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Economic Costs of Sharing the Harvester in the Control of an Invasive Weed

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Abstract: Spatial externalities, such as the sharing of harvesting equipment by many farmers, have an impact on the control of invasive species in the agricultural environment. In these cases, the regulator must design a set of measures to promote coordinated control by affected parties. We aim to analyze the determinants of private versus collective control efforts in the case of a particular invasive species (teosinte) occurring as a weed in corn fields throughout North-Eastern Spain. Using a simple discrete space-dynamic framework, we model the effect of the decisions made by the farmer of an infested plot on a noninfested plot, with the harvester being the only potential pathway for the invader to spread and assuming a one-way invasion. The results reveal that failure to adopt optimal cooperative strategies causes losses to other plots if they become infested amounting to an annual average of EUR 322/ha, when the infestation is low, and EUR 364/ha, when it is high. Results suggest that cleaning the harvester, a measure currently recommended by the regulatory agency in low-infestation cases but that does not guarantee that the machine is completely clean, is not socially optimal if monocropping practices are permitted in the region.

Keywords: bio-economic model; weed management; control strategies; economic impact

1. Introduction

The emergence of a new invasive species that behaves as a weed in crop fields is a major challenge for the agents involved in controlling it (farmers and regulators). Rapidly understanding how the new species adapts to local environmental conditions is vital in the early stages of detection to design the most appropriate prevention, containment and eradication strategies. Identifying possible dispersal pathways—which are normally affected by control externalities—among neighboring plots is also of great importance.

Evaluating these externalities is crucial in the practical framework so that regulators can adequately guide farmers in their control decisions. The primary reason why these externalities exist in the case of agricultural fields is that the individuals (or stakeholders) involved in control base their decisions on their own farms [1], in other words, on a subset of the total area at risk of invasion. This private perspective ignores the link between the control efforts made by neighboring fields, while spatial externalities are likely when control efforts affect the spread of an invasive species across the landscape [2,3].

Control decisions made by farmers are also often based on measures after the invader has already become established in the environment, thus neglecting prevention measures in what is known as "myopic" behavior [4]. In these cases, the role of the regulator, who approaches the problem

from a collective standpoint, is to design a set of measures that promote coordinated control by the affected parties.

Ultimately, the decisions made by the parties (farmers and regulators) involved in controlling the invader are influenced by an attempt to minimize the damage the invader causes by trying to reduce the probability of infestation through prevention measures, or by investing in control measures once the invader has become established [5]. The fact that every species has its own particular dispersal method is an additional difficulty in adopting preventive measures that must be addressed using a specific procedure.

The problem of evaluating externalities in the control of an invasive species and the available solutions is not new in the literature. In this context, solutions to internalize these externalities, many based on the spirit of [6], are diverse and include the introduction of side payments between producers [7], landowners' bilateral negotiation [2,8], and voluntary contributions to a cooperative control district [3]. In this vision, a farmer might offer to share eradication or containment costs with a neighbor invaded by a weed to avoid or postpone being invaded.

Advances in species knowledge, optimization techniques and computational tools have driven the design of simulation models that can serve to assist farmers in controlling weeds in their fields. Examples in the literature include weeds in natural environment [9–12], and in agroecosystems [13–15]. Usually, these models are designed as a decision tool for weed control in the fields, making recommendations based on weed densities and available alternative treatments. The inclusion of economic variables in these models makes it possible to calculate and compare expected benefits for the different control strategies and to identify the optimal ones according to the farmer's objective (e.g., minimum cost, maximum benefit or multicriteria based) [15–17].

Recently, some studies consider dynamic and spatial aspects in bioeconomic models of weed control in various agroecosystems [16,18]. These studies address the trade-offs between current weed control and future profitability of the land, and the effect of control effort in a particular plot on the neighboring land. This paper contributes to this growing literature by combining new knowledge on the spatial dispersion of an invasive weed with its impacts on economic costs. To our knowledge, there is no previous work on invasive weed control that incorporates a public cost function associated with monitoring.

Teosinte as an Invasive Plant in the Ebro Valley

In 2014, teosinte (*Zea mays* subspp.) infestations in corn fields in the Ebro Valley (Spain) prompted researchers to learn about unknown aspects of its biological behavior, such as germination, seed survival capacity [19] and available chemical and manual control methods in affected fields [20].

Since teosinte was first detected in Aragon, the Centro de Sanidad y Certificación Vegetal (CSCV), which is the region's Plant Protection Service Agency, has surveyed more than 7000 ha each year, and monitored and recorded the number of infested plots, the total affected area and the infestation incidence (low or high infestation levels). Table 1 contains the information from 2014 to 2018, which will be used in this analysis.

Table 1. Number of infested plots, affected area and infestation incidence in the study area.

Year	Number of Infested Plots	Number of New Infested Plots	Area with Low Infestation (ha)	Area with High Infestation * (ha)	Total Infested Area (ha)
2014	44	44	27	358 (93%)	385
2015	63	27	441	192 (30%)	633
2016	70	14	621	28 (4.3%)	649
2017	72	13	634	28 (4.2%)	662
2018	73	40	419	375 (47.2%)	794

* In brackets, percentage of the total area. Source: [21].

The data recorded in that period show an increase in both the number of plots and the total area affected, although the annual growth rate decreased from 2014 to 2017. The area with high infestation and its proportion of the total decreased significantly from the first year to 2017, from 93% in 2014 to 4.2% in 2017. The most recent survey data, from 2018, show that new infested plots have continued to appear, although they differ from previously identified plots [22]. Moreover, there is an increase in the area with high infestation levels, suggesting that spatial dispersal is not being fully controlled despite the CSCV's dissemination, surveying and monitoring efforts.

This evidence has led to new research aimed to identify the invader's possible spatial dispersal mechanisms in the area. Technicians considered two main probable dispersal pathways: shared harvesters and stubble sheep grazing in affected areas [23]. Although both have been shown to be potential sources of teosinte dispersal, studies have concluded that harvesters have played a determining role in dispersing teosinte into new plots [22], as it occurs with other weed species, such as *Avena sterilis* L. [24] and *Lolium rigidum* [25].

Based on the survey data, the CSCV has established some mandatory phytosanitary measures to control intraplot infestation level and interplot spread of teosinte [26]. These measures comprise a set of cultural controls such as false seedbed technique, manual control, harvester cleaning protocols and rotations without corn. The first two strategies are only recommended for plots with a low infestation level, while harvester cleaning protocols are mandatory when infestation is low and rotations are adopted only when infestation is high. In addition, stubble sheep grazing is prohibited in all infested plots until the infestation has been completely eradicated.

From an economic perspective, the shared use of a harvester by infested and noninfested fields involves the existence of an externality in the control of the invasive weed. In a previous study, [27] obtained the optimal control strategies in a model including weed and seed bank dynamics and the effect of available control methods on those dynamics. An issue that affects the dispersal of this invasive species and still needs to be studied is how a farmer's control decisions influence neighboring fields, in other words, identifying and analyzing externalities.

Consequently, we specifically focus on the shared use of a harvester in the area identifying how private control decisions on one farm affect the level of infestation on neighboring farms when infestation likelihood is uncertain. With this aim, we construct a bio-economic model comprising dynamic and spatial dispersal dimensions to identify profit-maximizing strategies to tackle the problem of teosinte. In addition, we quantify externalities in controlling the invasive species and we evaluate the possibility of establishing economic compensation mechanisms among farmers through voluntary agreements (cooperation) or enforced by the regulator (no cooperation).

2. Materials and Methods

2.1. Theoretical Model

Our aim is to compare private versus social optimal farmer behavior when negative externalities of teosinte control are included in a dynamic profit-maximization problem and to identify available options to encourage private farmers to undertake a socially optimal level of control. Consequently, we first developed a general theoretical model and then illustrated it with a numerical application using real data obtained in the study area. This allowed us to quantify externalities and to internalize them.

We chose to use a profit-maximization framework because data on market prices and margins of the focal crops were available. One of the advantages of this approach is that it allowed us to carry out sensitivity analyses of the results to these model parameters. In addition, this approach allowed direct estimation of the loss of profit associated with the no-control strategy.

We defined a general discrete space and time model to include the main biological processes of the teosinte, its economic impact and interactions among farms in their efforts to control infestations. We supposed there were $j = 1, \ldots, J$ different farms in the area where the same harvester is used. Each farmer j can choose among a set of control strategies $i = 1, \ldots, I$ involving a variety of efforts

e_i for the plot, which are related to a given cost function $c_i(\cdot)$. The control effort e_i was measured by the number of hectares controlled under strategy *i*. We defined the functions of the model depending on two state variables: *w* (weeds, in plants per m^2) and *s* (seed bank, in number of seeds per m^2); thus, we omitted the other inputs and costs related to the production process to focus attention on weed-crop interaction. The private decision problem of farmer *j* was the following:

$$Max_{e_i^j} B_t^j = \sum_{i=1}^{I} v_{i,t}^j\left(w_{i,t}^j\right) - c_{i,t}^j\left(e_{i,t}^j\right) \tag{1}$$

$$\text{s.t. } w_{i,t+1}^j = W\left(s_{i,t}^j, e_{i,t}^j\right) \tag{2}$$

$$s_{i,t+1}^j = S\left(s_{i,t}^j, w_{i,t}^j, e_{i,t}^j, \sum_{k\neq j}^{J} s_{i,t}^{k\neq j}\left(e_{i,t}^k\right)\right) \tag{3}$$

where B_t^j is the benefit from the control effort e^j made by farmer *j* in period *t*; v_i is the profit margin obtained from the crop production under strategy *i* (profit margin depends on weed); c_i^j is the cost of control on site *j*, which depends on the control effort made by *j*; w_i^j is the weed function, which depends on seeds and control effort e_i; s_i^j is the seed dynamics function, which depends on the control effort made on farm *j*, and also on the effort made on the other farms ($e_{i,t}^k$, with $k \neq j$). The externality in teosinte control is expressed by the first derivative of function $S(\cdot)$ with respect to e^k, which is considered negative, in other words, the greater the control effort in plot *k*, the smaller the seed bank in plot *j*. Thus, the increase in the control effort in site *k* in period *t* affects *j* by increasing its margin through a reduction in s^j at period *t* + 1, which in turn affects the number of plants w^j. The first-order conditions of this problem are:

$$\frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial s^j} \times \frac{\partial s^j}{\partial e^j} + \frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial e^j} - \frac{\partial c^j}{\partial e^j} = 0 \tag{4}$$

implying that, in each period, farmer *j* will equate the private marginal benefits and costs of the control effort.

The social decision problem takes the form:

$$Max_{e_i^j} SB_t = \sum_{j=1}^{J}\sum_{i=1}^{I} v_{i,t}^j\left(w_{i,t}^j\right) - c_{i,t}^j\left(\sum_{j=1}^{J} e_{i,t}^j\right) - D\left(\sum_{j=1}^{J} e_{i,t}^j\right) \tag{5}$$

subject to Equations (2) and (3), where SB_t denotes the social benefit in the total area of control and function $D(\cdot)$ includes the public costs accruing to the control program to manage teosinte infestations set by the regulatory agency. We included these public costs by formulating a linear $D(\cdot)$ function, which depends on the control effort made by all the farmers and will be explained in detail in the numerical application below. The necessary first-order conditions to solve this problem include:

$$\frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial s^j} \times \frac{\partial s^j}{\partial e^j} + \sum_{k\neq j}^{J} \frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial s^j} \times \frac{\partial s^j}{\partial s^k} \times \frac{\partial s^k}{\partial e^k} + \frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial e^j} - \frac{\partial c^j}{\partial e^j} - \sum_{j=1}^{J} \frac{\partial D}{\partial e^j} = 0, \forall j \tag{6}$$

where the term $\sum_{k\neq j}^{J} \frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial s^j} \times \frac{\partial s^j}{\partial s^k} \times \frac{\partial s^k}{\partial e^k}$ measures the impact that the control effort made in farm *k* has on the margin of all other neighboring farms, while the term $\sum_{j=1}^{J} \frac{\partial D}{\partial e^j}$ is the sum of the impacts of individual control efforts on the public cost incurred by the regulator (i.e., marginal public costs avoided). We then obtained a classical result of the economics of invasion: the spread of any invasive species depends on

the control efforts made by all those affected. In the private decision problem, the decision makers have no incentive to consider the effects of their actions on others, while solving the social problem requires that they do. The implication is again a well-known result: it is socially desirable to encourage farmers to consider all the impacts of their control efforts and to adopt the socially optimal level. In our specific case, in which we consider the shared use of the harvester as a source of expansion of the invader to neighboring farms, we explored existing incentives to encourage farmers to adopt optimal control strategies with and without the need for intervention by a central regulator.

To solve the problem numerically, we needed to estimate the marginal external benefits of control, in other words, the value of the term $\frac{\partial v^j}{\partial w^j} \times \frac{\partial w^j}{\partial s^j} \times \frac{\partial s^j}{\partial s^k} \times \frac{\partial s^k}{\partial e^k}$ and the specification of the functions included in the model.

2.2. Numerical Illustration: Data and Study Area

Our study was based on data obtained from 2014 to 2018 in the infested areas of Aragon, where the presence of teosinte was first detected. This region is one of the main corn-monocropping zones in Spain, with 20% of the country's total production.

The numerical solution of the bio-economic models required specifying the biological functions and parameters. For a better understanding of the dispersal mechanisms, we simplified our theoretical model to the case of $J = 2$ different farms, j and k. We supposed that field k is initially infested at a given infestation rate (low or high), while field j is initially noninfested. Thus, the initial values of weeds and seeds considered are $w_0^k = 0.001$ and $s_0^k = 0$ for a low infestation rate, and $w_0^k = 0.1$ and $s_0^k = 0.007$ for a high infestation rate, while $w_0^j = 0$, $s_0^j = 0$. We then focused on the effects that the control decisions made by farmer k have on farm j only considering the case when the harvester is used by farmer k and then by farmer j in the same period t. Figure 1 schematically illustrates the main biological processes in annual teosinte population dynamics.
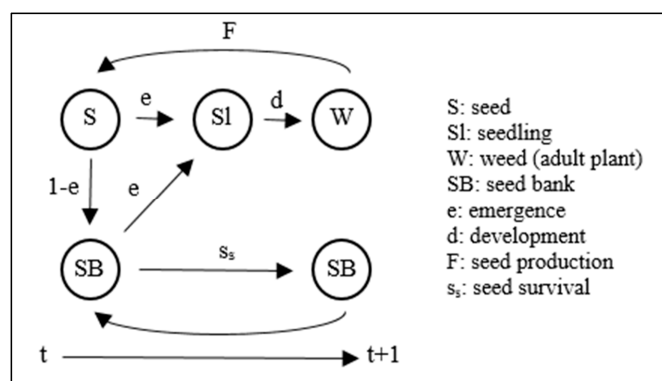

Figure 1. Life cycle diagram of teosinte.

The schematic diagram includes the three plant phenological stages of teosinte (S: seeds; Sl: seedlings; and W: adult plants) and the corresponding biological growth processes (e: emergence; d: development; and F: seed production). In addition, the life cycle contains the evolution of the soil seed bank, which is dominated by emergence (e) and seed survival parameters (s_s). This dynamic is affected by the available control strategies which affect the development process (d) and the seed survival capacity (s_s) in different ways [27].

Assuming that the invader's dispersal source is the harvester used in the first infested plot k, we considered there is a probability p_i^{in} that the harvester will move teosinte seeds from the infested field k to the clean field j, that is, the probability of infestation is $p_i^{in} \neq 0$ when corn is grown and $p_i^{in} = 0$ when rotations or alfalfa are cropped.

In accordance with the data recorded in the study area, the probability of infestation was drastically reduced (but not completely eliminated) when the harvester is cleaned after use in an infested plot and

before harvesting the next. These probabilities of infestation (with and without cleaning the harvester) were, however, unknown. Therefore, farmer j makes a decision by calculating the expected benefit ($EB_t{}^j$), which is the average benefit weighted by the probability of infestation. Consequently, the variable $B_t{}^j$ of Equation (1) is substituted by $EB_t{}^j$, which is defined as follows:

$$EB_t^j = B_t^j(infested) \times p_i^{in} + B_t^j(noninfested) \times \left(1 - p_i^{in}\right) \tag{7}$$

Since the probability of infestation $p_i{}^{in}$ depends on the cropping plan of farmer k, when $p_i{}^{in} = 0$, we obtained the case in which farmer j maximizes benefits without infestation, given that $w_0^j = 0$ and $s_0^j = 0$, in other words, the expected benefit of j is the same as without infestation $EB_t^j = B_t^j(noninfested)$.

We incorporated the decision to clean the harvester linked to the control alternatives i that include the cultivation of corn (i.e., no control, false seedbed and manual control) and we supposed that farmer k covers the cleaning cost. Thus, the model comprises 9 alternative control strategies (6 with corn crop and 3 rotations without corn):

(1) No control–no cleaning (corn crop).
(2) No control–cleaning (corn crop).
(3) False seedbed technique–no cleaning (corn crop).
(4) False seedbed technique–cleaning (corn crop).
(5) Manual control–no cleaning (corn crop).
(6) Manual control–cleaning (corn crop).
(7) Barley–sunflower rotation.
(8) Pea–sunflower rotation.
(9)   Alfalfa.

We initially set a value $p_i{}^{in} = 0.5$ for strategies in which the harvester is not cleaned ($i = 1, 3, 5$), $p_i{}^{in} = 0.1$ for strategies in which the harvester is cleaned ($i = 2, 4, 6$) and $p_i{}^{in} = 0$ for crop rotations ($i = 7, 8, 9$).

The possibility of plot j becoming infested was incorporated into the model through the specification of the seed bank function $S(\cdot)$ (Equation (3) in the model). In particular, we modified the formulation from [17] by incorporating the fact that the seed bank in site j is replenished by seeds from the infested field k. Thus, Equation (3) of the model takes the specific form:

$$s_{i,t+1}^j = S(s_{i,t}^j, w_{i,t}^j, e_{i,t}^j, \sum_{k \neq j}^J s_{i,t}^{k \neq j}(e_{i,t}^k)) = g\left(s_{i,t}^j, w_{i,t}^j\right) \times e_{i,t}^j + \varepsilon_i \times s_{i,t}^k \times e_{i,t}^k \tag{8}$$

where function $g(\cdot)$ represents the dynamics of the seed bank under farmer j control, while the second part of the sum includes the effect of the control decisions made by farmer k on plot j (i.e., the spatial externality). Parameter ε_i denotes the portion of teosinte seeds that leave plot k in the harvester and may infest plot j. A study of the infestation patterns of the plots in the area showed that in 66% of the fields teosinte very probably arrived by means of the harvester [22]. Although the value of ε is unknown, [23] found that only 1% of teosinte seeds come out of the harvester hopper, which may indicate that a smaller percentage could be transported in the harvester slits to other plots. Therefore, we set a value of $\varepsilon = 0.5\%$. When the harvester is cleaned after use in an infested plot, this value is considered significantly reduced, although it was difficult to quantify. We set $\varepsilon = 0.25\%$ in that case, in other words, cleaning the harvester results in a 50% reduction of the seeds that are left in the harvester and can potentially infest plot j.

Hence, we consider that cleaning the harvester affects 2 parameters in the model: the value of ε, and the probability of infestation p^{in}. In subsequent sections, we subject our results from both parameters to a sensitivity analysis.

For our numerical illustration, we considered a planning horizon of T = 15 years—to capture the primary biological and economic aspects of controlling teosinte—and a discount rate of 3%. Moreover, we included additional restrictions concerning average farm size (8 ha) in the models and, in the case of social decision problems, a crop rotation restriction, which is a mandatory measure introduced by the CSCV only in areas with highly infested plots and it means that a crop cannot be planted in the same plot for more than 1 year in a row, with the exception of alfalfa, which remains for 5 seasons. Furthermore, harvester cleaning is mandatory for plots with low infestation levels in the social model to capture the current situation. According to the data obtained in the study area, harvester cleaning costs EUR 120 [28].

Table A1 in Appendix A shows the complete description of the model functions and the values of the biological and economic parameters related to each control strategy. Both private and social problems were solved with the CONOPT2/GAMS algorithm (General Algebraic Modeling System) [29].

The biological data used in the model were obtained from the experimental trials started in 2014 to investigate the biology of teosinte in the growing conditions found in the study area under a research project funded by the Spanish National Agriculture Research Institute (INIA). Some research from this effort has been already published ([19–23]) and further related work is ongoing. In addition, the economic model incorporates actual data obtained from 2014 to 2018 by the CSCV on infested areas, farmer behavior, actual evolution of the invasive species in the affected regions and actual costs of monitoring.

Thus, the model was calibrated to capture the main phenological stages of teosinte and the results were validated using actual data on farmers' behavior and teosinte evolution in the infested areas. In addition, the robustness of the results has been strengthened by performing a sensitivity analysis on the parameters linked to uncertainty.

3. Results

Obtaining the numerical solution of the models allows us to: (i) identify and compare the pattern of private versus social optimal control strategies; (ii) quantify the value of the externality caused by farmer *k* to farmer *j*; (iii) explore the possibility of cooperation among farmers to internalize the external effect through side payments; and (iv) estimate the loss associated with the presence of teosinte in the area and the avoided costs when socially optimal control strategies are adopted.

Achieving the specific objectives (ii) to (iv) requires the quantification of the expected benefits of farmer *j* (i.e., Equation (7)) under each infestation scenario, which involves obtaining the farmer's optimal strategies when infested and without teosinte. In the real context, monocropping practices are allowed if there is no evidence of infestation; therefore, in the absence of teosinte evidence, farmer *j* maintains corn monocropping. Consequently, we must focus on the response of farmer *j* to the infestation caused by seeds from neighboring plot *k*. For this purpose, we calculate the optimal strategies of farmer *j* by assuming that plot *j* always becomes infested when the corn is grown by farmer *k*, in other words, $p_i^{in} = 1$ for $i = 1, \ldots , 6$ and the values of parameter ε_i are constant. Subsequently, the expected benefit of *j* will be calculated by modifying the probability of infestation as indicated in the previous section.

3.1. Private vs. Social Optimal Control Strategies

The problem defined in Equations (1) and (3) is solved for farmers *j* and *k* to provide the noncooperative solution, that is, the optimal private decision rule for farmers under both initially low- and high-infestation scenarios assuming that plot *j* is initially noninfested in *t* = 1. Figure 2 shows the optimal strategy pathway when farmer *k* adopts the controls that maximize private benefits, in other words, when the external costs/benefits caused to farmer *j*—whose plot is not initially infested—are not considered and cleaning the harvester is mandatory with low infestation levels.
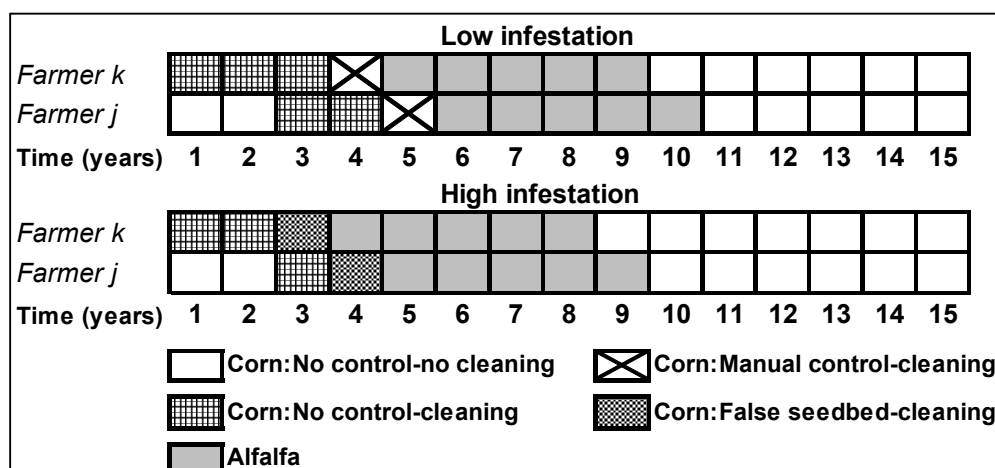
Figure 2. Optimal private control strategies.

In accordance with Figure 2, with low infestation (top cells in Figure 2), farmer *k* would select the "no control–cleaning" strategy for the first 3 years and then adopt "manual control–cleaning" in year four. From year five to year nine, corn would be substituted by alfalfa and then farmer *k* would return to corn monocropping in year 10. As a consequence of this noncooperative behavior of *k*, at the end of year one farmer *j* would receive teosinte seeds when using the harvester, and in year three this farmer would identify the presence of teosinte plants in the field. Figure 2 shows that farmer *j* adopts rotations one year after farmer *k*.

In the case of high infestation (bottom cells in Figure 2), the model establishes that farmer *k* would select the "no control–cleaning" strategy for 2 years, "false seedbed technique–cleaning" in the third year and alfalfa for 5 years. Afterwards, corn monocropping would be restored in year nine, because rotations are not mandatory in this context. Consequently, farmer *j* would detect the presence of teosinte plants in year three and would select "no control–cleaning", "false seedbed–cleaning" and rotations in year five.

These noncooperative strategies in plots (with an initial low infestation level in plot *k*) cause weed and seed density to increase until year five (data not shown), when all farmers have to introduce alfalfa due to the strong competition between teosinte and corn. The complete elimination of teosinte is achieved in year 10. Compared to low-infestation strategies, highly-infested plots adopt alfalfa one year earlier, thus allowing the eradication of teosinte in year nine on all farms.

These results are consistent with those obtained in [27], in the context of the optimal private decision, and demonstrate that farmers only pay the cleaning cost when it is mandatory.

However, our results show that when we include in the model the existence of an external effect on the control of teosinte, the timing when farmers adopt those control methods changes. Thus, the timing of the adoption of controls affects the period in which total eradication of the invader is achieved in a particular plot. This result may be a plausible explanation for the staggered detection of new infested fields in the study area over time. Of course, this issue influences the costs to be borne by the regulator and highlights the myopic behavior of agents when they do not consider the consequences of the spatial expansion in their decision-making process.

The social model is solved for two cases: (1) In the current situation, in which rotations are mandatory only when the plots have high infestation levels. (2) Considering the case in which crop rotations would be mandatory in all the plots for agronomic reasons, that is, with the aim of preventing future infestations, diseases and other phytosanitary problems. The second case serves to draw conclusions about the potential loss of profits for farmers due to rotations, and about the costs avoided by these measures in potential infestation events such as teosinte.

Figure 3 presents the results when the social problem defined in Equations (5) and (6) is solved with mandatory rotations only for highly infested plots and monocropping is permitted under no infestation.

In this case, the model indicates that farmer *k* should adopt rotations in the first year, both with low and high infestation levels, since growing corn in plot *k* would imply a nonzero probability of infestation in plot *j*; therefore, if cleaning the harvester does not ensure that the risk of infestation is eliminated, then rotation is the only way to avoid teosinte dispersal and the associated public costs.
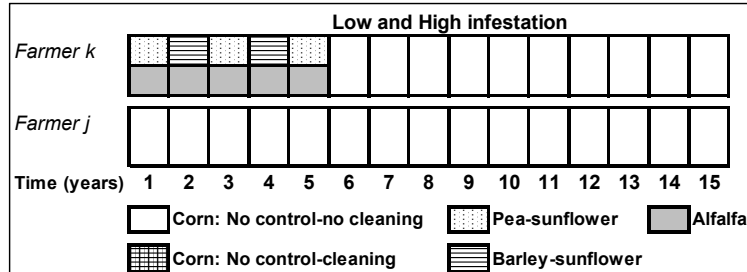

Figure 3. Optimal social control strategies in the current situation.

As a result, farmer *j* would not receive teosinte seeds and could, therefore, continue with corn monocropping. This means that cleaning the harvester is not socially optimal.

Figure 4, however, illustrates the optimal control strategies if crop rotations are always mandatory. In this case, plot *k* with low infestation selects the "no control–cleaning" strategy in year one and adopts rotations from years two to six with half the area devoted to alfalfa and the other half alternating with pea–sunflower and barley–sunflower. In year seven, the corn crop can be planted again because teosinte and its seed bank have been eradicated. From year eight, the area allocated to alfalfa is planted with pea–sunflower and corn in alternating years.
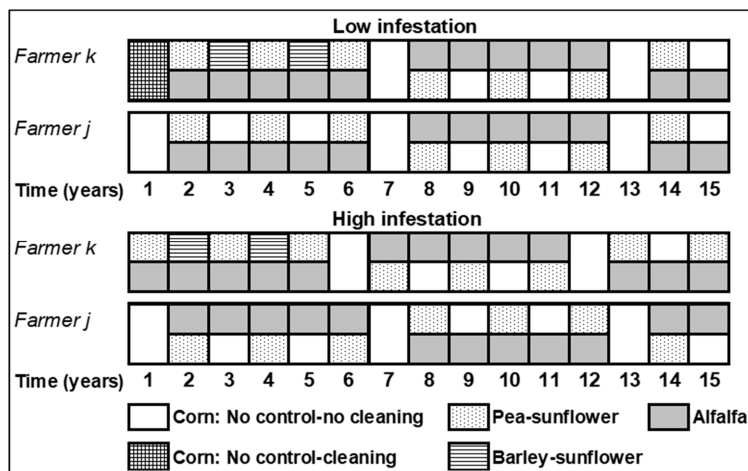

Figure 4. Optimal social strategies when rotations are always mandatory.

In addition, farmer *j* would replicate farmer *k*'s strategies, but may include corn in the rotations from the beginning, since cleaning the harvester would reduce the teosinte seeds *k* receives and rotations would prevent their proliferation.

When plot *k* is initially highly infested, the results suggest that plot *k* would adopt rotations starting in year one and could return to a corn crop by year six. In that case, farmer *j* would not receive teosinte seeds due to the immediate incorporation of rotations by *k*.

Comparing these results with those of the private noncooperative model (Figure 2) leads to two important conclusions: first, under the assumption that cleaning the harvester reduces the probability of infestation, the obligation to clean in infested plots only delays the detection of infestation in other initially noninfested plots and, therefore, from a social perspective, this measure is not appropriate in the current situation, in which rotations are not always mandatory; and second,

the obligation to adopt rotations in highly infested plots ensures that the invader is totally eradicated after 5 years and also prevents the spread to other plots. In agreement with [27], the results also confirm that manual control and false seedbed techniques are not socially optimal. Whether mandatory rotations are adopted has relevance to the control costs covered by the regulator, which are quantified in the section below.

Obviously, the above results depend significantly on the value of parameter ε, in other words, the percentage of seeds considered to enter plot j from plot k, which, as already mentioned, is difficult to determine precisely. For this reason, conducting a sensitivity analysis of the results of this parameter seems appropriate.

First, we vary the value of ε_i from 0.001% to 1% for no cleaning strategies ($i = 1, 3, 5$) and then we modify it between 10% and 90% (multiplying by 0.9 to 0.1) of its initial value and assign it to the cleaning strategies ($i = 2, 4, 6$). We record the effects of these variations on private strategies.

The analysis shows that the value of ε_i only influences the period in which plot j detects the presence of teosinte plants but not the optimal private strategies. In particular, values between 0.2% and 0.8% increase the number of seeds coming from plot k but do not influence the timing of rotations. For the private model, we find that only the values of $\varepsilon_i \geq 0.9\%$ anticipate the moment when the presence of teosinte plants is detected in plot j and, thus, rotations are advanced one period (until year five for low infestation and six for high infestation) due to the detection of more teosinte plants in the field. Our analysis shows that only for $\varepsilon_i \geq 2\%$ does plot j present low infestation ($w \geq 0.001$ plants m^{-2}) two periods earlier (year three and four for low and high infestation, respectively) and the rotations are adopted two periods earlier than with the initial parameter value. However, as mentioned above, it seems unrealistic to expect $\varepsilon_i \geq 1\%$.

Conversely, values of $\varepsilon_i \leq 0.01\%$ delay the adoption of rotations for one period (until year seven with low infestation or year eight with high infestation) and $\varepsilon_i \leq 0.001\%$ delay rotations for two periods (until year eight or nine for low-and high-infestation scenarios, respectively).

Regarding the sensitivity of the results to the ε_i value for cleaning strategies, we consider variations from 10% to 90% ($i = 2, 4, 6$) with respect to the value for no cleaning strategies. The analysis shows that if cleaning the harvester reduces the value of ε_i by less than 60%, then rotations in plot j are adopted in the same year. In contrast, if cleaning reduces the value of ε_i by more than 60%, then the rotations are delayed by one year. Values of $\varepsilon_i \leq 0.001\%$ would delay rotations for two periods. For example, considering the initial value for no cleaning strategies $\varepsilon_i = 0.5\%$ ($i = 1, 3, 5$), if cleaning the harvester reduces ε_i ($i = 2, 4, 6$), given that $0.001 \leq \varepsilon_i \leq 0.2$, then the rotations are delayed for one period (to year six for the low-infestation scenario and to year seven for the high-infestation scenario), while if $\varepsilon_i < 0.001\%$, rotations are delayed for two periods (to year seven or eight). Table 2 summarizes the previous results and shows the sensitivity of the benefits of j to changes in the values of parameter ε_i with and without cleaning the harvester.

Table 2. Sensitivity analysis of the expected annual average benefit of j to the parameter ε_i.

Values of ε_i for No Cleaning Strategies ($i = 1, 3, 5$)	Reduction in Values of ε_i for Cleaning Strategies ($i = 2, 4, 6$)	Annual Average Benefit of j under Low Infestation (in EUR /ha)	Annual Average Benefit of j under High Infestation (in EUR /ha)
$0.1 < \varepsilon < 1$	$\leq 50\%$	1052	1009.8
$0.1 \leq \varepsilon \leq 0.9$	$>50\%$	1061.3	1029.1
$0.9 < \varepsilon \leq 1$	Any value	1052	1009.8
$0.001 < \varepsilon < 0.1$	Any value	1061.3	1029.1
$0.0001 < \varepsilon \leq 0.001$	Any value	1070.4	1039.7
$\varepsilon \leq 0.0001$	Any value	1079.3	1051.4

In summary, the value of parameter ε_i influences the staggered detection of teosinte, which leads to the timing of control measures, total eradication of the invader and, consequently, public costs incurred in monitoring and controlling the invader as well.

The analysis shows that the use of shared harvesters, a common practice in many cereal-growing areas in the study area, makes it difficult to control infestations due to the risk of spatial dispersal. Although cleaning the machines reduces the risk of dispersal to neighboring plots, the results show that this practice does not ensure total eradication of teosinte and should be replaced by mandatory rotations also under low infestation if monocropping is not prohibited in the whole area. Alternatively, since crop rotations are the only measure capable of eradicating the invader and its spread, the regulator should insist on measures to promote the replacement of monoculture as a way of protecting against invaders and other potential phytosanitary hazards.

3.2. Quantifying and Solving Externalities

The estimate of the benefits obtained by farmers *j* and *k* with different infestation situations and its comparison with the case without infestation provides the quantification of the externalities generated in the control of teosinte.

As shown in the theoretical section above, the total external cost comprises two parts: a private cost covered by *j* and a public cost covered by the regulator. To quantify the former (the private external cost), we need to focus on the case in which farmer *k* selects the first strategy (no control–no cleaning) and how this behavior affects the benefit obtained by farmer *j*; in other words, we need to numerically calculate the losses farmer *k* causes to farmer *j* at both low and high infestation levels. This situation, in which farmer *k* selects the optimal private strategies, is shown in Figure 2. The private external cost is the difference between the benefits that *j* would obtain with no infestation minus those that *j* obtains after being infested by *k*. The public cost is calculated through the damage function defined in Equation (5).

Table 3 shows the average annual benefits per hectare obtained by farmers with low and high infestation levels and optimal private and social strategies, associated public costs and the quantification of external costs.

Table 3. Average annual benefits per hectare with cooperative vs. noncooperative strategies EUR/ha).

	Optimal Private Strategies		Optimal Social Strategies (Rotations Only with High Infestation)		Optimal Social Strategies (with Mandatory Rotations)	
	Farmer *j*	**Farmer *k***	**Farmer *j***	**Farmer *k***	**Farmer *j***	**Farmer *k***
(1) Benefits, noninfestation	1374	1374	1374	1374	920	920
(2) Benefits, low infestation (losses relative to noninfestation)	1052 (322)	1041.4 (332.6)	1374 (0)	999.5 (374.5)	920 (0)	693.5 (365.1)
(3) Public costs, Low infestation	37.6	49.5	0 *	0 *	0	12.9
(4) Total benefits, Low infestation (4) = (2) − (3)	1014.4	991.9	1374	999.5	920	680.6
(5) Benefits, high infestation (losses relative to noninfestation)	1009.8 (364.2)	1006.3 (367.7)	1374 (0)	999.5 (374.5)	920 (0)	623.4 (374.5)
(6) Public costs, high infestation	21.1	37.6	0 *	0 *	0	0
(7) Total benefits, high infestation (7) = (5) − (6)	988.7	968.7	1374	999.5	920	623.4

* In this case, costs associated with the risk of future infestations with other weeds or pests are not considered.

Results show that adopting optimal private strategies generates EUR 1041.40/ha for farmer *k* and EUR/ha for farmer *j* with low infestation and EUR 1006.30/ha and EUR 1009.80/ha with high infestation, respectively. This means farmer *j* would have an average annual loss of EUR 322/ha when farmer *k* initially has a low infestation, and EUR 364.20/ha when farmer *k* initially has a high infestation. These amounts correspond to the quantification of the private external cost when *j* becomes infested assuming that farmer *k* adopts the appropriate optimal private strategies (Figure 2). Furthermore, strategies adopted by *k* imply an annual public cost amounting to EUR 49.50/ha with low infestation and EUR 37.60/ha with high infestation, because rotations are adopted earlier with

high infestation. In the case of farmer *j*, the public costs amount to EUR 37.60/ha and EUR 21.10/ha for low and high infestation levels, respectively. Public costs are lower for farmer *j* compared to *k* due to delayed infestation.

When adopting socially optimal strategies in the current context (column 2 in Table 3), farmer *k* would obtain an average annual benefit of EUR 999.50/ha with both low and high infestation levels, while the benefit of farmer *j* is not to have teosinte. Public costs due to teosinte would be eliminated in this situation.

Finally, when rotations are mandatory, average annual benefit without infestation amounts to EUR 920/ha since the model includes crop rotation restrictions even without infestation. In this case, if farmer *k* adopts optimal social strategies, benefit is reduced to EUR 693.50/ha for low infestation and to EUR 623.40/ha for high infestation, but the private external cost borne by *j* is eliminated. These strategies only generate public costs with low infestation levels (EUR 12.90/ha) in plot *k* because the immediate adoption of rotations with high infestation levels in plot *k* eliminates public costs and prevents spread to plot *j*.

The estimates shown in Table 3 make it possible to explore several policy responses to the externalities identified in teosinte control. The externalities resolution theory establishes that the agent causing the negative (positive) externality must internalize all the costs (benefits) of the activity.

As we indicated above, these external costs can be eliminated in several ways: by introducing mandatory rotations (even in the case of low infestation), by designing taxes for farmers who plant corn and suffer teosinte infestations, etc. However, here we focus on the possibility of establishing agreements among farmers to reduce/eliminate the risk of teosinte dispersal.

If we look at the case of noncooperation in Table 3, the optimal strategies of farmer *k* cause farmer *j*'s private losses of EUR 322/ha in the event of infestation, and no losses with no infestation. Since the expected losses of *j* amount to EUR 161/ha when the probability of infestation is 0.5, we look at the possibility of both farmers agreeing to reduce or eliminate these losses in the context of uncertainty.

Given that cleaning the harvester reduces the probability of infestation p^{in} at a certain but unknown level, we estimate the average annual expected benefits for farmer *j* and the losses with respect to the noninfestation scenario considering different values of p^{in} ranging from 0 (no probability of infestation) to 1 (total probability of infestation) with an initial interval of 0.1. Next, we expand the analysis for an interval of 0.01 after verifying that the results are sensitive to this range. Although the complete results of the analysis are shown in Appendix A (Table A2), Table 4 contains the results for low infestation and p^{in} variations of 0.1 under the initial values for parameter ε_i and also for $p^{in} = 0.48$ and $p^{in} = 0.49$ to illustrate what happens with p^{in} variations of 0.01.

Table 4. Effect of the probability of infestation on expected benefits and losses of farmer *j* under low infestation.

Probability of Infestation (p^{in})	Expected Annual Average Benefits (EUR/ha)	Total Expected Discounted Average Benefits (EUR)	Total Expected Losses with Respect to Noninfestation (EUR)
0	1374	164,880	0
0.1	1341.8	161,016	3864
0.2	1309.6	157,152	7728
0.3	1277.4	153,288	11,592
0.4	1245.2	149,424	15,456
0.48	1219.4	146,333	18,547
0.49	1216.2	145,946	18,934
0.5	1213	145,560	19,320
0.6	1180.8	141,696	23,184
0.7	1148.6	137,832	27,048
0.8	1116.4	133,968	30,912
0.9	1084.2	130,104	34,776
1	1052	126,240	38,640

By calculating the expected losses of *j* with respect to the situation of noninfestation, we can evaluate this farmer's economic incentive to reduce/avoid the risk of infestation coming from plot *k*. For example, if cleaning the harvester reduces the probability of infestation to $p^{in} = 0.1$, then the total discounted expected losses of *j* would be EUR 3834 compared to the current EUR 19,320 ($p^{in} = 0.5$). Since the total discounted cost of cleaning the harvester amounts to EUR 459.42 (EUR 120 for the first four periods), *j* has an incentive to cover the total cost of cleaning.

This type of evaluation allows us to identify the p^{in} values for which farmer *j* would have incentives to pay for the cleaning of the harvester. Table 4 shows that farmer *j* has incentives to promote an agreement whenever cleaning the harvester reduces the probability of an infestation in the range of 0.1 in probability of occurrence. When cleaning the harvester eliminates the probability of infestation ($p^{in} = 0$), *j* receives a total discounted benefit of EUR 164,420.50 if the cleaning cost is covered, which is a higher benefit than in any situation if the harvester is not cleaned.

In the case of smaller variations of probability (0.01), we find that the incentive to establish agreements by *j* does not occur if the probability of infestation is reduced by 0.01 (one interval step). For example, if $p_{in} = 0.5$ when the harvester is not cleaned and $p_{in} = 0.49$ when the harvester is cleaned, the expected benefit from cleaning for farmer *j* amounts to EUR 386, while the cleaning costs come to EUR 459.42; therefore, *j* would not be willing to pay all these costs.

Since the possibility of an agreement depends on the quantification of externalities and losses caused by the presence of teosinte, which in turn depend on the value of parameters p^{in} and ε_i, we subjected our results from both parameters to a sensitivity analysis, as shown in Appendix A (Table A2).

The data in Table A2 demonstrate that the incentive to cooperate is maintained even if the infestation in plot *j* is delayed as a result of the smaller value of ε_i. In particular, reductions of more than 0.01 in the probability maintain the incentive for *j* to cover the total cleaning cost, while reductions of 0.01 maintain it only partially. The analysis reveals that there are several chances of a cooperative agreement among farmers but these are linked to the effectiveness of cleaning in reducing the probability of infestation.

In contrast, if the regulator decides that the cost of cleaning should be covered by farmer *k*, then the results of the Table A2 allow the identification of additional agreement possibilities among farmers, since farmer *j* would be willing to pay at least part of the cleaning cost provided that the expected losses resulting from becoming infested are higher than the cleaning cost. For example, if cleaning the harvester implies that p^{in} is reduced from 0.5 to 0.49, then farmer *j* would be willing to pay a positive amount with a maximum of EUR 386, which is the difference in the expected losses, while farmer *k* would be willing to accept any contribution to the cost of cleaning.

3.3. Estimating the Loss Associated with the Presence of Teosinte

Finally, the numerical data obtained in Table 3 for farmer *k* make it possible to estimate the losses associated with the presence of teosinte in the study area. For this purpose, we combine this information (Table 3) with the data provided by the CSCV regarding the number of infested hectares and the infestation level (Table 1).

Table 5 shows that private strategies lead to total losses over the whole period of EUR $18,271.40 \cdot 10^3$ relative to a noninfestation scenario; EUR $16,120.40 \cdot 10^3$ of this amount are private costs and EUR $2,151 \cdot 10^3$ are public costs covered by the regulator. Additionally, these strategies imply costs for the neighboring plots using the same harvester. These losses can be assessed by calculating the losses expected by farmer *j* when first infested (results shown in Table 4), to which the associated public costs must be added. Based on our model's parameter values, these annual expected profit losses amount to EUR 161 and EUR 166.30/ha for low and high infestation, respectively; the expected public costs amount to EUR 18.80/ha and EUR 10.50/ha (half the total public cost shown in Table 3) for low and high infestation, respectively.

Table 5. Estimates of total economic impacts in the study area from 2014 to 2018.

	Total Discounted Benefit/Cost (in EUR 10^3)		
	Privately Optimal	**Socially Optimal (Current Situation)**	**Socially Optimal (with Mandatory Rotations)**
(1) Benefits, non-infestation	64,365	64,365	43,098.4
(2) Benefits, low-infestation area	32,772.8	31,454.2	21,824.445
(3) Public costs, low-infestation area	1557.7	0	405.9
(4) Total benefit, low-infestation area (4) = (2) − (3)	31,215.1	31,454.2	21,418.4
(5) Benefits, high-infestation area	15,471.8	15,367.3	9584.7
(6) Public costs, high-infestation area	593.3	0	0
(7) Total benefit, high-infestation area (7) = (5) − (6)	14,878.5	15,367.3	9584.7
(8) Losses relative to non-infestation (8) = (1) − (4) − (7)	18,271.4	17,543.4	12,095.1
(9) Annual average losses relative to non-infestation (9) = (8)/5	3654.2	3508.6	2419

Adopting social strategies in the current context leads to losses with respect to the situation of noninfestation amounting to EUR $17,543.40 \cdot 10^3$, which corresponds to a loss of private profits, as the public costs would be eliminated. However, in this scenario, the risk of future weed infestations or other diseases is not avoided, since monocropping is still permitted. In contrast, the data show that permanent rotations lead to minor losses with respect to the noninfestation situation (EUR $12,095.10 \cdot 10^3$), while minimizing the risk associated with future diseases.

Obviously, this option implies private benefit losses of EUR $21,266.60 \cdot 10^3$ with respect to noninfestation, which explains why the regulator usually recommends permanent rotations without imposing them. In fact, [4] describe that managers' increased risk aversion may lead to less prevention and more control in situations in which there is uncertainty regarding the probability of being affected by an invader or a disease, because prevention does not eliminate the invasion, it only reduces the likelihood of becoming invaded. The economic explanation is that the manager values euros spent on control (with a certain benefit now) more highly than euros spent on prevention (with an uncertain benefits) [4]. Our results confirm this behavior in the area of study.

The results show that monoculture is a practice that many farmers adopt in their fields due to profit-maximizing behavior and the industrial nature of crop production in the study area. However, considering a more global ecological and economic context, rotations protect against invasive infestations, pests, diseases and help maintain soil fertility. Thus, rotations reduce the use of agrochemicals, which increases farmers' long-term benefits and results in greater sustainability of the agroecosystem [30,31]. In addition, as our results show, crop rotations substantially reduce the need for monitoring and control by the regulator, reducing public costs as a result.

To enhance the sustainability of the system, the regulator must incentivize farmers to adopt crop rotations. Our work estimates that the adoption of rotations would save EUR $5,448.3 \cdot 10^3$ in the control of teosinte from 2014 to 2018, without taking into account other advantages linked to soil fertility, pest and other weed controls.

4. Conclusions

The comparison of the results of the present study with those obtained in the previous work showed that a profit-maximizing farmer would never cover the cost of cleaning the harvester after using it in the infested plot when it is not mandatory.

Assuming that cleaning the harvester does not completely eliminate the probability of an infestation, we found that this measure is not socially optimal in the current situation, where corn-monocropping practices are not prohibited in noninfested plots. In this case, the model indicated that infestation and detection of the invader in initially noninfested fields is delayed over time, so that eradication is also delayed. Therefore, the pattern of temporal and spatial teosinte expansion observed in the affected areas can be explained, at least in part, by the use of the harvester, which causes seeds to enter new plots and increases the overall costs of controlling and eradicating teosinte.

The data suggested that if a monocrop is allowed, infested plots should adopt mandatory rotations, even when infestation is low, as this is the only way to avoid spatial dispersal of the invader. In addition, our results confirmed that manual control and seedbed techniques are not socially optimal so the regulator should reconsider these measures to control and eradicate teosinte.

The sensitivity analysis showed that a change in the value of parameters associated with the probability of infestation and the number of seeds before and after cleaning the harvester does not change the optimal strategies but can delay/advance their adoption.

Adopting socially optimal strategies would eliminate the externalities caused to the neighboring plots and also the public costs for the regulator, although monoculture maintains the risk of sustaining future phytosanitary problems. Quantifying the benefits and costs associated with several situations allowed us to affirm that adopting permanent rotations would avoid an annual average cost of EUR $1235.20 \cdot 10^3$.

Of course, the results depend heavily on the model's ability to represent reality and on the data available for the study area. However, our methodology can be easily adapted to the study of other crops, weeds, pests or diseases. On the other hand, the data used in this work correspond to the only case of teosinte infestation reported in Europe for which there are available biological and economic data, so the results can be useful for other areas where teosinte could appear in the future. Another promising future research area is including in the model (through a function or specific parameters) the relationship between rotations and long-term indirect benefits discussed above (i.e., improved fertility, ease of controlling other diseases, reduced need for regulator control, etc.).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Model functions and parameters.

Function	Specification	Parameter Values	Source
Weed dynamics	$w_{i,t+1}^{j} = w^{*}\left[1 - exp\left(-\alpha_0\left(\alpha_1 + s_{i,t}^{j}\right)\right)\right] \cdot e_{i,t}^{j}$	$w* = 22$ $\alpha_0 = 0.0704$ $\alpha_1 = 0.1876$	[27]
Seed bank dynamics	$g\left(s_{i,t}^{j}, w_{i,t}^{j}\right) = \begin{cases} \beta_1 \cdot s_{i,t}^{j} + \beta_2 \cdot w_{i,t}^{j} \text{ if } s_{i,t} < s^* \\ \\ s^* \text{ if } s_{i,t}^{j} \geq s^* \end{cases}$	$s* = 31.8$ $\beta_1 = 0.0738$ $\beta_2 = 98.97$	[27]
Profit margin	$v_{i,t}^{j}\left(w_{i,t}^{j}\right) = \delta_{0,i} + \delta_{1,i} \cdot w_{i,t}^{j}$	$\delta_0 = 11.334 \text{ if } i = 1, \ldots, 6$ $\delta_0 = 374.12 \text{ if } i = 7$ $\delta_0 = 505.36 \text{ if } i = 8$ $\delta_0 = 547.76 \text{ if } i = 9$ $\delta_1 = -0.5456 \text{ if } i = 1, \ldots, 6$ $\delta_1 = 0 \text{ if } i = 7,8,9$	[23,27]
Control costs	$c_{i,t}^{j}\left(e_{i,t}^{j}, e_{i,t}^{k}\right) = \gamma_{0,i}^{j} + \sum_{j=1}^{J} \gamma_{1,i}^{j} \cdot e_i^{j}$	$\gamma_{1,i}^{j} = 0 \text{ if } i = 1,2$ $\gamma_{1,i}^{j} = 546.7 \text{ if } i = 3, 4$ $\gamma_{1,i}^{j} = 142.8 \text{ if } i = 5,6$ $\gamma_{1,i}^{j} = 0 \text{ if } i = 7, 8, 9$ $\gamma_{0,i}^{k} = 120 \text{ if } i = 2, 4, 6$ $\gamma_0^{j} = 0, \forall j \neq k$	Own from available data
Public costs	$D_i(e_i) = d_0 + d_{1,i} \cdot \left(e_i^{j} + e_i^{k}\right)$	$d_0 = 1900 \text{ if } i = 1, \ldots, 6$ $d_1 = 160 \text{ if } i = 1, \ldots, 6$ $d_1 = 0 \text{ if } i = 7, 8, 9$	Own from available data
Total individual land restriction	$\sum_{i=1}^{9} e_i^{j} = \overline{E}^{j} \; \forall \; j$	$\overline{E}^{j} = 8$	Own from available data
Rotation restriction	$e_{i,t}^{j} \leq \sum_{z=1}^{8} e_{z,t-1}^{j} \text{ with } i \neq z \; \forall \; i, z = 1, \ldots, 9$	–	[27]

Table A2. Results of sensitivity analysis for ε_i and pin parameters.

ε_i Values When No-Cleaning (i = 1, 3, 5) and Multiplier Values	Probability of Infestation (p_{in}) When No-Cleaning	Probability of Infestation (p_{in}) When Cleaning	Annual Average Benefits under Infestationn (EUR/ha)	Expected Annual Average Benefits(EUR/ha)	Total Discounted Average Benefits (EUR)	Total Expected Losses with Respect to Non-Infestation (EUR)
	1	0	1054.7	1374	164,880	0
	0.99	0.01	1054.7	1370.80	164,496.84	383.16
	0.98	0.02	1054.7	1367.61	164,113.68	766.32
	0.97	0.03	1054.7	1364.42	163,730.52	1149.48
	0.96	0.04	1054.7	1361.22	163,347.36	1532.64
	0.95	0.05	1054.7	1358.03	162,964.20	1915.80
	0.94	0.06	1054.7	1354.84	162,581.04	2298.96
	0.93	0.07	1054.7	1351.64	162,197.88	2682.12
$0.1 < \varepsilon_i < 1$ (i = 1, 3, 5)	0.92	0.08	1054.7	1348.45	161,814.72	3065.28
and multiplier ≥50% or	0.91	0.09	1054.7	1345.26	161,431.56	3448.44
$0.1 < \varepsilon_i < 0.9$ and	0.9	0.1	1054.7	1342.07	161,048.40	3831.60
multiplier <50%	0.8	0.2	1054.7	1310.14	157,216.80	7663.20
	0.7	0.3	1054.7	1278.21	153,385.20	11,494.80
	0.6	0.4	1054.7	1246.28	149,553.60	15,326.40
	0.5	0.5	1054.7	1214.35	145,722	19,158
	0.4	0.6	1054.7	1182.42	141,890.40	22,989.60
	0.3	0.7	1054.7	1150.49	138,058.80	26,821.20
	0.2	0.8	1054.7	1118.56	134,227.20	30,652.80
	0.1	0.9	1054.7	1086.63	130,395.60	34,484.40
	0	1	1054.7	1054.70	126,564	38,316
	1	0	1064	1374.00	164,880	0
	0.99	0.01	1064	1370.90	164,508	372
	0.98	0.02	1064	1367.80	164,136	744
	0.97	0.03	1064	1364.70	163,764	1116
	0.96	0.04	1064	1361.60	163,392	1488
	0.95	0.05	1064	1358.50	163,020	1860
	0.94	0.06	1064	1355.40	162,648	2232
	0.93	0.07	1064	1352.30	162,276	2604
	0.92	0.08	1064	1349.20	161,904	2976
$0.9 < \varepsilon_i < 1$ or $0.001 < \varepsilon_i \leq$	0.91	0.09	1064	1346.10	161,532	3348
0.001 with any multiplier	0.9	0.1	1064	1343.00	161,160	3720
	0.8	0.2	1064	1312.00	157,440	7440
	0.7	0.3	1064	1281.00	153,720	11,160
	0.6	0.4	1064	1250.00	150,000	14,880
	0.5	0.5	1064	1219.00	146,280	18,600
	0.4	0.6	1064	1188.00	142,560	22,320
	0.3	0.7	1064	1157.00	138,840	26,040
	0.2	0.8	1064	1126.00	135,120	29,760
	0.1	0.9	1064	1095.00	131,400	33,480
	0	1	1064	1064.00	127,680	37,200
	1	0	1073	1374.00	164,880	0

Table A2. *Cont.*

ε_i Values When No-Cleaning (i = 1, 3, 5) and Multiplier Values	Probability of Infestation (p_{in}) When No-Cleaning	Probability of Infestation (p_{in}) When Cleaning	Annual Average Benefits under Infestationn (EUR/ha)	Expected Annual Average Benefits(EUR/ha)	Total Discounted Average Benefits (EUR)	Total Expected Losses with Respect to Non-Infestation (EUR)
	0.99	0.01	1073	1370.99	164,518.8	361.20
	0.98	0.02	1073	1367.98	164,157.6	722.40
	0.97	0.03	1073	1364.97	163,796.4	1083.60
	0.96	0.04	1073	1361.96	163,435.2	1444.80
	0.95	0.05	1073	1358.95	163,074	1806
	0.94	0.06	1073	1355.94	162,712.8	2167.20
	0.93	0.07	1073	1352.93	162,351.6	2528.40
	0.92	0.08	1073	1349.92	161,990.4	2889.60
0.0001 < ε_i < 0.001 with	0.91	0.09	1073	1346.91	161,629.2	3250.80
any multiplier	0.9	0.1	1073	1343.90	161,268	3612
	0.8	0.2	1073	1313.80	157,656	7224
	0.7	0.3	1073	1283.70	154,044	10,836
	0.6	0.4	1073	1253.60	150,432	14,448
	0.5	0.5	1073	1223.50	146,820	18,060
	0.4	0.6	1073	1193.40	143,208	21,672
	0.3	0.7	1073	1163.30	139,596	25,284
	0.2	0.8	1073	1133.20	135,984	28,896
	0.1	0.9	1073	1103.10	132,372	32,508
	0	1	1073	1073	128,760	36,120
	1	0	1081.78	1374.00	164,880	0
	0.99	0.01	1081.78	1371.07	164,529.34	350.66
	0.98	0.02	1081.78	1368.15	164,178.67	701.32
	0.97	0.03	1081.78	1365.23	163,828.01	1051.99
	0.96	0.04	1081.78	1362.31	163,477.34	1402.65
	0.95	0.05	1081.78	1359.38	163,126.68	1753.32
	0.94	0.06	1081.78	1356.46	162,776.02	2103.98
	0.93	0.07	1081.78	1353.54	162,425.35	2454.64
	0.92	0.08	1081.78	1350.62	162,074.69	2805.31
ε_i < 0.0001 with any	0.91	0.09	1081.78	1347.70	161,724.02	3155.97
multiplier	0.9	0.1	1081.78	1344.77	161,373.36	3506.64
	0.8	0.2	1081.78	1315.55	157,866.72	7013.28
	0.7	0.3	1081.78	1286.33	154,360.08	10,519.92
	0.6	0.4	1081.78	1257.11	150,853.44	14,026.56
	0.5	0.5	1081.78	1227.89	147,346.8	17,533.20
	0.4	0.6	1081.78	1198.66	143,840.16	21,039.84
	0.3	0.7	1081.78	1169.44	140,333.52	24,546.48
	0.2	0.8	1081.78	1140.22	136,826.88	28,053.12
	0.1	0.9	1081.78	1111.00	133,320.24	31,559.76
	0	1	1081.78	1081.78	129,813.60	35,066.40

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