesticide use at landscape level has been computed, we perform an analysis of the efficiency determinants using truncated regressions and bootstrap procedures as described in Section 3.2. The estimated coefficients and their bootstrapped confidence intervals[7] from the truncated regression are presented in Table 7. Given that the dependent variable is defined as the inverse of the efficiency in pesticide

[7]We use bootstrap estimates and the original estimates $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma_\sigma}}$ to construct confidence intervals. Habitual 95% and 90% confidence intervals can be constructed from:

$$Pr[-b_\alpha \leq (\widehat{\widehat{\beta_j}} - \beta_j) \leq a_\alpha] = 1 - \alpha \tag{6}$$

being α equal to 0.5 and 0.1. However, the distribution of $(\widehat{\widehat{\beta_j}} - \beta_j)$ is unknown. We can use the j^{th} element of $\widehat{\widehat{\beta_j}}$ to obtain a^*_α and b^*_α from:

$$Pr[-b^*_\alpha \leq (\widehat{\widehat{\beta^*_j}} - \widehat{\widehat{\beta_j}}) \leq -a^*_\alpha] = 1 - \alpha \tag{7}$$

From equation 7 we can obtain the bootstrapped confidence intervals $[\widehat{\widehat{\beta_j}} + a^*_\alpha, \widehat{\widehat{\beta_j}} + b^*_\alpha]$.

The interpretation of the bootstrapped confidence intervals is the same as in the case of habitual ones, that is, if both the upper and lower bound are positive (negative), the estimated coefficient is positive (negative) and statistically significant at the 5 or 10% level, that is, the coefficient is significantly different from 0.

use scores, a positive estimated coefficient indicates a positive impact on inefficiency and hence lower efficiency, whereas a negative estimated coefficient indicates a negative impact on inefficiency and therefore a higher level of efficiency.

With this in mind, and beginning with the agronomic factors, the positive estimated coefficient for *Grassland Agg* indicates that the more aggregated the fields allocated to grassland within a landscape, the higher the inefficiency in pesticide use. That is, this variable has a negative effect on the level of efficiency in pesticide use. This result indicates that it is preferable to allocate grassland dispersed through the landscape. This reinforces the intuition that grassland has a positive (local) spatial externality on pest reduction. However, the effect of aggregation of fields that apply pesticides has a negative but not significant effect on the inefficiency level.

Regarding the economic factors, as might be expected, the estimated coefficient for the *Pesticide Tax* variable is significantly negative, implying that those landscapes that have been subjected to a higher tax are more efficient in pesticide use. On the contrary, *Grassland Subsidy* has a positive and significant coefficient, indicating that the higher the subsidy, the lower the level of efficiency in pesticide use. A similar effect is observed for the indicator of *Price bonus*, there is a positive effect of this variable on the level of inefficiency.

		95% confidence		90% confidence	
	Estimated parameter	lower bound	upper bound	lower bound	upper bound
Intercept	1.1226	1.0583	1.2822	1.0844	1.2610
Grassland Agg	0.0903	0.0681	0.1239	0.0726	0.1189
Pesticide Intensity	0.0598	-0.1144	0.1250	-0.0928	0.1007
Pesticide Tax	-0.0013	-0.0018	-0.0007	-0.0017	-0.0007
Grassland Subsidy	0.0004	0.0002	0.0004	0.0003	0.0004
Price Bonus	0.0856	0.0239	0.1598	0.0330	0.1475
sigma	0.0926	0.0907	0.1003	0.0914	0.0993

Table 7: Truncated regression and bootstrapped confidence intervals

5 Discussion and concluding remarks

The analysis of efficiency in pesticide use at landscape level can shed light on the optimal landscape composition and provide useful information for policymakers in the design of policies to promote reductions in pesticide use and its substitution for natural predators.

Using data simulated from a spatially explicit ecological-economic model of agricultural land use and nonparametric frontier techniques, in this paper we provide a measure of efficiency in pesticide use at landscape level. This approach is particularly useful to this field of research, as it allows us to identify the pesticide-efficient land use proportions that would have remained unknown by simply analyzing the trade offs between agricultural production and pesticide use.

Efficiency in pesticide use scores are used in a second stage to evaluate the effect of several agronomic and economic factors on the estimated measure. This analysis indicates that, in order to minimize the use of pesticide for a given level of agricultural output, fields devoted to grassland need to be dispersed into the landscape. However, the level of pesticide aggregation does not seem to have a significant effect on the efficiency measure. Moreover, our results show that policymakers could implement public policies to promote efficiency in pesticide use. In particular, taxes on pesticide use have a positive and significant effect on the minimization of pesticides. However, subsidies and price bonus seem to have a perverse effect on this measure. The reason for this effect may be that these policies promote the switch to land uses that are not as productive, so that the remaining fields need to be devoted to more pesticide-intense land uses to maintain the level of production. In this sense, taxation has been considered as the policy tool that can achieve environmental objectives more effectively (OECD, 2010), as it provides clear incentives to reduce pollution and switch to cleaner substitutes by imposing a direct cost on pollution. This economic incentive has already been implemented by the National Action Plans in Sweden, Denmark and Belgium, and the introduction of an European Union wide pesticide tax scheme is among the future objectives for the EU policy (Skevas et al., 2013).

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Appendices

A Simar and Wilson's Algorith #2

This appendix is based on the work by Simar and Wilson (2007). Interested readers are referred to this study for a detailed explanation of the properties and the statistical performance of the procedure.

The double bootstrap procedure described below performs bias correction and improves on inference, therefore, leading to consistent estimates of β:

1. Use maximum likelihood to obtain estimates of β and σ_ϵ for the regression of the inverse of the efficiency in pesticide use scores on the environmental variables or determinants using (5).

2. Loop over the following steps L times to obtain a set of bootstrap estimates for the parameters β and σ_ϵ:
$$\mathrm{B}_1 = \left\{(\widehat{\beta}^*, \widehat{\sigma}^*_\epsilon)_b\right\}_{b=1}^{L} \tag{8}$$
   (a) For each observation draw ϵ_i from the N(0,σ_ϵ) distribution with left-truncation at (1- $z_i\widehat{\beta}$).
   (b) Compute for each observation $\varepsilon_i^* = z_i\widehat{\beta} + \epsilon_i$
   (c) Define $p_i^* = p_i$ and $v_i^* = v_i \frac{\widehat{\varepsilon}_i}{\varepsilon_i}$ for each observation.
   (d) Compute the DEA efficiency scores using equations (3) and (4) again by replacing v_i and p_i with v_i^* and p_i^* and take again the inverse of the obtained efficiency scores.

3. Calculate for each observation the bias-corrected estimator defined as $\widehat{\widehat{\varepsilon}}_i = \widehat{\varepsilon}_i - \widehat{\mathrm{BIAS}}(\widehat{\varepsilon}_i)$ using the original inverse of the efficiency and the bootstrapped estimates obtained in Step 2.

4. Use maximum likelihood again to estimate the truncated regression, but using $\widehat{\widehat{\varepsilon}}_i$ as the dependent variable. Obtain estimates of $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma}}_\epsilon$

5. Apply the following steps L times to obtain a set of bootstrap estimates:
$$\mathrm{B}_2 = \left\{(\widehat{\beta}^*, \widehat{\sigma}^*_\epsilon)_b\right\}_{b=1}^{L} \tag{9}$$
   (a) For each observation draw ϵ_i from the N(0,σ_ϵ) distribution with left-truncation at (1- $z_i\widehat{\widehat{\beta}}$).
   (b) As done in Step 2.b , compute for each observation $\varepsilon_i^{**} = z_i\widehat{\widehat{\beta}} + \epsilon_i$.
   (c) Use maximum likelihood to estimate the truncated regression with ε_i^{**} as dependent variable and z_i as explanatory variable. Obtain estimates of $\widehat{\widehat{\beta^*}}$ and $\widehat{\widehat{\sigma^*_\epsilon}}$

6. Finally, construct estimated confidence intervals for β and σ_ϵ by using the original estimates of $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma}}_\epsilon$ and the bootstrap values obtained in B_2.