## 1. Introduction

Teosinte, an invasive species native to South America, recently appeared as weed in corn fields throughout Northeastern Spain. This species is the wild ancestor of corn *(Zea mays* L.) and it shares a similar growth cycle in this region. That is, teosinte germinates in May and needs high temperature and humidity to develop. Next, it reaches the flowering stage between August and September and its seeds fall to the ground from October to December, remaining latent until the next cropping season.

Teosinte is a serious competitor of corn for several reasons. It is capable of producing a large number of seeds which remain viable in the soil for future cropping periods. It can also be hybridized with commercial corn. A heterogeneous set of undesirable plants can be observed in the fields as a result. A recent genetic study has determined that "Spanish teosinte" "does not group with any of the currently recognized teosinte taxa" (Tritikova *et al.*, 2017). Moreover, at present, there is no herbicide control method that distinguishes between corn and teosinte, making chemical control unfeasible.

Although the first reports of teosinte in Spanish fields come from the region of Aragon in 2014, some farmers have declared that rare, corn-like plants were observed some years before. At the same time, infestations in neighbouring areas of Catalonia have also been reported. Teosinte infestations were also reported further north, in the French region of Poitou-Charentes causing corn yield losses of more than 50% in 2013 (ARVALIS, 2013).[1]

Teosinte has become a major agronomic concern in important corn-producing regions. Corn is the third most important crop in Spain with 4.6 million tonnes annually, accounting for 17% of total Spanish cropland, of which 20% is produced in Aragon (Mapama, 2016). Additionally, since corn mono-cropping is common in many affected

[1] At present, it is not confirmed if the teosinte plants from France are genetically connected with plants from Spain.

areas, teosinte has a high potential for spreading rapidly and could cause severe yield losses and economic costs to farmers.[2]

Devising strategies for optimal control of an invasive weed like Spanish teosinte requires consideration of temporal and spatial dimensions. The temporal aspects of the invader require an understanding of the life cycle of teosinte to identify the most appropriate timing for the control method (Zimdahl, 1988; Recasens et al. 2005). This warrants research efforts to understand the demographic behaviour of teosinte, the teosinte-corn competition for resources, and the effectiveness of alternative control strategies. Research based on experimental trials can be used to estimate the expected economic benefits of weed control in the short- and long-run, after taking into account infestation scenarios in fields and the costs of available control methods (Recasens et al. 2005). With respect to the spatial dimension of teosinte control, it is important to consider the weed's diffusion pattern and how farmer behaviour could affect neighbouring fields, i.e., the identification of positive and negative externalities. This paper focuses solely on the temporal aspects of teosinte control. The spatial dimension is important but must be deferred to future research because different methodological approaches are required.

In addition to affecting individual farms, a regulator dealing with the management of a new invasive weed in field crops faces several wider policy issues, including: i) uncertainty about the biological behaviour of the invader in the new agroecosystem and attendant effects on crop yields; ii) limits on available control methods and/or the regulator's budget constraints; and iii) uncertainty about the economic efficiency of control methods. To overcome these uncertainties, dynamic mathematical models that combine biological and economic aspects of invasive species control is useful to

[2] A research project to study the biology and control strategies was funded by the Spanish National Agriculture Research Institute (INIA) and executed by Aragon and Catalonian Research Centres and Plant Protection Services.

identify promising control strategies and the costs associated with them. One of the advantages of bio-economic modelling is that an economic and biologic equilibrium can be obtained simultaneously. Additionally, it is possible to design economic incentives for farmers to achieve a specific invasive species control target.

A number of studies have demonstrated the usefulness of bio-economic models to study control of invasive weeds in natural ecosystems (e.g., Fechter and Jones 2001; Olson 2006; Cacho et al. 2008; Epanchin-Niell and Hastings 2010). While these studies are abundant, the literature regarding invasive weeds in agricultural settings are relatively scarce (Mackee 2006; Juliá et al. 2007; Grimsrud et al. 2008; Maher et al. 2013). These studies focus primarily on using a variety of methods to identify optimal control levels once the invader is established on farms.

The literature underscores the potential of bioeconomic models to identify optimal control measures when a weed invades a new environment because population growth and spread patterns vary across locations (Schereiber and Lloyd-Smith 2009). Also, there is consensus that invasive species impact assessments should recognize the multidisciplinary nature of the problem and should account for critical interdependence between economic and ecological factors (Perrings et al. 2002). Advances in knowledge of invasive species, optimization techniques and computational tools offer new opportunities for implementing models to help decision-makers identify appropriate strategies to control invasive weeds (Büyüktahtakın et al. 2015, Cacho et al. 2006). In the case of teosinte, which appeared only recently in Europe, the availability of data on its biology and its economic impacts sets the stage for development of bio-economic models to guide optimal control decisions of farmers and regulators.

The aim of this paper is to construct a bio-economic dynamic model in order to identify profit-maximizing strategies and devise policies to manage the teosinte problem in the

Spanish areas of Aragon and Catalonia. In this setting, the dynamic model is used to compare the optimal strategies under two scenarios: 1) when an individual farmer maximizes his/her own private benefits and 2) when a regulating agency maximizes social benefits (i.e., benefits to farmers minus the public costs resulting from the control program to manage teosinte infestations). This comparison sheds light on practical insights to improve the knowledge of teosinte weed and its optimal control.

The literature on invasive species management incorporating estimations of economic damages is relatively abundant since the 1990s in the United States, South Africa, Australia and New Zealand (see Born et al. 2005 and Pimentel et al. 2005 for a review of diverse species). Remarkably, however, with the exception of a few studies addressing the management of invasive species in natural ecosystems in Germany (Reinhardt et al. 2003; Nehring, 2005) and in the UK (Dehnen-Schmutz et al. 2004), research focusing on Europe is scarce. Even more surprising, little work has dealt with the impacts of invasive weeds in agroecosystems. To the best of our knowledge, Recasens et al. (2007) in Spain is the only exception. They estimate the impact of invasive weeds by calculating the sum of the annual losses in expected crop production caused by weeds and the costs of the corresponding herbicide controls.

This paper contributes to this growing literature by focusing on the case of teosinte in Spain, combining new knowledge on the biology of the invader with its impacts on economic costs. Our approach is similar to a study that used a bioeconomic dynamic model to determine the optimal combination of strategies to control an invasive weed in an Australian National Park (Odom et al. 2003). In our case, two different models are defined (private and social) and we incorporate a function to depict public costs.

## 2. Methodology

### 2.1. Study area

Although the date of the initial infestations of teosinte in the region is uncertain, the first reports were received in August 2014 at the Centro de Sanidad y Certificación Vegetal of Aragon (CSCV), which is the regional government's Plant Protection Service agency. The agency is responsible for monitoring and control of plants pests and diseases, and outreach to farmers with technical advice on these issues. From these consultations, the CSCV identified several invaded areas with either low or high infestation scenarios in three specific irrigation districts of the Huesca and Zaragoza provinces covering an area of approximately 400 has. A low infestation scenario is associated to the presence of isolated teosinte plants in the plot, while a high scenario implies the existence of teosinte plant patches or a high incidence of the weed in the affected plot. Table 1 shows the distribution of affected lands and their initial infestation scenarios.

Table 1: Crop area affected by teosinte (ha)

| Location | Low infestation | High infestation |
|---|---|---|
| Monegros district | | |
| *Candasnos* | - | 284 |
| *Bujaraloz* | 27 | - |
| *Peñalba* | - | 12 |
| Ejea district | - | 38 |
| Torralba district | - | 36 |
| **Total area (ha)** | **27** | **358** |

Source: CSCV (2017)

The origin of teosinte infestations and its propagation Aragon region are still unclear, but initial hypotheses point to the use of non-certified seeds and later propagation with harvesters and stubble sheep grazing in affected areas. Based on its initial prospecting data the CSCV published a technical report with control recommendations for farmers (Pardo et al. 2014). In addition, several experimental trials were started in 2014 to investigate the biology of teosinte under the growing conditions found in Aragon. These trials were initiated prior to the INIA-funded research project mentioned above, due to the urgency in providing responses to the teosinte problem. Results from this research were published recently (Cirujeda, 2017; Cirujeda et al. 2017; Pardo et al. 2017; Prado et al. 2017) and are employed in this paper to construct a bioeconomic model to examine farmer response to a teosinte infestation and to evaluate the social costs associated with this invasive weed.

### 2.2. Hypothesis used for the model construction

A particular concern with teosinte is that corn mono-cropping practices are common in the study area and can substantially accelerate its propagation. Growing corn in mono-cropping systems dates to the mid-1990s, when fields started to be irrigated. Lack of experience with other irrigated crops and high corn prices have reduced incentives to use crop rotations in the region. However, CSCV guidelines encourage farmers to rotate corn with other crops. These recommendations are considered in the model explained below.

In this work, the effect of mono-cropping practices over the temporal expansion of teosinte is evaluated under two initial infestation scenarios: low and high infestation scenarios. The modelling approach considers optimal strategies from two different perspectives: 1) an individual farmer maximizing his/her private benefits; and 2) a regulator that maximizes social benefits. The first model considers a farmer’s behaviour when corn mono-cropping is permitted. This model considers individual farmer decisions, assuming that the field average size of 8 ha, and it is solved to identify the control strategy that maximizes profits in the presence of teosinte.

The second model evaluates social impacts of alternative control strategies. A social planner selects the strategy that minimizes aggregate social costs in the infested areas (i.e. private costs of affected farmers plus public costs incurred by the social planner). In this context, the social planner is the institution responsible for the control of teosinte in the infested area (in our case the CSCV). The public costs include research, outreach activities and monitoring of infested areas. The model considers a region of 400 has in Aragon affected by teosinte and selects the best control strategies from the point of view of a social planner.

We compare and contrast optimal control strategies of the farmer and social planner optimization problems to assess the adequacy of regulatory measures introduced by CSCV to control teosinte in 2014. Data on the total area affected and the infestation incidence in monitoring plots from 2014 to 2017 is used in order to validate our results.

**2.3. Bioeconomic dynamic model**

We consider the behaviour of a representative farmer in the focal region to state the private benefit optimization problem. Subsequently, we extend the model to consider the problem of a regulator deciding how to control teosinte to maximize social benefits in the region.

In the presence of a teosinte infestation, the representative farmer problem is stated as the maximization of the total net annual benefit obtained from agricultural production in year $t$ ($B_{i,t}$) (in €) calculated as the difference between the profit margin of crops (in €·ha$^{-1}$) minus the costs (in €·ha$^{-1}$) associated with each weed control strategy $i$. Mathematically:

$$B_{i,t} = \max_{z_{i,t}} \left\lfloor v_{i,t}\left(w_{i,t}\right) - c_{i,t} \right\rfloor \cdot z_{i,t} \qquad [1]$$

where $v_{i,t}(w_{i,t})$ is the profit margin (in €·ha$^{-1}$) obtained from crops production in period $t$ under strategy $i$, which depends on teosinte density ($w_{i,t}$) (in plants·m$^{-2}$), $c_{i,t}$ is the cost of control strategy $i$ (in €·ha$^{-1}$) in period $t$ and $z_{i,t}$ is the farm area (in has) under control strategy $i$ in period $t$. Each strategy $i$ is linked to a specific crop, as explained below. In the private maximization problem, the farmer selects the area allocated to control strategy, $z_{i,t}$,. Equation [1] states that farmers adopt management regimes and control strategies in response to the presence of the weed. Thus, the model focuses only on the key variables directly related to teosinte that affects profit margins.

### *2.3.1. Teosinte control measures*

For simplicity, the only costs considered are those directly related to teosinte control and these depend on the control strategy $i$ ($i$=1,…,7). Therefore, seven control strategies to control for teosinte are available, following research and recommendations of the CSCV of Aragon (Pardo et al., 2014). Such recommendations include a set of preventive and cultural measures to avoid field infestations. Within the possible cultural controls, three primary strategies have been proposed: 1) the false seedbed technique, 2) manual control and 3) rotations without corn. The first two cultural control strategies are only recommended for plots with low infestation scenarios, while rotations are mandatory in highly-infested plots. In addition planting corn is prohibited in highly-infested areas until the elimination of teosinte seeds.[3] The use of crop rotations facilitates weed control because the identification of teosinte in fields is easier and non-selective herbicides of corn might be used, i.e. unspecific herbicides for grass weed control authorised for the corresponding crops (Pardo et al. 2017). The rotation crops recommended by the CSCV employed in the model are 1) barley-sunflower, 2) pea-

[3] The compliance of mandatory strategies in highly-infested plots is enforced and verified by the CSCV.

sunflower, 3) alfalfa and 4) wheat-alfalfa. Consequently, we consider seven control strategies:[4]

1. No control (corn crop),
2. False seedbed technique (corn crop),
3. Manual control (corn crop),
4. Barley-sunflower rotation,
5. Pea-sunflower rotation,
6. Alfalfa,
7. Wheat-alfalfa rotation.

The cost of each controls strategies in period *t* was calculated by Pardo et al. (2016). Specifically, the authors estimate the reduction in the annual net profit margins of such measures with respect to non-infested plots under alternative simulated infestation scenarios. The authors also underscore that under high infestations scenarios, manual control and false seedbed strategies are overly expensive and ineffective. Thus, these strategies are only considered under low infestation scenarios. Table 2 shows the costs associated to each control strategy. These costs were estimated by the CSCV collecting actual data in the infested area. In the case of manual control and false seedbed techniques these costs include management and labour costs as well as the profit margin losses resulting from lower yields because of competition between corn and teosinte. For the rest of strategies (i.e., rotations) no costs are directly related with teosinte control because common tillage and herbicides control it effectively. We note that rotations without corn imply lower profit margins which is captured in the model through the variable $v_{i,t}$ (profit margin per ha) for strategies $i$=4,5,6,7.

Table 2: Control costs related with control strategies.

[4] Preventive strategies (i.e. using certified seed, careful cleaning of equipment and water canals, and avoiding the use of crop residues of infested plots as feed for livestock) are not considered in the model.

| Control strategy | Cost (€/ha) |
|---|---|
| 1. No control | 0 |
| 2. False seedbed technique | 546.7 |
| 3. Manual control | 142.8 |

Source: Pardo et al. (2016)

### *2.3.2. Profit margin function*

The profit margin function represents the farmer benefits from planting each crop, conditional on control strategy *i*. For the case of continuous corn crop with no rotations ($i$=1, 2, 3) the profit margin function is defined as:

$$v_{i,t}(w_{i,t}) = m \cdot y_{i,t}(w_{i,t}) \qquad \text{for } i = 1, 2, 3, \qquad [2]$$

where $v_{i,t}(w_{i,t})$ is the profit margin obtained from corn (in €·ha$^{-1}$), $m$ denotes the per unit profit margin of corn (in €·t$^{-1}$) calculated as the difference between market price and per unit production costs; and $y_{i,t}(w_{i,t})$ is the yield function of crop when teosinte is controlled using strategy $i$ (in t$^{-1}$·ha). Note that yield function depends on weed density ($w_{i,t}$). The per unit profit margin of corn $m$ is from Lonja del Ebro (2011-2015) and Magrama (2011-2015), calculated as the average per unit profit margin of the last five years. The yield function $y_{i,t}(w_{i,t})$ takes into account the competition between teosinte and corn. Following experimental evidence, we assume that yields of other crops different to corn are not affected by teosinte. Thus, the values of variable $v_{i,t}$ (total profit margin) for barley, wheat, alfalfa, pea and sunflower are calculated as the average of the difference between revenues and production costs during cropping seasons 2010-2014 (Magrama, 2011-2015).

For the case of the corn (when $i=1,2,3$), we estimate a corn yield-weed competition function using experimental data in field trials collected during a 3-year period in areas affected by teosinte.[5] The specification of this corn yield-weed competition function is linear and it is estimated using the statistical package R,v-2-14.2 (R Development Core Team, 2014) as:

$$y_i(w_i) = \delta_0 + \delta_1 \cdot w_i \quad \text{for } i=1,\ 2,\ 3, \qquad [3]$$

where $\delta_0$ and $\delta_1$ are the intercept and slope coefficients of the function, with $\delta_0>0$ and $\delta_1<0$, meaning that corn yield decreases as the weed density increases (see Cirujeda 2017 for a complete presentation of the competition function and its validation).

### *2.3.3. Weed dynamics*

Figure 1 shows a schematic diagram of the teosinte annual population dynamics.

Figure 1: Demographic diagram for teosinte.

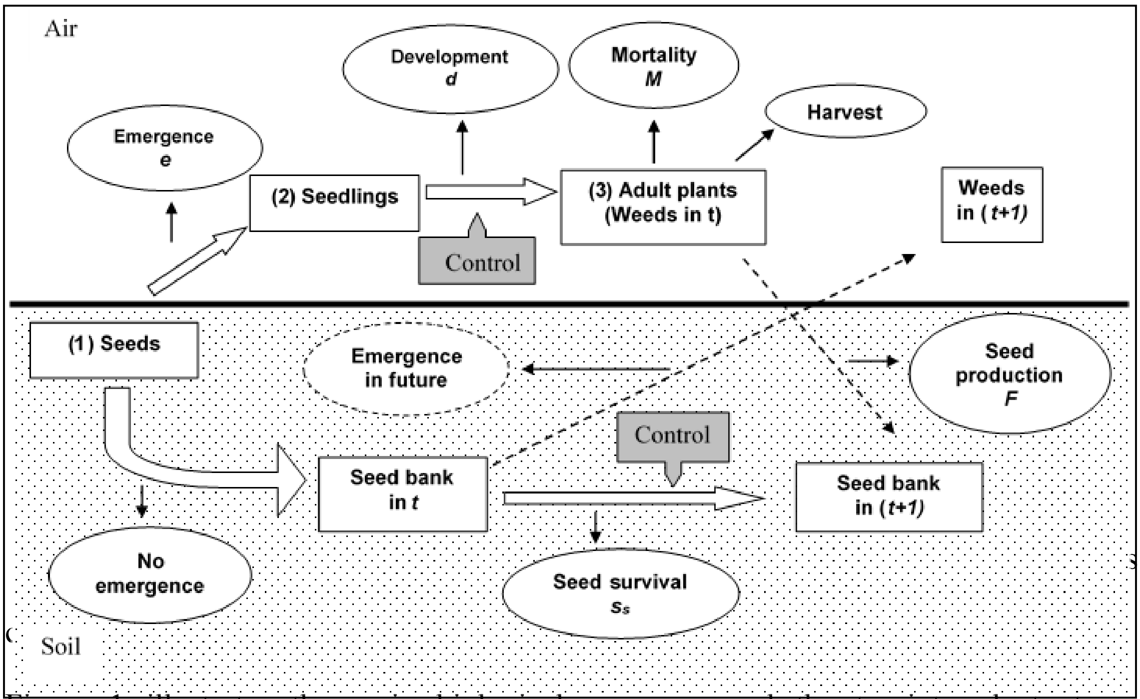



Figure 1 illustrates the main biological processes and the teosinte plant stages considered in our bioeconomic model. We consider three main plant phenological stages in each period *t*: (1) seeds; (2) seedlings; and (3) adult plants. These stages are determined by three corresponding biological growth processes (emergence,

[5] A detailed trial design description can be found in Pardo et al. (2017).

development and seed production) which affect the amount of weed and the size of the seed bank in the following period (*t+1)*.

Figure 1 starts with the amount of teosinte seeds in the soil (stage 1). A percentage *e* of total seeds in the soil become seedlings (stage 2) (see top of figure 1). Thereafter, some of the seedlings develop fully into teosinte adult plants (stage 3). Seedling recruitment and survival is determined by a linear function denoted by $d = d_0 + d_1 \cdot x$, where *d* is the number of adult plants and *x* is the number of seedlings. This function determines the number of adult teosinte plants, which in turn produce *F* new seeds as teosinte starts gradually producing seeds before the corn harvest. Finally, the process includes a mortality percentage rate *M* affecting mature seeds in the adult plants due to fungal diseases and corn borers. The remaining viable seeds increase the size of the seed bank in period *t+1*. At the end of the growing season, all adult plants are harvested as the same time as corn.

In addition to the process described above, seeds that not emerge in stage 1 (*1-e*) become part of the seed bank in period *t* (see bottom of figure 1). A proportion of these seeds survive in the next period, with $s_s$ denoting the survival percentage rate, becoming part of the seed bank in period *t+1*. Thus, the size of the seed bank in period *t+1* decreases due to rotted or predated seeds ($1-s_s$) and increases with the newly generated viable seeds by adult plants *F·(1-M).* In turn, this determines the size of the seed bank and the number of weeds in future periods.

Therefore, the weed density in period *t+1* depends only on the amount of seeds in the soil that emerge in period *t+1*. The amount of seeds in period *t+1*, for its part, is affected by two variables: the size of the seed bank in period *t* (seeds that did not germinate in the previous period and remain viable in the soil); and the weed density in period *t* (plants that have produced new viable seeds in period *t*).

The dynamics of teosinte population growth described in Figure 1 is represented mathematically in equations [4] and [5] below. Two variables are then considered in the model: $w_t$, which affects agricultural output directly; and $s_t$, which affects the weed population potential to increase in future periods. The initial values for these variables are denoted by $w_0$ and $s_0$ respectively. In addition, the mathematical formulation takes into account that control strategy $i$ affect the dynamics of both variables $w_t$ and $s_t$. Mathematically:

$$w_{i,t+1} = f\left(s_{i,t}\right) \quad [4]$$

$$s_{i,t+1} = g\left(w_{i,t}, s_{i,t}\right) \quad [5]$$

where $s_t$ is the size of the teosinte seed bank at time $t$ (seeds·m$^{-2}$). The functions $f(\cdot)$ and $g(\cdot)$ represent the spread of $w_t$ and $s_t$, and they depend on control strategy $i$ selected by the farmer. These functions are estimated from the data collected in field experiments. The function $f(\cdot)$ follows a Mitscherlich-Baule specification. This function allows for plateau growth and convex, but not necessarily, right angle isoquants. The intuition behind this specification is that weed density grows until a maximum value $w^*$ and thereafter the density remains constant due to plant competition for space and nutrients. It imposes a plateau growth which fits well with the observed behaviour of teosinte. This specification yields:

$$f\left(s_{i,t}\right) = w^* \cdot \left[1 - \exp\left(-\alpha_0\left(\alpha_1 + s_{i,t}\right)\right)\right] \quad [6]$$

Equation [6] implies that the increase in teosinte density in period $(t+1)$ due to a one-unit increase in the state variable ($s_t$) is proportional to the difference between that state variable ($s_t$) and the maximum value $w^*$. After reaching a certain high level, the density no longer increases due to high competition among teosinte plants, at which point the weed density reaches its maximum level $w^*$.

Function $g(\cdot)$ represents the evolution of the size of the seed bank:

$$g\left(w_{i,t}, s_{i,t}\right) = \begin{cases} \beta_1 \cdot s_{i,t} + \beta_2 \cdot w_{i,t} & \text{if} \quad s_{i,t} < s^* \\ s^* \quad \text{if} \quad s_{i,t} \geq s^* \end{cases} \qquad [7]$$

The size of seed bank in period (*t+1*) is a linear function of the weed density in period *t* and on the size of the seed bank in the period *t*, provided that the amount of seeds is lower than the maximum number $s^*$ observed in experimental trials.

In other words, the amount of seeds in period (*t+1*) is calculated as the sum of the seeds surviving from period (*t)* and the seeds generated by adult weed plants in period *t* with the upper limit at $s^*$. In this case, the linear relationship among variables affecting the dynamics of the seed bank incorporates the demographic processes observed in experimental trials.

The population dynamics sub-models were validated by comparing predicted to observed population growth rates in field experiments conducted by co-authors. Observed data from 2014 were used as the initial conditions for the model in the validation of the estimated weed and seed growth functions. This asymptotic behaviour of weeds and seeds has also been observed in other invasive weeds. For example, it has been used to study sericea (*Lespedeza cuneata*), a perennial legume threatening native grasslands in the Great Plains of Kansas, United States (Büyüktahtakın et al. 2015). The parameters of the population dynamics, the coefficients values of functions, as well as the sources are presented in Table 3.

Table 3: Biological parameters and coefficients of the functions.

| Parameters | Value | Description | Source |
|---|---|---|---|
| $F$ (plants·m$^{-2}$) | 414 | Seed production | Cirujeda (2017) |
| $e$ (%) | 47.7 | Emergence | Cirujeda (2017) |
| $s_S$ (%) | 7.38 | Seeds survival | Cirujeda (2017) |
| $M$ (%) | 50.0 | Mortality | Cirujeda (2017) |
| $w^*$ (plants·m$^{-2}$) | 22 | Maximum value of weeds | Cirujeda (2017) |

| | | | |
|---|---|---|---|
| $s^*$ (plants·m$^{-2}$) | 31.8 | Maximum value of seeds | Cirujeda (2017) |
| $d_0$ | 0.0704 | Coefficients of seedling survival | Cirujeda (2017) |
| $d_1$ | 0.03933 | function | |
| $\delta_0$ | 11.334 | Coefficients of yield-weed | Pardo et al. (2017) |
| $\delta_1$ | -0.5456 | competition | |
| $\alpha_0$ | 0.0704 | Coefficients of weed spread | Pardo et al. (2017), |
| $\alpha_1$ | 0.1876 | function | Cirujeda et al. (2017) |
| $\beta_1$ | 0.0738 | Coefficients of seed bank | Pardo et al. (2017), |
| $\beta_2$ | 98.97 | evolution function | Cirujeda et al. (2017) |

Figure 1 also illustrates how the control strategies alter the biological expansion of teosinte. Basically, control strategies directly affect the seed survival parameter ($s_s$) and the development function ($d$). Following results from data analysis collected in the field, rotation strategies ($i$=4,5,6,7) can eliminate weed density and reduce seed bank size as already observed in selected commercial plots (Cirujeda et al. 2017).

Table 4 shows the influence of control strategies on the parameters of weed density and seed bank size expressed as multipliers or proportions of the initial parameter values in Table 3. For example, a parameter value 1.0 indicates no effect on initial values, i.e. no-control option. Also, parameter values of 0.1 and 1.0 for manual control in Table 4 indicate that this strategy reduces the probability that a seedling becomes an adult plant to 0.9 of their original values, but there is no expected effect on seed survival. Values of the parameters in Table 4 were estimated based on the logical relationship between the control strategy and the parameter and on the observations taken in field trials, i.e., whether the parameter is expected to increase or decrease with a particular control.

Table 4: Effects of control strategies on parameter values.

| Control method | Multipliers | |
|---|---|---|
| | Weed (*development*) | Seed (*seed survival*) |

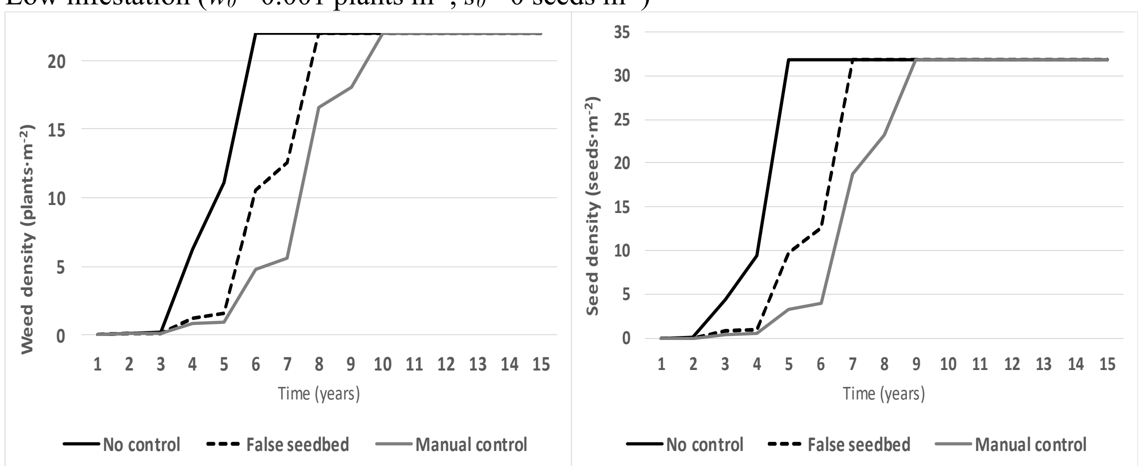
| | | |
|---|---|---|
| 1. No control | 1.00 | 1.00 |
| 2. False seedbed technique | 0.20 | 0.90 |
| 3. Manual control | 0.10 | 1.00 |
| 4. Barley-sunflower | 0.00 | 0.30 |
| 5. Pea-sunflower | 0.00 | 0.30 |
| 6. Alfalfa | 0.05 | 0.50 |
| 7. Wheat-alfalfa | 0.05 | 0.50 |

Source: Pardo et al. (2017), Cirujeda et al. (2017)

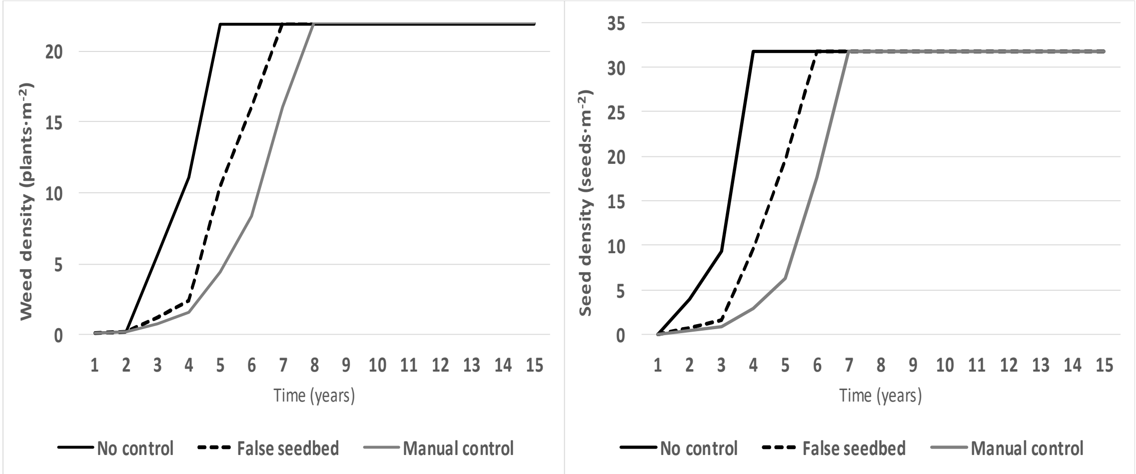
Figure 2 illustrates the effect control strategies with continuous corn crop (controls 1, 2 and 3) on weed and seed density dynamics using the multipliers in Table 4 when a given strategy is used consistently. For the case of fields with low infestation scenarios, the initial values of weed and seed densities are $w_0$=0.001 plants·m$^{-2}$ and $s_0$=0 seeds·m$^{-2}$, respectively; and for the high initial infestation they are $w_0$=0.1 plants·m$^{-2}$, $s_0$=0.074 seeds·m$^{-2}$ respectively. For example, in a scenario with initial low weed density and no-control strategy, teosinte attains the maximum weed density in year six and the maximum seed density value in year five, given that the entire corn crop is lost due to teosinte competition. The false seedbed technique delays the total loss of corn production to year eight, while manual control delays it until year ten.

Figure 2: Evolution of weed and seed dynamics depending on control and infestation scenarios.

Low infestation ($w_0$= 0.001 plants·m$^{-2}$; $s_0$= 0 seeds·m$^{-2}$)



High infestation ($w_0$=0.1 plants·m$^{-2}$; $s_0$= 0.074 seeds·m$^{-2}$)




When the initial teosinte density is high, the evolution is similar to the low density case, but the total loss of the corn crop occurs one period earlier (year five). The dynamics of weeds and seeds under manual control and false seedbed strategies show that they are unable to eradicate the infestation completely because they only delay the total loss of corn production by two or three years. Thus, these strategies recommended by CSCV are supposed to delay the teosinte infestation both in low and high-density situations but need additional control methods to reduce infestations.

When crop rotations combining winter and summer crops are considered (strategies $i$=4 and 5) teosinte is completely eliminated in year two (multipliers in table 4 are 0.0) while the incorporation of alfalfa (strategies $i$=6 and 7) eliminates infestations in year three through the use of herbicides and tillage.

These results suggest that only effective strategies to eradicate teosinte imply rotating corn with other commercial crops. Other cultural control strategies (e.g., false seedbed and manual control) have partial impact on reducing seed bank and limited effect on reducing weed dynamics.

### *2.3.4. Economic model*

The economic model is stated as the maximization of benefits from agricultural production activities, subject to the dynamics of teosinte in the field. In the model, a farmer selects the sequence of control strategies ($i$) in his/her land without considering any other costs different to the cost of the control strategy (e.g. negative externalities and public costs to regulatory services). Using a discrete time framework, the dynamic private benefit maximization model is defined as follows:

$$B_{private} = \underset{z_i, i}{Max} \sum_{i=1}^{7} \sum_{t=1}^{T} \frac{1}{(1+r)^t} \left[ v_{i,t}\left(w_{i,t}\right) - c_i \right] \cdot z_{i,t} \quad [8]$$

subject to:

$$w_{i,t+1} = f\left(w_{i,t}, s_{i,t}\right) \quad [9]$$

$$s_{i,t+1} = g\left(w_{i,t}, s_{i,t}\right) \quad [10]$$

$$\sum_{i=1}^{7} z_{i,t} = \overline{Z} \quad [11]$$

where $r$ is the discount rate (3%); the planning horizon $T$ is 15 years which is considered appropriate to capture the main biological and economic aspects of controlling teosinte and the fact that alfalfa (a key rotation crop) has a lifecycle of five years; $c_i$ is the cost per ha associated with each control strategy $i$, and $z_i$ is the amount of land allocated to control strategy $i$. The objective equation [8] is the net private benefit through the planning horizon expected from each control strategy. Constraints [9] and [10] capture the weed and seed bank density dynamics explained in the previous section, and equation [11] is the total land (in has) constraint. Hence, the main decision variable in the model is $z_{i,t}$, which is the amount of land devoted to each control strategy $i$. The model incorporates two state variables ($w_t$, $s_t$). The objective of the analysis is to choose the sequence of control strategies ($i$) that maximise the present value of net benefits given an initial state of teosinte infestation scenario ($w_0$, $s_0$). This private benefit optimization problem reflects a farmer' behaviour when no mandatory control strategy is imposed by the regulator. Note that the problem described in equations [8]-[11] does not take into account the public costs of regulatory agencies from establishing a program to control the teosinte problem (i.e., carrying out divulgation activities, conductions surveys in affected areas, monitoring and enforcing mandatory strategies). Thus, this maximization problem reflects the initial situation of the region, when teosinte became a problem for farmers and the CSCV did not have a program to control this invasive weed.

The economic model defined in equations [8] to [11] can be extended to represent the problem of a social planner who maximizes the social benefit (SB) by including additional equations. Following current land-use patterns on the study area, the model assumes that a total area of 385 has is affected by teosinte infestations, the affected area in 2014 (CSCV, 2017).

In this setting, we assume that there are two types of perfectly competitive farmers $j$, ($j$= 1, 2). Both types of farmers have identical characteristics (i.e. they can be described by the same profit margin functions $v^j(\cdot)$, the same control costs $c^j$ and the same functions governing weed and seed dynamics). The main difference between these two farmer types are 1) the initial teosinte infestation scenarios in field, 2) the number of farmers $n^j$ that belong to group $j$ and 3) the total area $\overline{Z}^j$ of group $j$. Mathematically, the SB is given by:

$$SB = \underset{z_i^j, i, j}{Max} \sum_{j=1}^{2} \sum_{i=1}^{7} \sum_{t=1}^{T} \frac{1}{(1+r)^t} \left[ v_{i,t}^j \left( w_{i,t}^j \right) - c_i^j \right] \cdot z_{i,t}^j \cdot n^j - D_i \left( z_{i,t}^j \right) \cdot n^j \qquad [12]$$

subject to:

$$w_{i,t+1}^j = f\left(s_{i,t}^j\right) \qquad [13]$$

$$s_{i,t+1}^j = g\left(w_{i,t}^j, s_{i,t}^j\right) \qquad [14]$$

$$\sum_{i=1}^{7} z_{i,t}^{j} = \overline{Z}^{j} \quad [15]$$

$$z_{i,t}^{j} \leq \sum_{k=1}^{5} z_{k,t-1}^{j} \text{ with } k \in i; k \neq i \quad \forall i = 1,....,5 \quad [16]$$

$$\sum_{j=1}^{2} \overline{Z}^{j} \cdot n^{j} = H \quad [17]$$

The SB is defined as the total benefit from production activities in the region minus the sum of the private costs of implementing control strategies and the public costs accruing to the control program to manage teosinte infestations set by the regulating agency. In order to capture these public costs we formulate a linear function $D_i(\cdot)$, which depends on the number of hectares under control strategy $i$ by each type of farmers $j$. The function incorporates the information on actual spending from the CSCV in affected areas (CSCV, 2017).[6] The public costs function is defined as follows:

$$D_i(z_{i,t}^{j}) = b_0^{j} + b_{i,1}^{j} \cdot z_{i,t}^{j} \quad [18]$$

where $b_0^j$ represents a fixed cost (in €) of establishing the control program (divulgation activities, research on plant biology, etc), and $b_{i,1}^j$ is a variable cost which depends on control strategy $i$ (in €·ha$^{-1}$) and is related with the amount of land under control (surveys in infested plots, monitoring farmer' strategy, etc). Equation [18] assumes that the first derivative of function $D_i(\cdot)$ is positive ($D_i'>0$) when control strategies include corn crop (strategies $i=1,2,3$). In the case of rotation strategies ($i=4,5,6,7$), the model assumes that $D_i'<0$. This means that the costs of monitoring the infested areas increase when corn is planted but decrease when rotations are introduced.

[6] The control program includes the monitoring of more than 7,000 ha of crops in the areas where the presence of teosinte was detected.

Equations [13] to [15] and [17] are extended versions of equations [9] to [11] for the case of multiple farmers belonging to the low or high infestation group. Finally, equation [16] is a crop rotation restriction that affects all rotations except for those that include alfalfa. The left side of equation [16] denotes the area allocated to strategy *i* in period *t* ($z_{i,t}^{j}$); and the right side ($\sum_{k=1}^{5} z_{k,t-1}^{j}$) is the sum of areas covered by all crops that use control strategies different than strategy *i* in period *t-1*, which could be followed by strategy *i* in the same area. Including this restriction in the model is necessary for agronomic reasons (i.e., improved soil fertility, pest and disease control) and implies that each crop cannot be planted in the same plot for more than one year in a row. This crop rotation restriction is a mandatory measure introduced by the CSCV in the affected areas with high infestation scenarios but not in areas with low infestation scenarios. The coefficient values of the function as well as the economic parameters of the model (and their sources) are shown in Table 5.

Table 5: Economic parameters of the model

| Parameters | Value | Description | Source |
|---|---|---|---|
| $c_i$ (€·ha$^{-1}$) $i=1,4,5,6,7$ | 0 | Control costs | Pardo et al. (2016) |
| $i=2$ | 547 | | |
| $i=3$ | 142.8 | | |
| $m$ (€·t$^{-1}$) | 152.3 | Per unit profit margin of corn | Lonja del Ebro (2011-2015) and Magrama (2011-2015) |
| $b_0$ | 1600 | Coefficients of public costs function | Pardo et al. (2016) |
| $b_{i,1}$; $i=1,2,3$ | 134.43 | | |
| $i=4,5,6,7$ | -25.80 | | |
| $\overline{Z}^{j}$ (ha) ; $j=1$ | 27 | Area with low infestation | CSCV (2017) |
| $j=2$ | 358 | Area with high infestation | |

| | | | |
|---|---|---|---|
| $H$ (ha) | 385 | Total infested area | CSCV (2017) |

The solution of the social planner problem in equations [12] to [17] allow us to obtain the optimal choice of control strategies in the area taking into account all the private and social costs associated with the dynamics of teosinte. Both private and social problems were programmed with GAMS (General Algebraic Modeling System, Brooke et al., 1998) and solved with the CONOPT2 algorithm.

## 3. Results

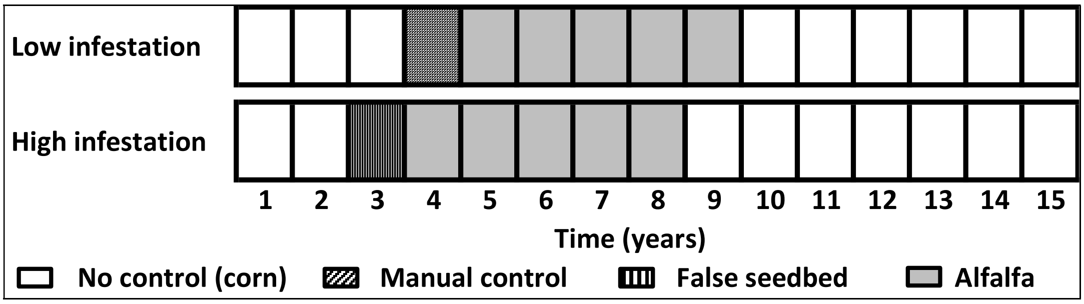
### 3.1. Optimal private farmer decision

The problem defined in equations [8]-[11] is solved to provide the optimal decision rule for farmers with low and high initial infestation scenarios. These optimal decisions are specified in a 'package' of control measures that can be used to tackle the private problem each year depending on the current weed density and seed bank.

Figure 4 shows the optimal control strategies for the private farmer problem. From the economic point of view, farmers with low infestation scenarios (top cells in figure 4) would select a no control strategy during the first three years, and then adopt manual control during year four. Corn is then substituted by alfalfa for five years and then the farmer would return to plant corn mono-cropping in year ten.

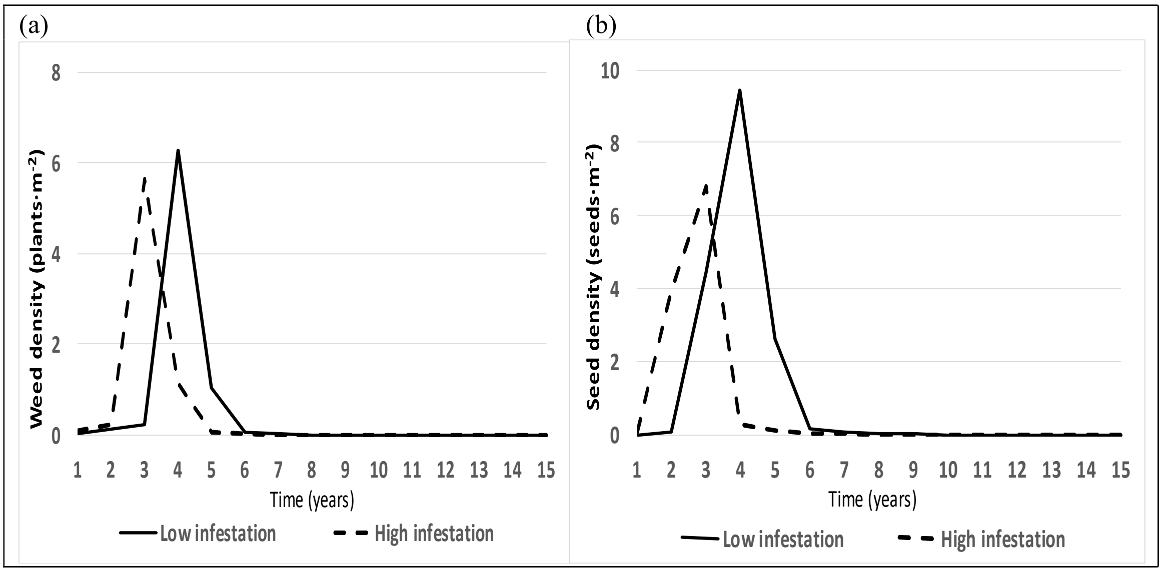
For farmers with highly-infested plots (bottom cells in figure 4), the model suggests that they select a no control strategy during the first two years, adopt a false seedbed technique in the third year followed by alfalfa during its total cropping cycle of five years. Farmers plant continuous corn starting in year nine, because rotations are not mandatory in the model.

Figure 4: Optimal private control strategies under different infestation scenarios.




These decisions maximize benefits and result in optimal transitions for state variables ($w_t$ and $s_t$), i.e. the relationship between the state at period $t$ and the state at $t+1$ when control strategies are employed. Figure 5 illustrates the optimal weed and seed densities path under low and high infestations if the optimal control strategies are followed by an individual farmer. The objective of this figure is to show the effect of control measures obtained in figure 4 (optimal strategies) on the state variables.

Figure 5: Optimal trajectory of the state variables for the private problem for both situations of low and high initial density: weed density (a) and seed density (b).



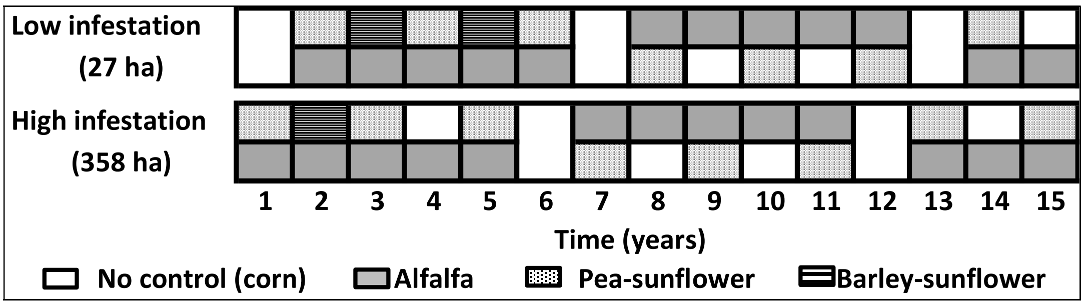

Trajectories for the state variables indicate that farmers with low infestation scenarios tend to adopt rotations later than those owing plots with high initial infestation scenarios. This causes that weed and seed density increase up to period five, when rotation with alfalfa is introduced. At this point, weed density attain up to 6.2 plants·m$^{-2}$

and seed bank density up to 9.4 seeds·m$^{-2}$. In contrast, highly-infested plots adopt the alfalfa rotation one year earlier, which allows the elimination of invasive species already in year eight.

### 3.2. Optimal social control strategies

Figure 6 presents results for the optimal set of control strategies when the social problem is solved. In the case of plots with low infestation scenarios (top of the Figure 6), the model suggests that rotations are adopted in the second year, after the first year of no control. Half of the low infested area (13.5 ha) is allocated to alfalfa in year two which is a crop that will remain for five years in field (i.e., through year six). The other half of low infested area is allocated to pea-sunflower or barley-sunflower (alternating each year) in years 2 to 6. Thereafter, corn can be planted again because teosinte and its seed bank are eradicated. The area allocated to alfalfa from year 2 to 6 (13.5 ha) is planted to pea-sunflower and corn alternating each year, starting in year seven. The remaining area is allocated to alfalfa from years 8 to 12. In contrast, results suggest that fields with high scenarios of infestation should adopt rotations starting in the first year of the period and could return to corn crop in half the area (179 ha) by the fourth year.

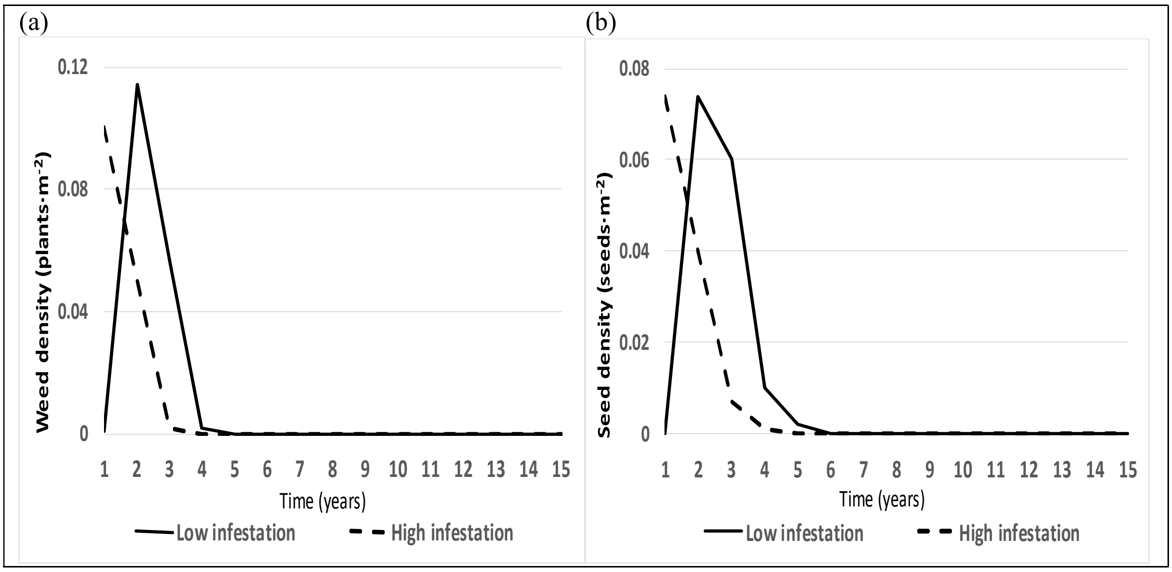
Figure 6: Optimal social control strategies for the total area under different infestation scenarios.




Note: Divided columns indicate that half of the cultivated area is sown with each crop.

Figure 7 illustrates the optimal trajectories of state variables (i.e., weed and seed densities) in the case of adopting the optimal control strategies obtained in Figure 6 from the social problem point of view. In this case, plots with low infestation scenarios attain weed density up to 0.12 plants·m$^{-2}$. Next, half the area is allocated to alfalfa and the other half to rotation annual crops until teosinte is eradicated in year five. Under this set of optimal control strategies, the seed bank would be totally eliminated in year six, when corn crop could be planted again. The evolution of weeds in plots with high infestation decreases until total eradication in year four, after which corn is planted in half the area. The seed bank decreases until its complete elimination in year five. In comparison with Figure 5, both weed and seed bank densities attain much lower values because rotations are adopted earlier when public costs are considered in the model (we note that the scales of vertical axis in Figures 5 and 7 are quite different).

Figure 7: Optimal trajectory of the state variables in the social problem for both situations of low and high initial density: weed density (a) and seed density (b)




### 3.3. Estimation of economic impacts

In Table 6 we present the estimated economic impacts of teosinte in three possible cases: i) doing nothing (i.e., no control strategy); ii) implementing the optimal private control strategies; and iii) implementing the optimal social strategies. Economic losses caused by teosinte are calculated as the average net present value of 15-year period for 1) losses for the total area and 2) per hectare.

Table 6. Estimates of economic impacts in the study area.

| | Total discounted benefit (in $10^3$ €) | | | Average annual benefit per hectare (in €·ha$^{-1}$) | | |
|---|---|---|---|---|---|---|
| | Doing nothing | Private Optimal | Social Optimal | Doing nothing | Private Optimal | Social Optimal |
| (1) Benefits, No-Infestation (baseline) | 7,933 | 7,933 | 7,933 (5,314)[a] | 1,374 | 1,374 | 1,374 (920)[a] |
| (2) Benefits, Low-Infestation Area | 105.3 | 424.3 | 281.3 | 260 | 1,048 | 695 |
| (3) Public costs, Low-infestation Area | 78.4 | 20.9 | 5.2 | 193.6 | 51.6 | 12.9 |
| (4) Total Benefit, Low-Infestation Area* (4)=(2)-(3) | 26.9 | 403.4 | 276.1 | 66.4 | 994.6 | 682.1 |
| (5) Benefits, High-Infestation Area | 943.2 | 5,423 | 3,562 | 175.6 | 1,010 | 663 |
| (6) Public costs, High-infestation Area | 745.8 | 149.2 | 0 | 138.8 | 27.8 | 0 |
| (7) Total Benefit, High-Infestation Area* (7)=(5)-(6) | 197.3 | 5,274 | 3,562 | 36.8 | 982.2 | 663 |
| (8) Losses relative to No-Infestation (8)=(1)-(4)-(7) | 7,709 | 2,256 | 4,095 | 1,271 | 391 | 709 |

[a] Values in brackets in row (1) inform on benefits under no-infestation and mandatory rotations.
*The low-infestation area is 27 has, and the high-infestation area is 358 has.

To do this, we first calculate the benefits obtained from corn production for the private and the social benefit maximization problems under the no-infestation scenario (see row (1) in Table 6). We use these values as the baseline for comparison across control strategies. We note that these baseline scenarios are the same for the private and the social maximization problems, given that farmers are not compelled to rotate crops under a no-infestation scenario. However, we also consider the case of mandatory rotations under no-infestation to estimate the economic impacts of the social problem (see values in parenthesis in row 1 under the 'Social Optimal' column) to understand why farmers do not rotate crops voluntarily.

Second, we calculate private benefits obtained with in the three cases (doing nothing, optimum private and optimal social) under two infestation scenarios (low- and high-infestation scenarios) which account for losses in production as well as costs of implementing control strategies. We calculate the public costs associated to low- and high-infestations and calculate total costs (i.e., private plus public costs) of controlling for teosinte.

According to our model, if a farmer selects a do nothing strategy, then corn production is completely lost by period four and three, for the low- and high-infestation scenarios respectively (Figure 4). This implies that private economic benefits are 105.3 and 943.2 $10^3$ € for low and high infestation scenarios, respectively; and public costs are 78.4 and 745.8 $10^3$ € for low and high infestation scenarios, respectively. Consequently, if nothing is done to control teosinte, economic losses for the 15-year planning horizon can reach up to 249,199 (9,229 €·ha$^{-1}$) in the low-infested area and 3,364,700 € (9,398 €·ha$^{-1}$) in the high-infested area, in comparison to the socially-optimal strategies.[7]

When optimal private control strategies are adopted by farmers, results indicate that the private annual average benefits of low- and high-infested plots is 1,048 and 1,010 €·ha$^{-1}$ per year, respectively. This implies a margin reduction of 23.7% and 26.5% with respect to the non-infestation case (1,374 €·ha$^{-1}$), respectively. When optimal strategies from the social point of view are adopted, these values are substantially lower, reaching 695 and 663 €·ha$^{-1}$ for the low- and high-infestation scenarios respectively. This implies margin reductions of 49% and 52% with respect to the baseline scenario without rotations (1,374 €·ha$^{-1}$) and 24.4% and 27.9% when we consider the no-infestation scenario with

[7] These results are obtained from Table 6 by subtracting values on 'Social Optimal' column minus 'Doing nothing' column in rows (4) for low infestation and (7) for high infestation scenarios, respectively.

rotations (920 €·ha$^{-1}$). These results explain the reluctance of farmers to adopt rotations when public costs are not considered.

The impact of teosinte is quite different when public costs are taken into account. Recall that farmers do not take into account the public costs in their decisions in the private benefit maximization problem. However, under infestation scenarios (high and low) public costs do exist when corn is grown, although farmers do not consider them when making control decisions. In this case, public costs for the total period are 170,096 € (20.9 and 149.2 $10^3$€ corresponding to low- and high-infestation scenarios, respectively), and only 5.2 $10^3$ € for the social problem. Interestingly, if annual average per hectare public costs is considered in the private optimization problem, then we observe that low-infested plots cause higher economic costs than highly-infested plots (51.6 €·ha$^{-1}$ versus 27.8 €·ha$^{-1}$, respectively) because corn is produced during a longer period in plots with initial low-infestation scenarios. Thus, if public costs are taken into account, the average annual per hectare benefit from the optimal private strategies diminishes by 28.5% with respect to the no infestation scenario, while the socially optimal strategies diminish it slightly less, by 27.7%.

The estimates for the case of no infestation allow us to calculate the total economic cost of teosinte in the infested area for the period considered. The total costs if nothing is done to control for teosinte is 7.7 million euros. In the private benefit maximization model, such losses are lower, amounting to 2.25 million euros. In the social benefit maximization problem, the losses are 4.09 million euros when rotations are enforced, which are higher than in the private benefit maximization problem. Nevertheless, if crop rotations are adopted by farmers as a preventive measure, for the social optimal strategies result in the smaller losses (1.4 million euros) due to teosinte.

## 4. Discussion

The definition of private and social benefit maximization problems facilitates a comparison between the strategies currently used by farmers to control teosinte in the focal area and the socially optimal strategy. The analysis of optimal private versus social control strategies indicate that farmers who are not forced to introduce rotations will maintain continuous corn until year six under low infestation scenario, and until year four under high infestation scenario (see Figure 4). This behaviour was in fact observed in many monitored plots of the study area during the initial stages of teosinte detection in the study area: farmers with low-infested plots did not control for teosinte, nor used cultural controls (manual or false seedbed control) because of high corn market prices and lack of knowledge regarding the potential competition of teosinte with corn. Afterwards, most farmers introduced rotations because the invasion was becoming out of control and they realized that other cultural control methods were too costly and ineffective for eradication.

Socially optimal control strategies require that corn is planted only in the first year with low-infestation scenarios; and rotations are used afterwards to avoid teosinte propagation and public costs caused to society (Figure 6). The mandatory inclusion of rotations implies that farmers in the affected area would diversify crops with half the land allocated to alfalfa and the other half allocated to rotations with winter and summer crops. In addition, this proposed behavior reduces the public costs for low-infested plots and would eliminate them for highly-infested ones.

Since rotations are the only way to completely eradicate teosinte plants and seeds in fields, our results indicate that rotations should be adopted in the first 5 or 4 years in the case of low- and high-infestation scenarios, respectively. Thereafter, corn can be cultivated again under the assumption that teosinte has been totally eradicated. Although teosinte can be eliminated with the use of herbicides, given the botanical similarity between corn and teosinte, there is no herbicide for teosinte that does not affect corn. Thus, the only way to avoid re-appearance of the invader is to use crop rotations, as far as teosinte seeds remain in the soil. These results suggest that the introduction of rotations could have prevented the teosinte propagation and the associated economic costs, as has been often claimed by scientists for other plant and pest diseases (Altieri and Liebman, 1988).

The examination of optimal trajectories obtained for weed and seed bank as a result of the optimal private strategies application (Figure 5) shows that the total elimination of teosinte infestation in low-infested plots is attained in a later period in comparison to high-infested plots. The reason is that rotation strategies are adopted later in low-infestation plots because farmers expect higher benefits from adopting no-control strategies in the short-run and underestimate the potential of this weed to compete with corn in subsequent years. As a consequence, low-infested plots become highly-infested plots after three years of no teosinte control, and farmers have to adopt rotation strategies thereafter to minimize teosinte negative impacts. The optimal trajectories of state variables (Figure 5) also confirm that other cultural control strategies (i.e., false seedbed and manual control) do not eradicate teosinte infestations. In addition, data from experimental trials reveal that the survival of teosinte seeds is drastically reduced by crop rotations. Thus, data used in this paper regarding the survival capacity contrast with the hypothesis of long survival rate stated in Tritikova et al. (2017) and Pardo et al. (2016).

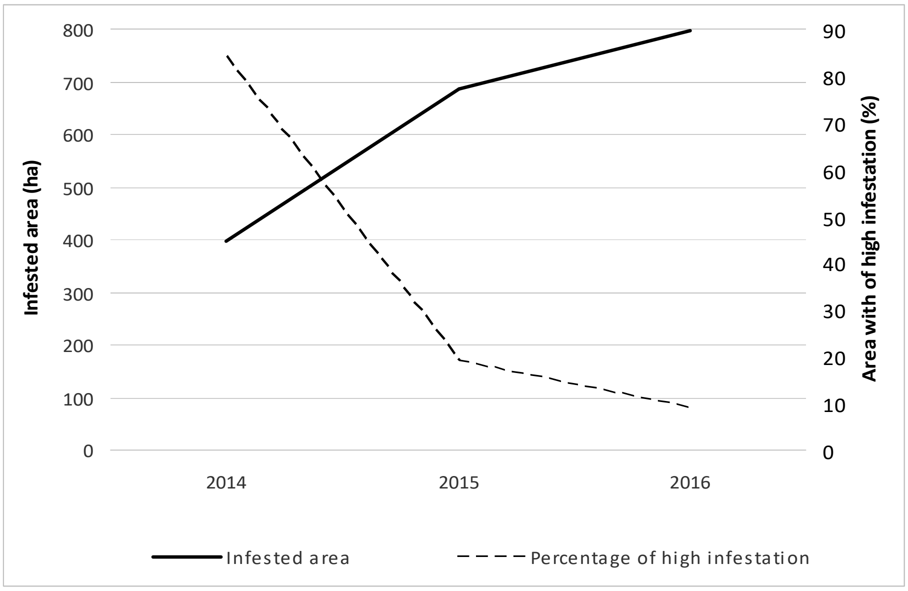
When social strategies are adopted, the teosinte eradication is attained in year five because rotations are adopted earlier and reduce the public costs for the 15-year production plan horizon (Figure 6). The comparison of private and social trajectories suggest that control strategies based in false seedbed and manual means are not optimal from the social point of view since eradication of teosinte is achieved only with crop rotations. Hence, this result indicates that the regulatory authority must reconsider these measures not only in high-infested plots but also in the case of low-infested plots.

With respect to the economic impacts of the optimal strategies, results suggest that private strategies are not optimal from a social perspective and impose a total public cost of 170,096 €. The reason is that in the private optimization problem, corn is produced in infested plots during the first three or two years, given that public costs are not considered by the farmers. In contrast, when socially optimal strategies are adopted, public costs are reduced dramatically because control strategies planting corn in the presence of an infestation are only selected in the first year, and monitoring costs are not incurred when rotations are introduced.

The economic estimates of average losses show that the socially-optimal strategies reduce private benefits by 33%. Therefore, farmers have no incentive to adopt them voluntarily in the short-run because public costs are not taken into account in their private decisions. These results highlight the importance of considering the public costs in the social problem and underscore the importance of mandatory rotations to avoid public costs of teosinte control.

Regarding the temporal and spatial evolution of teosinte in the region, Figure 8 summarizes the available data obtained by the CSCV on the monitored area and the infestation scenarios from 2014 to 2016. The figure indicates that although the total infested area has increased since 2014, the number of plots with high infestation scenarios has decreased rapidly from 93% (358 ha) to 9% (72 ha) of the total area due to mandatory rotations. According to the data (consistent with CSCV technicians' assessment), the new infected areas located in 2015 and 2016 were plots with previous infestations but not yet identified in 2014. The observed temporal evolution confirms that rotations have been effective in reducing the infestation incidence in the affected plots.

Figure 8: Data on the real evolution of infested areas.




Source: CSCV (2017)

Of course, the results depend heavily on the ability of the models to represent reality and on the values of the parameters used to calibrate them. The economic model incorporates actual data obtained by the CSCV on invested areas, farmer behavior, actual evolution of the invasive species in the affected regions, and actual costs of monitoring. This feature of the model provides face validity to the economic impact estimates in the focal region of this investigation.

If certain economic parameters change (e.g., the crop prices), the economic value of the control strategies would also change because some of the crops may become more economically attractive with respect to others. For example, higher (lower) prices for alfalfa could make this strategy more (less) desirable compared to corn and this could affect the period when corn would be substituted by this rotation in the benefit maximization problem. However, the average prices of the last five years have been used in our calculations to partially avoid the impact of price effects on the validity of the results. Hence, although the estimates of losses associated to the optimal strategy path would change, the critical conclusions on private versus social decisions would remain valid. Changes in parameters would affect all farmers in the same way but the biological process of teosinte is not affected.

Finally, regarding the teosinte population dynamics, results are validated using data obtained in experimental trials from 2014 to 2017. These data confirm that rotations are the most effective measure to eradicate Spanish teosinte and its seed banks.

## 5. Conclusions

The bio-economic model developed here integrates a dynamic model of teosinte's population growth and an economic model selecting control strategies to optimise private and social benefits. The teosinte biology is characterized by its formidable ability to compete with corn and its fast propagation rates. In contrast, the survival capacity of the seed bank has proved to be limited (Cirujeda, 2017). The dynamic model developed here takes into account these characteristics by introducing two state variables. The specification of both private and social optimization problems allows a comparison of teosinte impacts between the farmer optimal decisions and the adoption of socially-optimal control strategies. In addition, considering two infestation scenarios (low and high) allows modeling the effect of control strategies in a more realistic way and estimating the public costs of the regulatory authority.

A key result of our analysis is that controls based in false seedbed and manual control are not optimal strategies to eradicate teosinte because they extending the problem in the future. Therefore, the regulatory authority must reconsider recommending these control strategies in low-infested plots. Our results indicate that, if the proposed social optimal strategies are introduced in all infested plots, the invasion will be totally eradicated after six cropping periods and public costs would disappear completely thereafter. Of course, this estimate depends on farmers' compliance with the technical advice of the regulatory authority in terms of control and prevention strategies.

Our results also shed light on approaches to completely eradicate teosinte. First, it is crucial that incipient infestations are monitored due to the fast propagation capacity of the weed. In addition, the use corn mono-cropping has contributed to the rapid expansion of initial infestations in the area. Both aspects reveal the importance of farmer involvement in adopting control strategies, and to train them on the economic and agronomic negative effects of not following the recommendations of the regulatory authority.

Although possible externalities associated with the spatial diffusion of teosinte has not been analyzed in this paper, field observations indicate that preventive actions play an important role in the spatial dispersion of this invasive weed. That is, the control strategies adopted by a farmer may influence teosinte infestation in neighbouring farms and vice versa. To account for such externalities, future research should incorporate the spatial dimension of teosinte invasions into the model to evaluate the influence of preventive actions on the optimal control strategies. Future research can also incorporate other externalities in teosinte control. For example, what the benefits of cleaning harvesters after using them are (in terms of reduced weed spread), considering that farmers in the same district share the same harvester.

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