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Mitigating Farmland Biodiversity Loss

A Bio-Economic Model of Land Consolidation and Pesticide Use

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Abstract

Biodiversity loss driven by agricultural intensification is a pressing global issue, with significant implications for ecosystem stability and human well-being. We design an integrated bio-economic agent-based model, informed by historical data from the French agricultural sector, to project future biodiversity trends and evaluate policy interventions. Our model predicts further biodiversity decline under a business-as-usual scenario, primarily due to intensified land consolidation. We evaluate two policy options: reducing pesticide use and subsidizing small farmers. While pesticide reduction rapidly benefits biodiversity in the beginning, it eventually leads to increased land consolidation and further biodiversity loss. In contrast, subsidizing small farmers by reallocating a small fraction of existing subsidies, stabilizes farm sizes and enhances biodiversity in the long run. The most effective strategy results from combining both policies, leveraging pesticide reduction alongside targeted subsidies to balance economic pressures and consistently improve biodiversity.

1 Introduction

In recent decades, Europe has witnessed a dramatic reduction in biodiversity [1], with significant declines in both the overall biomass [2] and the number of different species [3]. Likewise, the number of species at risk of extinction has risen [4]. The decline is particularly severe in farmlands, where bird populations have shrunk [5], the number of pollinators has dwindled [6], and invasive species are increasingly infiltrating agro-ecosystems [7]. Modern agriculture is widely recognized as the primary driver of this trend [8, 9].

Agriculture covers nearly a third of Europe's land area (and about half of France), making it the predominant land use. Rising food demand has driven agricultural intensification [10], which relies heavily on chemical inputs like fertilizers and pesticides. These chemicals disrupt ecological balances, harming biodiversity and leading to population declines [11, 12, 13]. Additionally, international competition has prompted significant land consolidation [14, 15], merging smaller farms into larger, uniform fields to boost efficiency. While this transformation benefits large-scale farming, it adversely affects biodiversity by removing diverse habitats such as hedgerows, ditches, and grass strips with wild vegetation, which are crucial for supporting various species [16].

Biodiversity plays a crucial role in the functioning of our ecosystem [17, 18], underpinning essential services for societal well-being such as water provision and air purification. Extensive research has thus been conducted by ecologists and economists to try to halt the ongoing environmental degradation. This being said, effectively addressing agro-environmental sustainability requires a holistic approach that integrates both ecological and economic perspectives [19]. In other words, interdisciplinary research (in terms of both concepts and methods) is key if we are to comprehensively grasp the complex interplay between farmland ecosystems and their economic counterparts [20]. To that end, various models have been proposed, which can be broadly categorized into (i) static and (ii) dynamic approaches.

Static models primarily aim to quantify the monetary value of ecological services like pollination, pest control, and soil fertility [21, 22]. In the vein of cost-benefit analyses [23], these models typically assess the trade-offs between agricultural practices and the ecological impact associated with different land-use decisions. However, by their very nature, static models are bound to overlook crucial dynamics of agro-ecological systems, which exist in a continually changing, non-stationary environment [24]. For

example, one should account for resource scarcity [25]; vital elements like water and nutrients become less abundant and more valuable over time [26]. Additionally, one should also consider ecological tipping points [27], where gradual changes can suddenly trigger dramatic shifts in the ecosystems. The limitations of static models can lead to oversimplified views and inaccurate predictions, hindering the development of optimal policies [28]. Dynamic models, in contrast, aim to capture the temporal and spatial evolution of the systems at hand across their various components. Although extensive models exist separately for (i) agricultural practices [29] and (ii) ecological landscape evolution [30], there are few examples in the literature that integrate both aspects in a balanced manner [31].

Having settled on dynamics models, the usual debate then arises between standard economic models, which rely on representative profit-optimizing agents, and agent-based models (ABMs) that are more behaviorally oriented. The former are primarily aimed at evaluating worldwide trade policies [32] to determine the optimal allocation of agriculture for enhancing biodiversity, as well as national-level land-use policies [33]. Considering agricultural production at the aggregate level, these models use the concept of “representative farms” to capture the behavior and characteristics of a group of farms. As an example, Mouysset *et al.* [33] developed a bio-economic model to study sustainable biodiversity management, combining the community dynamics of 34 bird species with a representative farmer who makes decisions about land use over time. Such models face criticism for relying on a single representative agent, whereas the real agricultural landscape consists of a diverse mosaic of agents shaped by their interactions and behavioral biases [34, 35, 36]. In that regard, agent-based models (ABMs) emerge as more promising candidates [37]. By representing farmers as interacting autonomous agents, each with specific goals, resources, and constraints, ABMs may effectively capture the diversity of agricultural practices and their impact on land use and biodiversity [38]. This capability makes ABMs particularly valuable for evaluating policies in agro-ecological systems, where understanding the variability in farmers’ responses to policy measures is crucial for assessing their effectiveness [39]. That said, ABMs also present challenges due to their detailed granular nature, which often restricts their spatial and temporal resolution. This can complicate their application to large scales or long time periods. Moreover, calibrating this kind of ABMs is consistently arduous because it demands comprehensive data that are often scarce [40].

In this paper, we propose a minimal bio-economic agent-based model designed to capture both macroscopic trends and individual farmer behavior. In Section 2, we detail the model’s structure and the rationale behind its design. Using French data, we set the parameters and initial values by fine-tuning the model to replicate historical patterns in biodiversity loss, pesticide reduction, and farm size increases over the past 30 years. In Section 3, we present the model’s predictions under a “business as usual” scenario, demonstrating that further declines in biodiversity occur due to continued farmland consolidation. Finally, we evaluate different policy options and show that the most effective approach for achieving both environmental and economic sustainability involves a combination of tighter pesticide regulations and support programs for small farms. In Section 4, we conclude.

2 A bio-economic agent-based model

Here we introduce the ecological and economic features of the model. We present the data that supports it, and explain how such data is used to set model parameters and initialise variables.

2.1. Ecological description

Measuring and characterizing biodiversity is a topic of ongoing discussion [41]. Bird population trends are often reliable indicators of environmental health [42]. Indeed, as birds occupy high trophic levels in food chains, they are good candidates to reflect systemic changes [5]. Consequently, we will use farmland bird populations as a proxy for overall biodiversity. Denoting $\varepsilon_t = M_t/M_0$ the rescaled bird population, and in line with existing literature [33, 43], we describe the dynamics of ε_t with a logistic equation:

$$\dot{\varepsilon}_t = r_\varepsilon \left(1 - \frac{\varepsilon_t}{K_t} \right) \varepsilon_t, \quad (1)$$

where r_ε is the intrinsic growth rate of the bird population, and K_t is a measure of the carrying capacity [44]. To understand bird population dynamics in agricultural landscapes, it is crucial to take into account both (i) the impact of harmful agricultural practices (in particular pesticide use) [13] and (ii) the effects of structural changes due to varying farm sizes [16]. While the effect of (i) is quite intuitive [12], (ii) deserves further explanations: large-scale farms often lead to the reduction of field margins. These margins,

encompassing features like hedgerows, ditches, and grass strips, are vital refuges for a diverse range of plant and animal life. Their loss due to land consolidation simplifies ecosystems and poses a significant threat to biodiversity [45]. To account for these effects in the simplest effective manner, we assume they both act against the carrying capacity as:

$$K_t = \mu \frac{\bar{L}_0}{\bar{L}_t} + (1 - \mu) \frac{\bar{P}_0}{\bar{P}_t}, \quad (2)$$

where \bar{L}_t and \bar{P}_t respectively denote the average farm size and pesticide use per hectare¹ at time t , and μ reflect their relative importance.

Equations (1) and (2) explain how economic factors like pesticide use and farm sizes influence ecological dynamics. Conversely, the environment itself also impacts agricultural production, notably through pest exposure for which biodiversity plays a critical role [47]. Indeed, with greater biodiversity comes a lower risk of major pest outbreaks and the potential for higher crop yields (see Eq. 5 below). Denoting by π_t the pesticide-free typical yield loss due to pests, we write:

$$\pi_t = \pi_0 \left(\frac{\varepsilon_0}{\varepsilon_t} \right)^a, \quad (3)$$

where the exponent $a < 1$ reflects empirical evidence of non-linearities in the relationship between pest exposure and bird population [48] (see Section 2.3).

Let us stress that our description of biodiversity is not spatially explicit. Although this important simplification inevitably misses potential geographical variations, it can be somewhat justified by the fact that birds, due to their larger range areas compared to many other taxa, are less sensitive to regional differences [49].

2.2. Economic description

Consider a dynamic population N_t of farmers² producing a standardized good, the agronomic and economic characteristics of which are based on wheat due to its significant contribution to land use in France ($\approx 16\%$) [46]. Focusing on two critical production factors – utilized agricultural land and pesticide use – we assume that farmers adjust their pesticide usage to achieve a specific yield target, taking ecological conditions into account. Profitability results from a combination of internal factors (pesticide efficiency, farm size) and external influences (market conditions, policies, and pest pressure). When profitable, farmers can invest in improving their efficiency, potentially reducing pesticide use, and adjust their land holdings by renewing, terminating, or signing new rental contracts on an annual basis. Note that land in the model is rented, in line with the fact that 80% of utilized agricultural land in France is indeed rented [50].

Timeline

The dynamics proceed as follows (see also Fig. 1). At each time step (here assumed to be one year), farmers

- produce their agricultural goods based on planned pesticide use, available land and ecological conditions,
- sell their goods in the market, realizing profits or losses,
- invest some of the profit (when positive) to improve pesticide use efficiency,
- engage in the land market to renew, terminate, or sign new rental contracts based on economic performance,
- and plan the next period’s pesticide use based on updated economic and environmental conditions.

In the following we detail each one of these sub-steps.

¹Note that \bar{P}_t is computed as a weighted average over farm sizes, in line with the usual reporting methods [46].

²In the following we shall refer to “farms” and “farmers” indifferently.

Production of goods

The total production $Y_{i,t}$ of farmer i at time t is computed by multiplying his land area $L_{i,t}$ by his yield per hectare $y_{i,t}$:

$$Y_{i,t} = L_{i,t}y_{i,t}. \quad (4)$$

The latter is assumed to be given by a Mitcherliche-Baul production function [51]:

$$y_{i,t} = y_{\max} \left[1 - \pi_t \exp \left(-\frac{e_{i,t}P_{i,t}}{P_{\text{ref}}} \right) \right] (1 + \xi_{i,t}), \quad (5)$$

where y_{\max} denotes the maximum attainable yield, according to agronomic choices not explicitly detailed here. $P_{i,t}$ denotes the pesticide application rate aimed at protecting the yield from pest damage π_t (see Eq. 3), while $e_{i,t}$ reflects the efficiency of pesticide use, with P_{ref} serving as a normalizing reference level. The efficiency $e_{i,t}$ encompasses variability in modern technology use (see below). Finally, $\xi_{i,t}$ is a white Gaussian noise accounting for further inter and intra-farmer variability.

Goods market

After harvest, farmers sell their grain at a central market where the price fluctuates according to supply and demand. The total grain supply $Y_t = \sum_i Y_{i,t}$ is the sum of the quantities produced by each individual farmer.³ Demand D , on the other hand, is an external factor assumed constant in the model, consistent with the only weak fluctuations observed (over the past 30 years) and forecasted in Europe [52]. In its simplest form we write

$$p_{m,t} = p_{m,t-1} \left(1 + \alpha \frac{D - Y_t}{D} \right) \quad (6)$$

for the price adjustment mechanism, where α reflects market frictions determining the speed at which the price adjusts to imbalances between supply and demand. Farmers' individual profit $\mathcal{P}_{i,t}$ is then given by

$$\mathcal{P}_{i,t} = p_{m,t}Y_{i,t} - \mathcal{C}_{i,t} + \frac{L_{i,t}}{L_t}\mathcal{S}, \quad (7)$$

where production costs $\mathcal{C}_{i,t}$ write

$$\mathcal{C}_{i,t} = L_{i,t}(p_{p,t}P_{i,t} + \mathcal{C}_o) - (L_{i,t})^b\mathcal{C}_{\text{no}}, \quad (8)$$

and where \mathcal{C}_o and \mathcal{C}_{no} are operational and non-operational expenses respectively. Operational costs encompass all expenses directly tied to producing grain per hectare, like fertilizer, seeds and fuel expenses (excluding pesticide costs). We assume these costs to be equal for all farmers. Pesticide application costs are factored in separately with $p_{p,t}P_{i,t}$, where $p_{p,t}$ denotes the price of pesticide. Non-operational costs include fixed expenses such as land rental fees, depreciation, and wages. These costs generally scale sub-linearly with the amount of land ($b < 1$), reflecting economies of scale. Larger farms have lower average costs per unit because they can spread fixed costs over more units, benefit from bulk purchasing, and achieve other efficiencies [53, 54]. Finally, the model incorporates direct payment of subsidies \mathcal{S} proportional to the amount of land utilized by each farmer, in line with the Common Agricultural Policy (CAP) over the past three decades [55].

Technology adoption

Farmers strategically allocate a fraction η of their profits to adopt advanced technologies that improve pesticide application efficiency. Examples of these technologies include drones for real-time monitoring of crop health, and predictive models from decision support systems to enhance pest control strategies [56]. In line with the Evolutionary ABMs literature [57], we assume that the success of these investments follows a Bernoulli trial, indicating that each adoption attempt has a random chance of success. The probability of success $\mathbb{P}_{i,t}^e$ depends on the amount invested and the effectiveness in translating investment into successful innovations program (P_{ref}) as

$$\mathbb{P}_{i,t}^e = 1 - \exp \left(-\frac{\eta\mathcal{P}_{i,t}}{P_{\text{ref}}} \right). \quad (9)$$

³We shall henceforth systematically use the notation $A_t = \sum_i A_{i,t}$.

shows that pesticide adoption is largely influenced by behavioral factors [59]. Pesticide use evolves according to the following behavioral rule:

$$P_{i,t+1} = P_{i,t} \left(1 + \gamma \frac{\tilde{y}_{i,t} - y_{i,t}}{y_{i,t}} \right), \quad (15)$$

where γ is the speed of adjustment and $\tilde{y}_{i,t}$ is the yield target (see below). We find this approach more realistic than pure rational optimisation as it accounts for the absence of complete information regarding both the level of pest exposure and the efficiency of the technology used. Here, the yield target $\tilde{y}_{i,t}$ evolves according to market price fluctuations:

$$\tilde{y}_{i,t+1} = \tilde{y}_{i,t} \left(1 + \lambda \frac{p_{m,t} - p_{m,t-1}}{p_{m,t}} \right). \quad (16)$$

This equation reflects the willingness of farmers to decrease or increase their production target according to market price: when the market price has been decreasing (resp. increasing), farmers might lower (resp. increase) their yield target to reduce pesticide related costs.

2.3. Real data and numerical simulations

Henceforth, we apply the model to French agricultural production and biodiversity. Indeed, France’s extensive agricultural history and its position as the leading agricultural producer in the EU [46] make it an ideal case study.

Data sourcing

The data for calibrating and initializing the model are sourced from various databases. To characterize biodiversity, we use the common farmland bird index, which monitors the abundance of 34 farmland bird species across Europe [60]. Data on the agricultural sector’s structure are derived from the Food and Agriculture Organization (FAO)’s “Structural Data from Agricultural Censuses” [61]. This dataset is compiled through decennial monitoring of UN countries’ agricultural censuses and includes detailed information on the size and number of agricultural holdings. Due to the lack of individual farmer data, agronomic information related to wheat production is sourced from the European Farm Accountancy Data Network (FADN) [46]. This provides average values for wheat yield and pesticide use. Finally, the wheat producer price index is used to track annual changes in selling prices for farmers. This index is constructed using price data in standardized local currency [62] (from FAO) on an annual basis.

Calibration

Model parameters are categorized into three groups (see Table 1): (i) those directly inferred from data and literature, henceforth called *measured* parameters (**M**), (ii) those set by hand to ensure consistent dynamics, namely *estimated* parameters (**E**), and (iii) those obtained through calibration to reproduce trends during the 1990-2021 period, or *calibrated* parameters (**C**) (see Fig. 2). The main trends within the agricultural landscape are biodiversity degradation (Fig. 2a), decline in average pesticide use due to technological innovation depicted (Fig. 2b), and land consolidation (Figs. 2e-g).

Although derived from existing data, the values of the parameters in the **M** category are influenced by model assumptions and simplifications. For example, some quantities—such as non-operating costs, operating costs, and pesticide prices—fluctuate over time, but are assumed constant and equal to representative values over the 1990-2021 period.

Parameters in the **E** category are set to reasonable values that ensure consistency between the data and the model’s functional forms. For example, the ecological parameter μ in Eq. 2 is set to reproduce the biodiversity curve using Eq. 1 with historical values of average pesticide use and farm size.⁴ Similarly, the value of a (Eq. 3) was derived using biodiversity interpolated values, assuming a pest exposure value of 0.3 in 1990 and 0.4 in 2021 [63]. On the economic side, P_{ref} is computed by inverting Eq. 5 using average values from 1990 data and $\bar{e}_0 = 1$, while r_{ref} and D are based on the equilibrium hypothesis (see *Initialization* below).

Parameters in the **C** category are primarily related to technology adoption and behavioral aspects of the model. Realistic values for these parameters are not directly available due to the high-level description of

⁴Given the noisy nature of the data, we use a rolling average as a more stable proxy of these trends.

Section	Notation	Description	Value	Group	Source
Initialization	N_0	Number of farms	1006120	M	[61]
	\bar{P}_0	Average pesticide use [$\text{kg} \cdot \text{ha}^{-1} \text{year}^{-1}$]	5	M	[46]
	\bar{y}_0	Average yield [$\text{ton} \cdot \text{ha}^{-1} \text{year}^{-1}$]	7	M	[46]
	π_0	Potential pest damage [year^{-1}]	0.3	M	[63]
	r_0	Average return on investment [year^{-1}]	0.05	M	[46]
	D	Demand [$\text{ton} \cdot \text{year}^{-1}$]	21e7	E	
Ecological factors	r_ϵ	Intrinsic growth rate [year^{-1}]	0.1	M	[43]
	μ	Carrying capacity weights	0.9	E	
	a	Pest-biodiversity nonlinearity	0.5	E	
Production factors	y_{\max}	Maximum yield [$\text{ton} \cdot \text{ha}^{-1} \text{year}^{-1}$]	8.5	M	[64]
	P_{ref}	Reference pesticide [$\text{kg} \cdot \text{ha}^{-1} \text{year}^{-1}$]	10	E	
	$\text{std}(\xi)$	Production noise	0.05	M	[65]
Other economic factors	α	Price frictions	0.05	C	
	p_p	Pesticide price [€]	10	M	[66]
	C_O	Operating costs [€ · year ⁻¹]	500	M	[67]
	C_{NO}	Non-operating costs [€ · year ⁻¹]	600	M	[67]
	b	Economy of scale	0.9	M	[53]
	S	Total subsidies budget [€ · year ⁻¹]	8e9	M	[68]
Technology adoption	η	Profit share for technology	0.2	C	
	P_{ref}	Reference profit for technology [€ · year ⁻¹]	1500	C	
	v_{\max}	Maximum efficiency gain [year^{-1}]	0.2	C	
Behavioural factors	β	Land adjustment speed [year^{-1}]	0.5	C	
	r_{ref}	Reference return on investment [year^{-1}]	0.05	E	
	γ	Pesticide adjustment speed	1	C	
	λ	Yield target adjustment speed	0.1	C	

Table 1 – Parameters of the model. We indicate their units, value, estimation method, and source (see Section 2.3).

the model, and they cannot be estimated as they depend intrinsically on the model’s dynamic realization. Therefore, we opted for calibrating these parameters to ensure the model replicates well the major trends observed in the reference data from 1990 to 2021. Figure 2 illustrates the calibration results. To verify the stability of this calibration, we performed a sensitivity analysis (see Fig. 5 in the Appendix), demonstrating that our results are robust to reasonable variations in the calibrated parameter values.

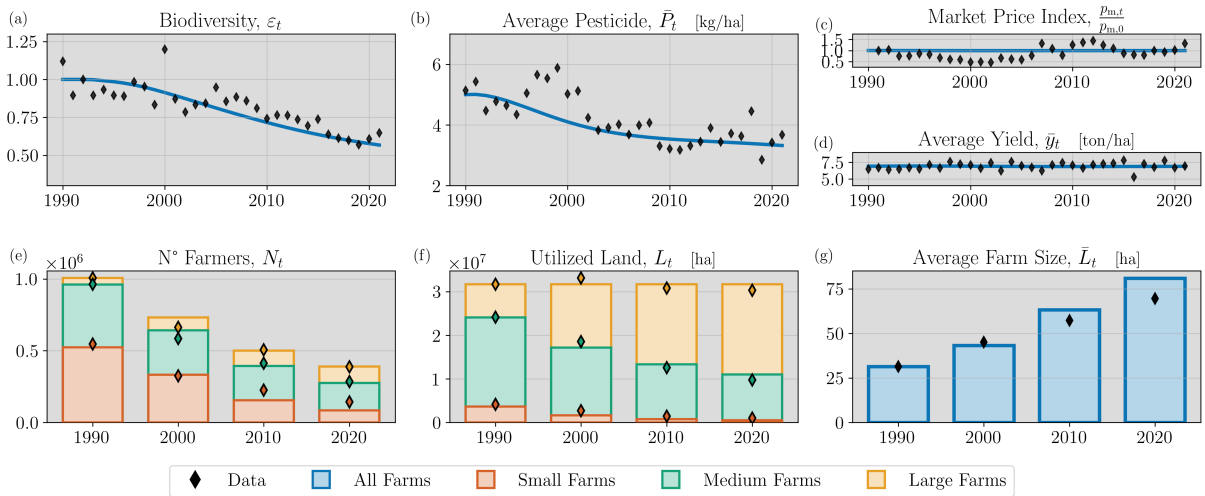


Figure 2 – Calibration of the model: diamonds represent real data, while blue lines and colored bars display the calibration results. (a) Biodiversity degradation (EU common farmland bird index [60]). (b) Decline in average pesticide use (FADN [46]). (c) Market price index (FAO [62]). (d) Average yield (FADN [46]). (e-g) Land consolidation illustrated with FAO data [61] in terms of (e) total number of farmers, (f) total utilized land for different farm sizes (small farms: less than 20 ha, medium farms: 20-100 ha, large farms: more than 100 ha), and (g) average farm size.

Initialization

Having set the parameters, the model can now be initialized. On the economic side, the initial number of farmers and their land holdings are sourced from the FAO’s ”Structural Data from Agricultural Censuses” dataset for 1990, which covers the behavior of approximately 1 million French farmers at that time. For agronomic information related to wheat production, we use average values from the FADN dataset. Each farmer is assigned an initial pesticide use and yield as follows:

$$\begin{aligned} P_{i,0} &= \bar{P}_0(1 + \zeta_i) \\ y_{i,0} &= \bar{y}_0(1 + \psi_i) \end{aligned} \quad \text{where} \quad \zeta_i, \psi_i \in \mathcal{N}(0, 0.1) \quad (17)$$

with $\mathcal{N}(0, 0.1)$ a Gaussian distribution with zero mean and a standard deviation of 0.1. Further assuming an initial pest exposure of 30% (see above) [63], we calculate the initial efficiency rate and total costs using Eqs 5 and 8, respectively. The initial market price is set to reflect an average return on investment equal to the opportunity cost, ensuring a competitive agricultural sector at the beginning of the period. Finally, the initial demand is set equal to the total initial production, simulating a market close to equilibrium.

Simulation

With all parameters set and variables initialised, various scenarios can be explored through extensive numerical simulations. For each scenario, we conduct 10 simulations with different random seeds over a timeframe extending from 1990 to 2075.⁵ The results presented are Monte Carlo averages, with their relative standard errors omitted due to their negligible values (below the line width). It is important to note that we do not account for global fluctuations in either ecological or economic aspects, so the relative differences between simulations are solely due to farmer-to-farmer variability. Given the large number of farmers, this variability averages out when examining macro trends.

Instead of relying on a single indicator, we shall propose a stratified analysis to examine each variable’s role through its interactions with others, providing a more comprehensive understanding of the dynamics of the model.

3 Future trends and policy perspectives

We begin by examining a baseline scenario without additional policy interventions. Our model predicts a decline in biodiversity by 2075 of 10% compared to 2021, and a concerning 55% decline compared to 1990 levels. This significant drop underscores the urgent need for policy changes to protect and, when possible, restore biodiversity. To address this challenge, we explore two potential policy options: (i) reducing pesticide use and (ii) implementing subsidies for small farmers. Our analysis shows that both approaches positively impact overall biodiversity, albeit with some caveats. The most effective strategy appears to be a combined approach that leverages the strengths of both policies.

3.1. Baseline scenario

The business-as-usual predictions of our model are represented by the solid blue lines in Fig. 3. In this baseline scenario, the ongoing biodiversity degradation process (Fig. 3a) proceeds in two distinct phases. In the short term (2022-2050), biodiversity drops to 40% of its 1990 levels. However, in the latter part of the simulation (2050-2075), we observe a slight recovery to eventually reach 45%.

The initial decline is primarily driven by intensified land consolidation. Although pesticide use (Fig. 3d) decays over time due to increased efficiency (Fig. 3h), the positive effect of such decay on biodiversity is offset by the increase of average farm size (Fig. 3c). The land consolidation, where the number of farms continuously decreases (Fig. 3f) with smaller farms being absorbed by larger ones, is driven by the following mechanism. Since the market price remains relatively constant (Fig. 3b), farmers must compensate for the increase in pest exposure, due to biodiversity loss (Eq. 3), by enhancing efficiency to maintain their marginal profit. However, investments in technology adoption depend on current profitability (Eq. 9), favoring larger farmers with greater margins due to economies of scale. Over time, small struggling farms terminate rental contracts, sacrificing further economies of scale and profitability, leading to sector abandonment and further biodiversity decline.

⁵We select 2075 as a suitable temporal horizon, distant enough to explore long-term effects given the model’s inherent inertia, yet close enough for our approximations to remain reasonable throughout the period.

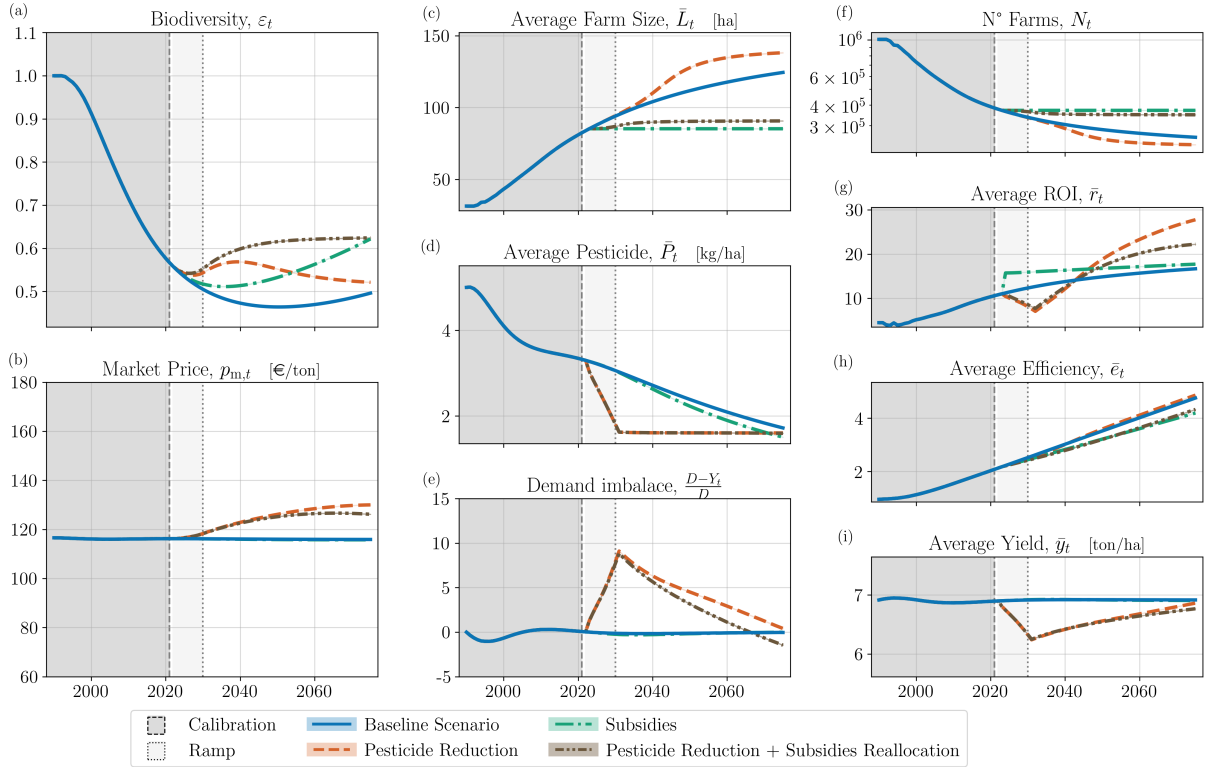


Figure 3 – Numerical simulations. The gray-shaded area indicates the calibration period (1990-2021). In the baseline scenario (solid blue lines), biodiversity continues to decline due to intensified land consolidation. The pesticide reduction scenario (dashed orange line) shows initial biodiversity recovery, followed by a decline caused by intensified land consolidation due to reduced yields. The light-gray-shaded area marks the 2022-2030 ramp to halving pesticide. The subsidy program favoring small farmers (dash-dotted green line) effectively halts land consolidation, leading to improved biodiversity outcomes. The combined approach of pesticide reduction with subsidies for small farmers (dash-dot-dotted brown line) appears as the most promising solution for biodiversity conservation by mitigating the negative effects of land consolidation while benefiting from pesticide reduction.

In the long term, the number of farmers stabilizes as most farms reach a size sufficient to secure a return on investment greater than the opportunity cost (Fig. 3g). Consequently, in this phase, the continued reduction in pesticide use does explain the slight recovery of biodiversity.

Lastly, it is noteworthy that, as mentioned above, the market price remains nearly unchanged because total production remains aligned with demand (Fig. 3e). This equilibrium is achieved by maintaining yield levels (Fig. 3i) equivalent to the period 1990-2021, indicating that average efficiency gains offset the effects of increased pest exposure.

3.2. Pesticide reduction

Although the decay rate is indeed slowing down, the forecasted biodiversity decline in the baseline scenario remains unacceptable. Indeed, biodiversity is critical for ecosystem functioning and supporting essential services such as water provision and air purification, vital for societal well-being [17, 18], though these aspects are not the focus of this study. One widely discussed policy proposal to enhance biodiversity is reducing pesticide usage [69, 70, 71]. Various methods can be thought of, such as pesticide taxes [70] or incentives for organic farming [71]. Our analysis focuses on a straightforward approach: mandating a gradual reduction in pesticide use by farmers. Specifically, we model a policy requiring farmers to halve their pesticide usage linearly over 2022 to 2030 the period,⁶ in line with the European Union considerations [69].

The outcomes of the pesticide reduction policy are illustrated as orange dashed lines in Fig. 3. In the beginning, biodiversity recovers rapidly (Fig. 3a) due to the immediate effect of reduced pesticide use (Fig. 3d). However, this initial boost is quickly followed by a strong decline. Indeed, reduced pesticide

⁶This is achieved via the following equation: $P_{i,t+1} = \min \left\{ P_{i,2021} \min \left[\max \left(\frac{t+1-2021}{2030-2021}, 0 \right), 1 \right], P_{i,t} \left(1 + \gamma \frac{\bar{y}_{i,t} - y_{i,t}}{y_{i,t}} \right) \right\}$.

use leads to an estimated 10% decrease in crop yield (Fig. 3i), consistent with existing literature [72]. Consequently, the reduced yield results in a significant drop in return on investment for farms of all sizes (Fig. 3g). Smaller farms, already operating with narrow profit margins, are particularly affected and tend to exit the farming sector even faster. This accelerates land consolidation, as evidenced by a decrease in the number of farmers (Fig. 3f) and an increase in average farm size compared to the baseline scenario (Fig. 3c). Ultimately, exacerbated land consolidation neutralizes the positive impacts of pesticide reduction, resulting in a net decrease in biodiversity that falls below 2021 levels.

Finally, we observe an increase in market price which can be attributed to an underproduction regime (Fig. 3e) resulting from decreased yields (Fig. 3i) without corresponding expansion in cultivated land. However, and perhaps surprisingly, such increase in price is not sufficient to outweigh the profit degradation due to yield loss, resulting on average in a lower ROI (Fig. 3g). This can be explained by the influence of international competition, which is factored in here as friction in the price dynamics ($\alpha < 1$ in Eq. 6). Indeed, in a global market, one expects that local decreases in crop yield are offset by higher production levels in other countries not subject to the same pesticide reduction policies.

3.3. Subsidies

As argued above, land consolidation significantly influences biodiversity dynamics. Therefore, it is logical to consider a policy involving subsidies that favors small farmers to maintain a diverse landscape. To this end, we introduce a subsidy program in the form of a direct payment to all farmers (in addition to the existing subsidies per ha), providing a 200-euro coupon regardless of farm size. This policy inherently benefits small farmers due to the marginal increase in profit it provides.

The results of this policy are shown in Fig. 3 as green dash-dotted lines. The number of farmers (Fig. 3f) rapidly stabilizes after the application of the new policy, as does the average farm size (Fig. 3c). Consequently, biodiversity degradation slows down compared to the baseline scenario to eventually increase (Fig. 3a). In addition, biodiversity restoration positively affects pesticide use. As pest exposure decreases accordingly to Eq. 3, the amount of pesticide required to achieve the same yield also decreases (Figs. 3d and i). Finally, the reduction in pesticide use is reflected in slightly lower prices (Fig. 3b), due to the slow adjustment behavior of farmers, which results in a phase of overproduction.

The results of this section highlight the critical role of favoring small farmers in halting land consolidation and enhancing biodiversity.

3.4. Combined policy: pesticide reduction and subsidies reallocation

Thus far, we have demonstrated that biodiversity decreases under a business-as-usual scenario. The pesticide policy alone is ineffective in improving the situation due to its associated impact on land consolidation. Conversely, a subsidy policy favoring small farmers tends to mitigate land consolidation.

Regarding policy makers motivations and constraints, on one hand, they may seek to reduce pesticide use regardless of biodiversity benefits given the well-documented negative impact of pesticide use on human health [73]. On the other hand, they may be reluctant to add new subsidies to the already existing ones due to funding constraints. Therefore, we propose a coordinated policy that targets (i) pesticide reduction (through the same mechanism as before), while (ii) reallocating a fraction of existing subsidies from a per-hectare basis to a per-farmer basis. The results of this combined policy, assuming a reallocation of 0.3% of existing subsidies, are reported in Fig. 3 (dash-dot-dotted brown line). This reallocation choice corresponds to a new subsidy of 65 euros per farmer and a negligible different in subsidy per hectare (see Figs 4a-b).

The positive impacts of both policies pesticide reduction and targeted subsidies are successfully combined. Biodiversity rapidly increases due to pesticide reduction (Fig. 3a), and, unlike with the pesticide reduction policy alone, such increase is stabilized by the action of the subsidies. Indeed, the number of farmers (Fig. 3f) and the average farm size (Fig. 3c) stabilize. We also observe that market prices benefit from this increase in biodiversity (Fig. 3b). Indeed, due to biodiversity recovery, lower pesticide use is required to achieve the same yield targets (Eq. 5), reducing the duration and magnitude of the underproduction phase (Fig. 3e). This leads to an overall price level lower than under the pesticide reduction policy alone, thereby benefiting society as a whole.

As stated above, the results of Fig. 3 are given for a reallocation fraction of 0.3% of pre-existing subsidies. One may wonder how varying this reallocation fraction affects the overall outcomes. In Fig. 4, we report

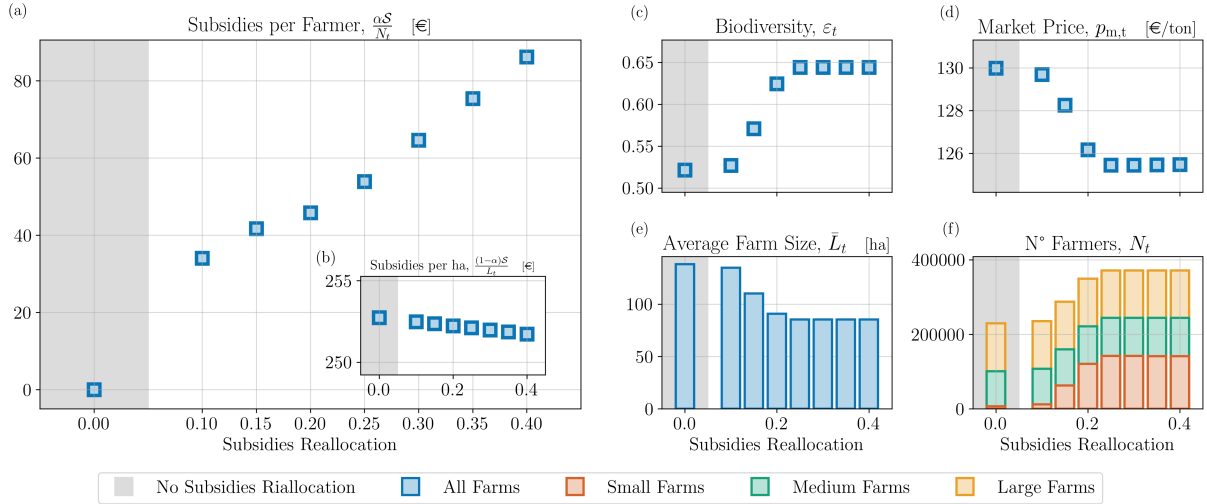


Figure 4 – Impact of the combined policy in 2075 for different levels of subsidies reallocation. (a) Subsidies per farmer as function of the percentage of subsidies reallocation. (b) Subsidies per hectare negligible decrease. (c) Biodiversity improves significantly with increased subsidies reallocation as the average farm size (e) decreases, indicating a reduction in land consolidation. However a plateau is reached when the numbers of farmers (f) is no longer affected by a further increase in subsidies. (d) The market price decreases slightly with higher subsidies reallocation, as a consequence of biodiversity recovery, ultimately benefiting societal well-being.

results at the end of the period (year 2075) for different reallocation fractions. When the reallocation fraction is too small, the positive effects are limited, with biodiversity showing only a slight improvement over the pesticide reduction policy alone (Fig. 4c). However, increasing this fraction by a few basis points leads to a strong increase in overall benefits, as highlighted by higher levels of biodiversity and lower prices (Fig. 4d). Increasing further the reallocation fractions is not necessary, indeed benefits saturate as the distribution of farm sizes is no longer affected (Figs 4e-f).⁷

4 Discussion

Using the French agricultural landscape as a case study, we present a parsimonious, integrated bio-economic model based on historical data. Our approach stands out by leveraging micro-foundations to understand past and future trends in biodiversity loss, pesticide use, and land consolidation. This model also enables the assessment of policy interventions on both ecological and economic sustainability.

Our framework specifically incorporates feedback loops between bird population dynamics (as a proxy for overall biodiversity) and a granular description of farmer decision-making processes. The model projects a significant decline in biodiversity under a business-as-usual scenario, primarily driven by land consolidation. This highlights the urgent need for effective policy measures, given the well-documented role of biodiversity in societal well-being. To address this challenge, we analyze the potential impact of two policy interventions: pesticide reduction and subsidies targeted at small farmers. Both policies demonstrate their capacity to positively impact biodiversity, although through different mechanisms.

Pesticide reduction initially boosts biodiversity but ultimately leads to decreased crop yields and financial stress on small farms, accelerating land consolidation and negating initial biodiversity gains. Consequently, the most effective approach appears to be a combined strategy that incorporates both pesticide reduction and targeted subsidies for small farmers, which can be achieved by reallocating a modest fraction of the already existing subsidies. By mitigating the economic pressures on small farms, these subsidies can help maintain a more diverse agricultural landscape, thereby balancing the benefits of pesticide reduction with economic stability for small farms.

While quite comprehensive, the model presents opportunities for further development. A key limitation is its current lack of consideration for sustainable farming practices, such as organic farming. Organic agriculture, which relies less on synthetic pesticides and fertilizers, is a growing area of interest for mitigating biodiversity loss while maintaining agricultural productivity. Future research should extend

⁷Recall that we have not allowed for entry of new farmers in this version of the model.

the model to incorporate the possibility of farmers transitioning towards sustainable practices. Another limitation is the model's current lack of a spatial dimension. While this simplification facilitates the analysis, it overlooks the inherent complexity of real-world agro-ecosystems. Current agricultural landscapes are a mosaic of different land uses, with varying levels of biodiversity influenced by factors like hedgerows, field margins, and natural habitats. A spatially explicit version of the model could account for these landscape characteristics and their influence on the spatio-temporal dynamics of biodiversity. Additionally, such a model could be extended to study broader environmental challenges, including climate change, soil degradation, and water availability, which vary significantly across regions.

By addressing these limitations, future models can achieve greater applicability to real-world settings and provide more region-specific policy recommendations tailored to the unique challenges faced by different agricultural regions.

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A Sensitivity analysis

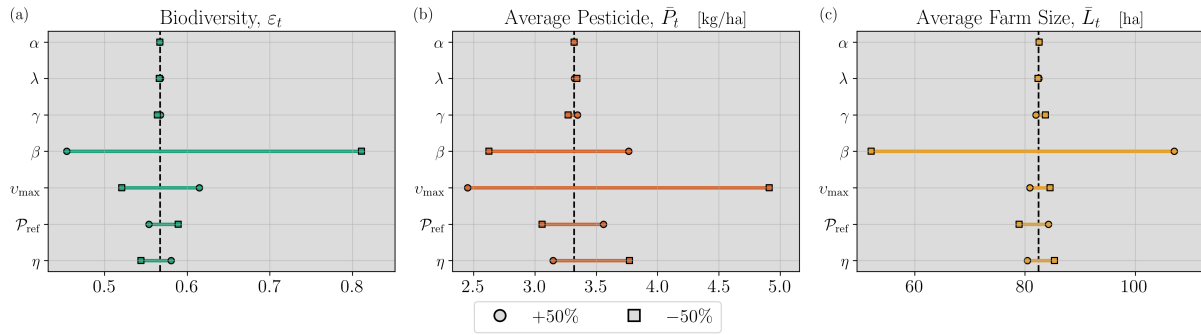


Figure 5 – Sensitivity analysis for the calibrated parameters (see Table 1). This figure shows the variation in three main variables ε_t , \bar{P}_t and \bar{L}_t in the year 2020 when the values in Table 1 are independently perturbed by $\pm 50\%$. This demonstrates robustness in the results of the model, underscoring the only weak impact of behavioral details, thereby addressing one of the main criticism of agent-based models [40]. As expected, the parameter β , which determines the land speed update, exerts the most significant influence on the dynamics across all variables.