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A modeling framework of a territorial socio-ecosystem to study the trajectories of change in agricultural phytosanitary practices

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ABSTRACT

Despite the growing societal demands to reduce pesticide use, public policies struggle to reverse the current upward trend. Agroecology emerges as a promising solution, as it promotes ecological regulation and sustainable practices. The systemic nature of the agro-ecological transition requires the development of an interdisciplinary approach. In this respect, models integrating ecological, economic, and social aspects are valuable for understanding the dynamics of agroecosystems. The objective of this article is to investigate the trajectories of change in the pesticide practices of agricultural territories taking into account ecological and economic dynamics. We built a socio-ecological modeling framework of a socio-ecosystem at the territorial scale. This generic agent-based model is developed to simulate both farmers' decision-making (based on its own profit and that of others, and its willingness to change) and disease dynamics (based on the inoculum, the probability of infection, the probability of disease escape, and the previous disease). We first used the model to simulate the impact of different economic or ecological territorial characteristics on the trajectories of agricultural practices in the territory. Second, we aimed to analyze the final states of the territories (at equilibrium) based on scenarios of variations in the economic (the cost of pesticides), ecological (the dispersal capacity of the disease), and agronomic (the ability to escape the disease of no-input farming) parameters. The final states of the territories were analyzed using four categories of indicators (farming practices, the profits, the number of infected fields and the use of fungicides). The study revealed strong threshold effects, non-linear effects and linear effects, on the number of farmers performing the different practices in the territory. These effects are highlighted respectively for the scenarios of increased cost of pesticides, increased disease escape of no-input farming and increased the disease dispersal. Our results highlighted the need to take into account combinations of levers and to study trajectories of change in order to promote sustainable agriculture. Finally, we discussed the possibility of using such models to guide public policies in favor of agroecology.

1. Introduction

Global pesticide use has increased over the last 30 years (FAO, 2022; Özkara et al., 2016), even though they are recognized to cause various environmental and health problems (Aktar et al., 2009; Frische et al., 2018). Although pesticide reduction is a strong societal demand and a necessity in order to preserve human health and biodiversity, public policies in several countries are struggling to reverse the current upward trend (Mesnage and Séralini, 2018). At the European level, fundings has been devoted to pesticide reduction for more than 15 years (European Parliament and Council, 2009). However, the Nature and Human Foundation (Faraldo et al., 2022) reports that despite allocating 11 % of European funding to reduce pesticide use, only 1 % of this funding is estimated to effectively contribute to achieving this objective. In many cases, the subsidies do not necessitate the implementation of concrete changes or are not proportionate to the environmental demands (Faraldo et al., 2022).

Agroecology offers a promising solution to decrease pesticide use (Altieri et al., 2015; De Schutter, 2012; Holt-Giménez and Altieri, 2012). Its implementation on their farms depends on the farmers' individual choices (Catalogna et al., 2018). However, the desired effects are also on a territorial scale (Altieri et al., 2015). For example, the agroecological

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practices of increasing plant diversity in plots and agricultural landscapes by integrating crops and semi-natural elements can promote ecological regulation (Barberi, 2002; Frison et al., 2011; Malézieux et al., 2009; Obrycki et al., 2009; Wezel et al., 2014). This helps to limit the territorial process of the spread of disease (Bebber et al., 2014) and therefore to reduce farmers' dependency on pesticides. The diversity of interactions between organisms in agroecosystems results in multiple ecological functions, particularly pest regulation (Altieri, 2018).

In addition to ecological interactions, agroecosystems along with the agroecological transition encompass various environmental, economic, and social aspects that interact in a non-linear and complex way (Darnhofer et al., 2010; Gunderson and Holling, 2002; Wezel et al., 2020). Achieving the reduction of pesticide use in agroecosystems requires the simultaneous consideration of these interconnected aspects (Lescourret et al., 2015; Rebaudo and Dangles, 2013). It includes understanding farmers' decision-making in response to ecological, economic, and social factors (e.g., level of disease in the field, pesticides prices, networks of actors in territories), which can shed light on relevant levers for the agroecological transition (Meunier et al., 2024). Furthermore, the territorial level is a promising level of implementation (Wezel et al. 2016). Conceived at the landscape scale, agroecological principles require collective actions that involve multiple actors and require the mobilization of economic and social levers. This is visible for example with the implementation of hedges, whose effects increase when management is done collectively on a territorial scale (Montgomery et al. 2020). The application of agroecology to the design and management of sustainable agroecosystems brings sustainability to all components of food systems (Gliessman, 2018; Wezel et al., 2020, 2014). The systemic nature of the agro-ecological territorial transition requires the development of an interdisciplinary approach. In this respect, models that integrate the dynamics of the ecological, economic, and social aspects of agroecosystems at the territorial level are relevant tools for simulating trajectories of change. In particular, simulation-based tools such as agent-based modeling have been proven to be particularly appropriate for studying the complex interactions between components (Müller-Hansen et al., 2017; Schulze et al., 2017).

Regarding ecological aspects, agroecosystem modeling has been used to characterize ecologically optimal landscape mosaics for pest regulation (Gaudio et al., 2022; Malard et al., 2020; Tixier, 2020). This modeling approach has also led to a better understanding of the links between planned biodiversity (*i.e.,* biodiversity intentionally chosen by the farmer) and biological regulation (*i.e.,* all the interactions and transformations within the biotechnical systems of the agroecosystem). For instance, models have been developed to study biological regulation in field crop landscapes, which depend on crop diversity and the density of semi-natural elements in the agricultural landscape (for an overview, see Begg et al., 2017; Le Gal et al., 2020; Précigout and Robert, 2022; Rusch et al., 2016). These studies showed that models can be useful tools for understanding and quantifying the impacts of agroecological practices on epidemic dynamics and associated yields as well as for proposing ecologically optimal mosaics for regulating pests or maximizing yields.

However, the existing agroecological models rarely consider the decision-making of farmers about farming practices. It is therefore crucial for these models to incorporate such decision-making processes and therefore factors that may influence farmers' decision. Indeed, the emergent behavior of the agroecosystem is the result of individual actions. Indeed, the emergent behavior of the agroecosystem is the result of individual actions. Moreover, the factors affecting farmers' decision-making, particularly with regard to the adoption of sustainable farming practices, are highly diverse and may include cognitive aspects (Meunier et al. 2024), resistance to change, environmental issues, and economic concerns (Dessart et al., 2019). Economic concerns are often cited as one of the primary motivators (*e.g.*, Crase and Maybery, 2004; Greiner, 2015; Honlonkou, 2004). These diverse motivations can include profit (*e.g.*, Läpple and Kelley, 2013), maximizing production (*e.g.*, Greiner, 2015), and reducing production costs (Mzoughi, 2011). Factors affecting farmers' decision-making may be related to themselves and the status of their farm, related to others farmers (*e.g.*, competitive advantage), or linked to the ecological system (*e.g.*, disease intensity). Including farmers' behavior, by taking these different factors into account, is a key step towards gaining a better understanding of the dynamics of changes in practices in the agricultural territories.

The overall goal of this article is to investigate, via modelling, trajectories of change in the pesticide practices of agricultural territories in response to interactions between ecological, social and economic components. The model can be used to simulate trajectories of change in the face of various economic, ecological, social, or cognitive factors. For this we aimed to develop an agroecosystem modeling approach by coupling ecological (crop diseases) and social (farmers) dynamics. This raises questions about the spatial and temporal scales involved in coupling various types of dynamics (Neumann et al., 2011; Qiu et al., 2020; Wezel et al., 2020). Bearing this in mind, we built an agent-based model of a farming territory. Agent-based models that simulate the dynamics of individuals under the influence of different factors in the territory, which in turn affect the trajectories of the territories themselves, are relevant for modeling the agroecological transition (Feola and Binder, 2010; Rebaudo and Dangles, 2013). Our model simulates the decision-making of farmers with regard to their pesticide practices in response to different ecological (crop and disease in particular), economic (profit and yield in particular) and social factors (practices of the neighbors in particular). Reciprocally, farmers' practices influence the ecological dynamics (of diseases in particular). With the model we analyzed how some economic (pesticide prices), ecological (disease levels), and agronomic (efficacy of alternative crop protection practices) factors impact pesticide use and how they could be potential territorial levers to reduce them. Here, we used the model to explore how the economic and ecological characteristics of an agricultural territory influence its trajectory of change and final status. To characterize the transition year after year and at equilibrium, we constructed various indicators that correspond to the economic, agronomic, environmental, and ecological state of the territory.

2. Material and methods

To describe our model, we follow the ODD (Overview, Design concept, and Details) protocol (Grimm et al., 2010) as prescribed in Jakeman et al. (2024). This protocol was created to standardize the published descriptions of agent-based models and to make model description more understandable and complete. The Overview section (2.1) provides a high-level description of the model and mentions the procedures to be explained in further detail in the sub-models. The Design concepts section (2.2) describes the general concepts involved. The formulaic expressions of the sub-models are then given in the Details section (2.3). Section 2.4 describes the parametrization and initial conditions of the model. We finish with the scenario and indicators in section (2.5).

2.1. Overview

2.1.1. General purpose

The purpose of the model is to simulate changes in pesticide practices in a territory in response to different factors taken into account ecological and social components. The model first simulated the simplified spatiotemporal ecological dynamics of a wheat-growing territory attacked by airborne fungal diseases such as leaf rust (*Puccinia triticana*). These diseases require systematic fungicide treatments and can cause yield losses of up to 50 % in the case of strong epidemics. The model also includes farmers' decision-making about their own practices. We investigate how the interactions between farmers' decision-making and the ecological system can influence the trajectories of change in pesticide practices. To characterize the territorial agricultural transitions, we estimate several economic, agronomic, environmental, and ecological indicators in the territory. Here, we present the framework of the model and the choices made.

2.1.2. System modeled and main assumptions of the model

2.1.2.1. The simplified farming and territory. The territory is represented by a constant number of fields. Each field (cell) is characterized by a type of practice and a farmer who has to make decisions about his field each year. For the sake of simplicity, we have represented the farm as a single field and farmer.

2.1.2.2. Type of practices and associated disease and yields. In this paper, we chose to greatly simplify the model by considering only two types of agricultural systems: no-input system (NI) and high-input system (HI). NI corresponds to an "agroecological system". It corresponds to a set of agricultural practices that allows avoiding chemical inputs, particularly pesticides, using resistant varieties and crop diversity such as the mixture of varieties or species (Wezel et al., 2014), providing ecological resistance (or disease escape) to disease. HI corresponds to "intensive monoculture system". It is associated with systematic pesticide treatments and the use of varieties optimized for their yield under conditions of pesticide use. These two agricultural systems cover a whole range of agricultural practices, such as choice of crops, sowing dates and densities, choice of varieties, rotation, tillage. However, here we chose to focus on the issue of pests and crop protection.

HI and NI are characterized by their global level of resistance to diseases and their associated yields. The NI practice are assumed to allow for the ecological regulation of pathogens (Alvarez, 2022; De Ponti et al., 2012; Seufert et al., 2012). In terms of pesticides use, we make thus the assumption that for the NI farming practice, pesticides are never applied. By contrast, in the model, the farmers with HI farming practices systematically use at least one treatment of pesticides and a second treatment in case of severe disease infection.

In terms of yields, we assume that maximal reachable crop yields are higher with the HI practice than with the agroecological NI practice (Knapp and Van Der Heijden, 2018). However, the difference in yield between diseased and non-diseased crops is smaller in the case of NI practices, which corresponds to a higher crop tolerance with greater yield stability (Knapp and Van Der Heijden, 2018). Here, we therefore consider a set of practices named HI and NI resulting in the characteristics presented above without considering effects of individually variables such as sowing date, plant density and genotypes in the potential yield.

2.1.2.3. Factors taken into account to simulate disease in field and landscapes. In this paper, the level of diseases in each field depends on the residual inoculum and the type of practice in the field and on the disease spreads from the other infected fields of the territory. In the model we assume that the disease spreads from the infected fields at a maximum dispersal distance, and that fields are more or less susceptible to the disease depending on the residual inoculum and the type of practice. Despite their potential strong impact (Gahlot et al., 2020; Wan et al., 2022) we do not consider environmental variables such as temperature, humidity or winds on disease development. The environmental conditions are considered similar for every field. In this paper we focus on the interactions between fields in terms of spore dispersal. In terms of type of diseases, we in particular consider biotrophic rust disease that are known to disperse by wind their reproductive structures to other fields.

2.1.2.4. Factors taken into account to simulate the probability of changes of practices by the farmers. In this paper, the probability of change depends on two aspects: (i) the resistance to change of farmer and (ii) the economic profit of the farmer in relation to the profit of farmers in the other practices. It represents the farmer's willingness to have a higher profit than these other farmers. The more the agent-farmer is willing to have a higher profit, the more likely it is to change practices. It also takes into account his own previous year's profit. In this first version of the model, we therefore do not include social and environmental aspects in the probability of change.

2.1.3. State variables and scales

We represented an agricultural territory as a square domain discretized in N x N cells, with each cell representing a field. This spatial domain has both ecological dynamics (*i.e.,* spread and epidemics of pathogens) and social dynamics (*i.e.,* evolution of farmers' choice). One agent-farmer is associated with each cell, which represents the spatial unit of the decision-making about farming practices (HI and NI practices here). Decisions are taken at each time step, which corresponds to one year. The type of practices influences the ecological dynamics in terms of disease development (the NI practices are more resistant to the pathogens). In return, the level of disease (ecological dynamics) influences the choice of the farmers (social dynamics) in terms of practices: the presence of pathogens determines the yields, and the farmer's profit is taken into account in their decision-making about farming practices. In the model, the social and economic (farmer's choice) and ecological (disease development) components therefore interact and respond to each other at field and territorial level.

We divided our state variables into five types corresponding to agent-farmers, practices, profit, pests, and territory. While presenting the framework of the model, we specify our choice for each variable for the simplified representation of the territory. All variables (name, symbol, domain, and unit) are listed in Appendix 1.

An agent-farmer is characterized by three time-dynamic ecological disease variables: the epidemic status of its field, $s_{i,t} \in \{0;1\}$, which represents the absence ($s_{i,t} = 0$, *healthy field*) or presence ($s_{i,t} = 1$, *infected field*) of the disease; the probability $u_{i,t}$ of the field being infected; and, in the case of infection, the probability $h_{i,t}$ of escaping the disease and being healthy (hereafter, *escape probability*). An agent-farmer is also characterized by a farming practice in year t, $k_{i,t}$. In this paper, we consider two simplified practices, $k_{i,t} \in \{\mathrm{NI}, \mathrm{HI}\}$, which *correspond to* no-input (NI) and high-input (HI). It is also associated with the quantity of pesticide treatments used that is counted by the variable $q_{i,t}$ of pesticide treatments used by the agent-farmer i in each year t.

For each agent-farmer, we also estimate the level $y_{i,t}$ of yield in year t. It is defined as a relative proportion of the maximum potential yield, hereafter referred to as *yield* of agent-farmer i in year t and depend of the type of practice and of the level of disease. Knowing the yield, and other costs (such as the price of pesticide) the model estimate for each agent-farmer a level $\pi_{i,t}$ of profit in year t (relative proportion of the maximum potential profit).

Each year, the model estimates for each farmer the probability of change of practice. In the version of the model presented here, the probability of change depends on two aspects: (i) the personal resistance to change of each farmer and (ii) the profit made by the farmer in relation to his own yield history and the yield of other farmers (in particular of the other practice). For this, an agent-farmer has the following attributes: a change-practice-threshold v_i that represents resistance to change of practice and a probability $p_{i,t}^{a\rightarrow b}$ of change from practice a to farming practice b in year t. The probability $p_{i,t}^{a\rightarrow b}$ is composed of the metric profit comparison $\chi_{i,t}^{a\rightarrow b}$. It is a comparison between his profit and the average profit of farmers performing the other practice. It represents the agent-farmer's willingness to have a higher profit than these other agent-farmers. The more the agent-farmer is willing to have a higher profit, the more likely he is to change. The willingness is higher if its profit is lower than that of others.

Agricultural practice a is characterized by a number of treatments of pesticides $q^{a,s}$, a yield $y^{a,s}$, and a disease escape probability h^a. The first two depend on the epidemic status s of the field where the practice is applied. If the field is infected, the yield decreases and the number of treatments increases. The yield loss in the case of disease infection is higher for HI than for NI. The disease escape probability is the probability that the disease will not develop within the field, even if it has been infected. We consider an escape probability of the NI practice higher than for the HI practice (Beillouin et al., 2021; Malézieux et al., 2009; Ratnadass et al., 2012). This corresponds to the lower development of disease in fields with agroecological practices such as species or cultivar mixtures (Boudreau, 2013; Guo et al., 2020; Luo et al., 2022; Schoeny et al., 2010; Zhang et al., 2019). On the other hand, wheat crops grown intensively in monocultures and with susceptible varieties are prone to disease (Ekroth et al., 2019).

The economic variables are the maximal potential profit π^{max}, the selling price per yield unit *w,* and the cost *c* per treatment of pesticides. The pest variables are the dispersal capacity *d* (*i.e.,* the probability that pests from an infected field will reach the agent-farmer's field and infect it), the radius of dispersal *r* (*i.e.,* the maximum distance at which the disease can disperse from field to field in the territory), and the primary inoculum *l* (*i.e.,* an additional probability for a cell being infected at the beginning of each year from an external inoculum).

2.1.4. *Process overview and scheduling*

Within each time step, the model simulates three main processes in the following order: (1) the agent-farmers take decisions about their practices; (2) a procedure simulates the spread of the disease in the territory and eventually in each field; and (3) the agent-farmers update their profits depending on their practices and the evolution of the disease in the territory and particularly in their own fields. These three processes are interlinked, as the practices modify the spread of the disease, which, in turn, modifies the yields. The yields are included in the calculation of profits, which will be taken into account the following year when the agent-farmers choose their practice. The events are modeled with the processes described in detail in Section 2.3.

2.1.4.5. Agent-farmer decision-making. For each agent-farmer, the procedure *Decision_to_change* (see Section 2.3.1) calculates the probability of changing practice for each farmer, depending on his previous year's profit, the average profits of the previous year of the other agent-farmers (using the same or the other farming practice), and the maximum observed yields with the two practices. For each agent-farmer, this procedure determines whether they change or keep the same farming practice. The idea is that the agent-farmer wants to have a sufficiently large profit, relative to the other practice as well. It also takes into account their personal change-practice-thresholds.

2.1.4.6. Ecological dynamics. The procedure *Disease_spread* (see Section 2.3.2) simulates the spread of the disease in the territory on the basis of the inoculum, the probability of infection, the probability of escape, and the epidemic status. This procedure relies on the suppose that the disease spreads from the infected fields at a maximum dispersal distance, and fields are more or less susceptible to the disease depending on the residual inoculum and the type of practice.

2.1.4.7. Updating of profits. The procedure *Profit_update* (see Section 2.3.3) calculates the profit for each agent-farmer as a function of their practice and the epidemic status of their field after the simulation of the disease spread.

Actions are taken by each agent-farmer and processed one by one in a random order at each iteration. The model flow is shown in Fig. 1.

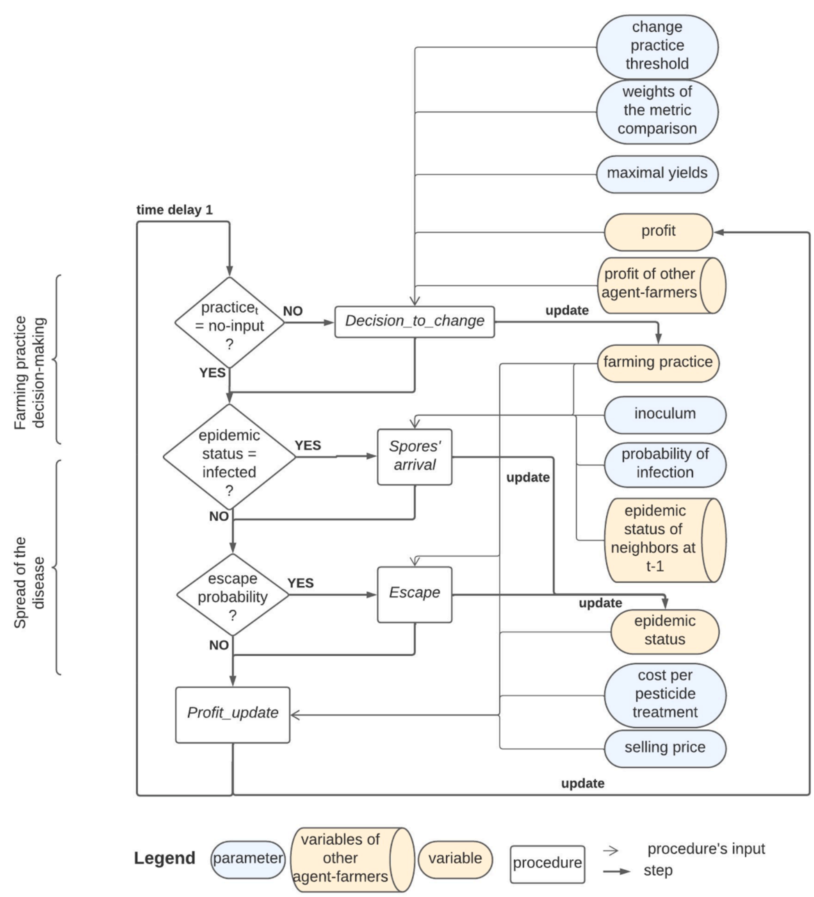

Fig. 1. Model flow with the variables and parameters affecting the processes.

2.2. Design concept

2.2.1. Emergence

The main properties that emerge from the model are (1) the spatial spread of the disease and the number of infected fields each year, and (2) the number and spatial distribution of agent-farmers in the agricultural territory who apply each farming practice each year. These properties influence each other and vary in a non-linear way depending on the initial conditions and model parameter values.

2.2.2. Individual decision making

Agent-farmers choose their farming practice at each time step. The model calculates a probability of change from the current practice to the other farming practice according to different economic factors: their own profits, the average profits of agent-farmers with NI or HI practices, and the maximum observed yields in the territory, and to their own change-practice-thresholds.

2.2.3. Individual sensing

Agent-farmers are aware of the epidemic status of their own field at each time step. They have access to global information about the average profit of agent-farmers depending on the farming practice. We assume that such perception is accessible and not erroneous.

2.2.4. Interaction

We modeled two types of interactions. The first interaction is direct between the agents. They know the average profit of agent-farmers and use it to decide whether or not to change their practices (procedure *Decision_to_change* (see Section 2.3.1)). The second type is mediated by the environment: the practice implemented by the agent-farmers affects the spread of the disease (procedure *Disease_spread* (see Section 2.3.2)).

2.2.5. Heterogeneity

At initialization, the agents are heterogeneous in terms of their change-practice-thresholds, farming practice, and epidemic status.

2.2.6. Stochasticity

The elements of stochasticity in the model are part of the initialization, the ecological dynamics, and the agent-farmers *Decision_to_change* procedure. At initialization, the epidemic status of the agent-farmers' fields, their initial farming practices (see Section 2.4. Parametrization and initial conditions), and their change-practice-threshold are randomly assigned. The distribution of the change-practice-threshold among agent-farmers follows a normal law independent of the spatial location. During the *Disease_spread* procedure, the infection of a field is a stochastic event based on two probabilities: the probability of the field being infected and the probability of escaping the disease once infected. In the *Decision_to_change* process, the probability of change for the agent-farmers is computed.

2.2.7. Observation

We tracked the changes of disease spread and farming practices over time. In addition, we tracked the total amount of pesticides used by all the agent-farmers, the yield (average and by farming practice), and the profits (average and by farming practice). In Section 2.4, we describe the various indicators based on these observations.

2.3. Details

The model was implemented in NetLogo 6.2.0 (Wilensky, 1999). It is available on: https://zenodo.org/record/8208555.

2.3.1. Decision_to_change procedure

The core of the *Decision_to_change* procedure is the probability of change $p_{i,t}^{a\to b}$ from farming practice a to farming practice b for an agent-farmer i in year t (see Eq. (1)). A probability of change equal to 0 represents no interest in changing and a probability to change of 1 represents a full interest in changing.

$$
\mathrm{p}_{\mathrm{i,t}}^{\mathrm{a}\to\mathrm{b}} = \begin{cases} 0 \text{ if } \chi_{i,t}^{a\to b} < \mathrm{v}_i \\ \chi_{i,t}^{a\to b} \text{ if } 1 > \chi_{i,t}^{a\to b} > \mathrm{v}_i \\ 1 \text{ if } \chi_{i,t}^{a\to b} > 1 \end{cases} \tag{1}
$$

The probability $\mathrm{p}_{\mathrm{i,t}}^{\mathrm{a}\to\mathrm{b}}$ depends the decision-metric $\chi_{\mathrm{i,t}}^{\mathrm{a}\to\mathrm{b}}$. If this decision-metric is less than the change-practice-threshold v_{i} of the agent-farmer, the probability of change is set to zero. Agent-farmers remember during the current year if they wanted to change the farming practices last year. Agent-farmers can only make one decision per year but this change becomes applicable if they want to change for two years in a row. This represents the inertia of change. Indeed, farmers have a resistance to change (Anastasiadis and Chukova 2019). Once an agent-farmer has changed practice, they cannot change again until the end of the simulation. Indeed, we also assumed that agent-farmers could not return to their previous farming practice given the significant up-front costs (David et al., 2022).

The metric $\chi_{\mathrm{i,t}}^{\mathrm{a}\to\mathrm{b}}$(see Eq. (2)) is composed of different factors affecting farmers' decision-making (*e.g.*, cognitive aspects, social factors, environmental issues, and economic). Here, the metric represents the farmer's willingness to have a profit higher than the average of farmers with the other practice. In other words, the farmer will only change if the average profit of the alternative practice is higher. Indeed, most farmers will not adopt sustainable farming practices if they are not profitable (Defrancesco et al., 2007; Mettepenningen et al., 2013; Wilson, 1992).

$$
\chi_{i,t}^{a\to b} = \frac{\overline{\pi_{t-1}^{\mathrm{b}}} - \pi_{\mathrm{i},\ t-1}}{\left|\overline{\pi_{t-1}^{\mathrm{b}}} - \overline{\pi_{t-1}^{\mathrm{a}}}\right|} \tag{2}
$$

Eq. (2) represents a standardized difference. The numerator is the difference between $\overline{\pi_{t-1}^{b}}$, *i.e.,* the average profit of the agent-farmers performing practice b and $\pi_{i,t-1}$, *i.e.,* the previous profit (see Eq. (2)). The denominator is the absolute value of the difference between the average profits of the agent-farmers performing farming practices b and a *last year,* $\overline{\pi_{t-1}^{b}}$ and $\overline{\pi_{t-1}^{a}}$, respectively. See Section 2.3.3 *below for the calculation of the profits.* A negative profit comparison metric indicates that the agent-farmer's profit is higher than the average profit of agent-farmers performing the other practice. A profit comparison metric greater than 1 indicates that the agent-farmer's profit is lower than the average profit of agent-farmers performing the same practice. A profit comparison metric that is strictly greater than 0 and strictly less than 1 indicates that the agent-farmer's profit is lower than the average profit of agent-farmers performing the alternative practice.

2.3.2. Disease_spread procedure

The epidemic status of the fields in year t is updated in two steps. In the first step, the procedure determines whether a field is potentially infected. In the second step, the procedure determines whether the infected field escapes the disease.

Step 1: Arrival of spores in each field

Following Precigout et al. (2022), our model distinguishes three different origins of the spores for each field: (1) spores coming from within the field left behind from the previous year's epidemic; (2) incoming spores from infectious neighboring cells; and (3) the external primary inoculum, *i.e.,* spores entering the landscape from outside the territory. As in Précigout and Robert (2022), the spores arriving in a field depend on the distance from the infectious neighboring fields. Moreover, we assumed that the spores survive one interculture period. So, if the field of an agent-farmer i was infected in the previous year ($e_{i,t-1} = 1$), it is still infected in the current year, *i.e.,* $e_{i,t} = 1$. If the field of an agent-farmer i was not infected, the field has a probability $\mathrm{u}_{\mathrm{i,t}}$ of being infected (see Eq. (3)). This probability depends on various factors:

the epidemic status of the field of agent-farmer i in the previous year t-1, the epidemic status of the fields at a distance r (radius of dispersal) in the previous year t-1, and the probability d that pathogens from an infected field will reach the agent-farmer's field and infect it. The fields of agent-farmers within a distance r from the agent-farmer i constitute the set $\Omega(i, r)$. In this way, the spores spread a certain distance from the infected fields. The probability of being infected also depends on the inoculum l, which represents the arrival of external spores every year.

$$u_{i,t} = \min\left(1; d * \left[\frac{\sum_{j\in\Omega(i,r)} s_{j,t-1}}{\sum_{j\in\Omega(i,r)} 1}\right] + l\right) \tag{3}$$

Step 2: Disease escape

In the fields, not all the arriving spores succeed in infecting new leaves (*e.g.*, spores fall to the ground or to non-susceptible plant surfaces; Levionnois et al., 2023). There is the probability h^a that fields of the agent-farmers escape the disease after being infected, and therefore their epidemic status will be healthy. This depends particularly on the type of practice. For example, monocultures of susceptible varieties are much less likely to escape than the mixtures of species (Levionnois et al., 2023).

2.3.3. Profit_update procedure

The profit $\pi_{i,t}$ (see Eq. (4)) depends on the selling production price w, the cost c per pesticide treatment, the number $q_{i,t}$ of pesticide treatments used by the agent-farmer i at each year t, and the yield of the field $y_{i,t}$ of the agent-farmer i in year t. The values $q_{i,t}$ and $y_{i,t}$ depend on both the current farming practice $k_{i,t}$ and the epidemic status $s_{i,t}$ (Table 1).

$$\pi_{i,t} = y_{i,t} * w - c * q_{i,t} \tag{4}$$

2.4. Parametrization and initial conditions

For the simulations, the parameterizations of the model entities are required, namely: (1) for the agent-farmers, the level of the change-practice-threshold; (2) for the practices, the associated pesticide treatments and the disease escape probability; (3) for the pathogens, their radius of dispersal; (4) for the chemical products, their selling price; (5) for the territory, the number of agent-farmers, their affiliation with each practice, and their location in the territory. *The change-practice-thresholds are assigned with random values to the agent-farmers following a normal law ($\mu = 0.5$, $\sigma = 0.05$) at initialization. The radius of dispersal is initialized at two ($r = 2$).* The dispersion is different between a radius of zero (no dispersal) and one and between a radius of one and two. Above two, the results do not differ. As leaf rust (Pucciniales) can spread over long distances (Bannon and Cooke, 1998; Visser et al., 2019), we chose a radius of two to reduce the simulation time. The characteristics of farming practices are provided in Table 1.

Based on the characteristics of the farming practices, we identified four distinct cases: an agent-farmer with a HI practice in a healthy field, an agent-farmer with a HI practice in an infected field, an agent-farmer with a NI practice in a healthy field, and an agent-farmer with a NI practice in an infected field. For each case, there is an associated number of pesticide treatments ($q_{i,t}$) and the yield of the field ($y_{a,s}$). By setting the selling price at 1 ($w = 1$), we calculate the profit as a function of the cost of the pesticides as shown in Fig. 2. We identified four crossover points, A ($c = 0.05$) when the profit of an agent-farmer performing HI practice in an infected field becomes lower than the profit of an agent-farmer performing NI practice in a healthy field; B ($c = 0.75$) when the profit of an agent-farmer performing HI practice in an infected field becomes lower than the profit of an agent-farmer performing NI practice; C ($c = 0.2$) when the profit of an agent-farmer performing HI practice in a healthy field becomes lower than the profit of an agent-farmer performing NI practice in a healthy field; D ($c = 0.25$) when the profit of an agent-farmer performing HI practice in a healthy field becomes lower than the profit of an agent-farmer performing NI practice.

We chose $N = 41$, thus the grid is composed by 1681 cells. We assumed that one cell represents 110 ha (average size of arable farms in France (INSEE, 2020), therefore the territory modeled is about 185,000 ha. We chose this size for several reasons. The model behaves well in relation to its resolution time. It also provides a good representation of the epidemic level. Indeed, according to Precigout et al. (2023), a grid of at least 1089 cells permits a consistent representation of the epidemic level for disease such as leaf rust. Finally, we had to avoid edge effects and have a sufficiently large size so that there was no effect of size-related stochasticity.

At initialization, 30 % of the fields are randomly infected and 7.5 % of the agent-farmers use NI farming practices, which corresponds to the percentage of agricultural areas currently used for organic farming in Europe in 2018 (Agence Bio, 2019).

2.5. Scenarios and indicators

2.5.1. Two main simulation scenarios

In the paper, we chose to study two types of scenarios to explore how the economic and ecological characteristics of an agricultural territory influence the trajectory of practices in the territory and its final status. These are just two examples of what can be explored with the present socioecological model. Here, we chose two fairly simple sets of scenarios to test the model's behavior and consistency.

The first scenarios simulate the impact of some territorial characteristics on the trajectories of agricultural practices in the territory. Along with the practices, we also characterize these trajectories with economic (agent-farmer's profit), ecological (level of disease), and environmental (number of pesticides treatments) indicators. In these simulations, the parameters characterizing the components of the territory are fixed. We follow the simulation for 60 years. We simulate the dynamic behavior of four territories corresponding to four different economic and/or ecological territorial characteristics. The four simulated territories are similar except for the economic or disease parameters. Two types of parameters are used to modify the simulated territories: the cost of pesticides (the economic characteristic) and the dispersal capacity of disease (the ecological characteristic) (see Table 2 for the parameter values). First, in a territory with low dispersal (corresponding to low disease pressure), we varied the pesticide cost from low (first territory) to medium (second territory) and high (third territory). Then, we simulated a fourth territory with a high disease dispersal associated with a medium cost of pesticides. The four simulated scenarios represent a territory with: *LowCost-LowDispersal*, low cost of pesticides and low dispersal disease capacity (low disease pressure); *MedCost-LowDispersal*, medium cost of pesticides and low disease

Table 1
Characteristics of 4 types of field being characterized by: the farming practices High-input (HI) and No-input (NI) and by the epidemics status: 1 being infected, and 0 being healthy.

Farming practice	*a*	High-input practice (HI)		No-input practice (NI)	
Epidemic status	*s*	1(infected)	0 (healthy)	1(infected)	0 (healthy)
Number of pesticide treatments	$q_{a,s}$	2	1	0	0
Yield of the field	$y_{a,s}$	0.9	1	0.75	0.8
Disease escape probability	h_a	0.2		0.4	

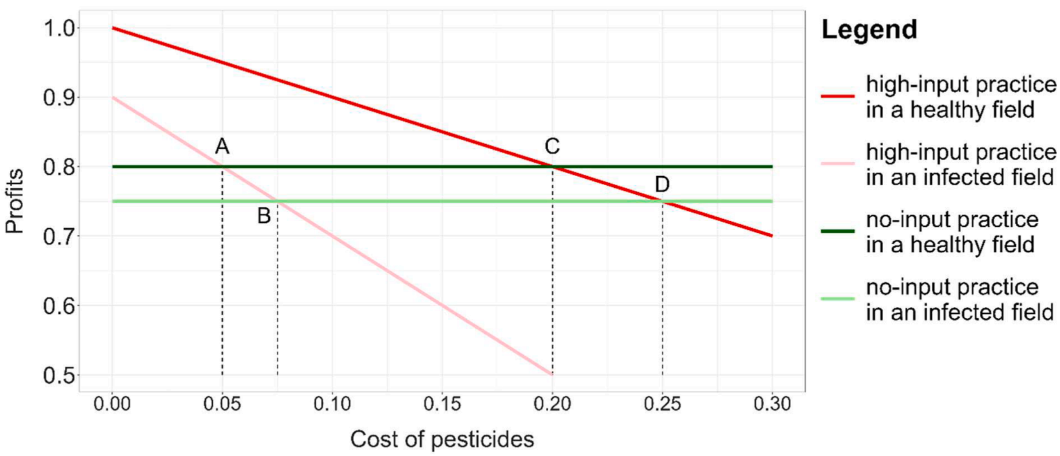

Fig. 2. Profits of agent-farmers (y-axis) depending on the cost of pesticides (y-axis). Each line corresponds to the profit of agent-farmers performing a particular practice (high-input or no-input) with a certain epidemic status (infected or healthy field). In red: high-input practice in a healthy field, in pink: high-input practice in an infected field, dark green: no-input practice in a healthy field, and clear green: no-input practice in an infected field.

Table 2
Values of the parameters used in the two mains scenarios simulated in the paper. *The parameter to be varied is indicated as a range, while the others are constant. The columns represent the values for each scenario for the cost of pesticides, the dispersal capacity and the escape probability of no-input.

			Cost of pesticides	Dispersal capacity	Escape probability of no-input
Symbol			c	d	h^{NI}
Domain			[0; 0.2]	[0; 1]	[0; 1]
Step			0.01	0.02	0.05
Two types of Scenarios	*Simulation of the trajectory*	*LowCost-LowDispersal*	0.05	0.1	0.4
		MedCost-LowDispersal	0.075	0.1	0.4
		HighCost-LowDispersal	0.1	0.1	0.4
		MedCost-HighDispersal	0.075	0.3	0.4
	Simulation of the territorial equilibrium	*Economic*	[0, 0.2]*	0.2	0.4
		Ecological	0.07	[0, 1]*	0.4
		Agronomic	0.07	0.2	[0, 1]*

dispersal capacity; *HighCost-LowDispersal*, high cost of pesticides and low disease dispersal capacity; and *MedCost-HighDispersal*, medium cost of pesticides and high disease dispersal capacity (high disease pressure). We selected these combinations to highlight contrasting results. We excluded certain combinations, as they were redundant with others (results not shown here). We analyzed the variations in the territory's trajectory using varied indicators (see below).

The second simulation scenarios aim to analyze the final states of the territories (at pseudo-equilibrium after a transient so that the dynamics are not affected by the initial state) in response to variations in the economic, ecological, and agronomic parameters. To do this, we run a sensitivity analysis of the model with three parameters: pesticide cost (*Economic scenario*), disease dispersal capacity (*Ecological scenario*), and ability of the agroecological NI practice to escape disease (*Agronomic scenario*). We explored the parameter ranges, akin to sensitivity analysis, by varying of the cost of the pesticide (from 0 to 0.2, with an interval of 0.01), the capacity of disease dispersal (from 0 to 1, with an interval of 0.02), and the escape probability (from 0 to 1, with an interval of 0.05) to investigate their impacts. We chose a reference territory with a moderate range of economic, ecological, and agronomic factors to underscore the dependence of the results on the explored parameter. The initial conditions were the same for all the simulations and all the other parameters except the varying ones. Details of the parameters used in each scenario are presented in Table 2. Because the model contains elements of stochasticity, we ran each scenario 300 times to explore the effect of stochasticity on the results, while averaging the results. The observed viability of the results is shown with error bands in Fig. 4.

To remove the influence of the initial state, we ran simulations over 300 years and collected the last 100-time steps of the trajectory of the observed indicators and average them to have an indicator of the pseudo-equilibrium situation. The simulations were done on this timescale so as to generate regime behavior. The standard deviation of the last 100 trajectory indicators represents the importance of the random fluctuations.

2.5.2. *Indicators of territory status*

To characterize the simulations, we defined indicators representative of the different aspects of the territory (Table 3). We used five types of indicators to characterize the territory: farming practice indicators (proportion of different types of farming practices in the territory), agronomic indicators (yield of fields for each practice and average for the entire territory), economic indicators (average profits of each practice and profits average for the entire territory), an ecological indicator (number of infected fields for each practice and average for the entire territory), and environmental indicators (number of pesticide treatments). These indicators are calculated using simulated variables. (Table 3)

3. Results

3.1. *Influence of pesticide costs and disease dispersal capacity on the trajectory of agricultural practices in the territory*

For the four scenarios representing different economic and ecological characteristics in the territories, we present the first 60 years of the simulated trajectories, which correspond to a transition phase between the initial configuration and a pseudo-equilibrium regime (Fig. 3).

In the scenario *LowCost-LowDispersal* (Fig. 3A), all the agent-farmers

Table 3
Definition and calculation of the four main types of indicators of the simulated territory. * The **1**( ) operator is equal to 1 if the argument is true, otherwise it is 0. The columns represent the type of indicator, the variable observed, the indicator and its mathematical notation, respectively.

Type	Variable observed	Indicators – Average of the last 100 time steps of the simulation	Notation
Farming practices	Farming practice of agent-farmers	Proportion of agent-farmers with no-input farming practice	$\overline{k_t^{NI}} = \frac{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=NI)}{N^2}$ *
		Proportion of agent-farmers with high-input farming practice	$\overline{k_t^{KI}} = \frac{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=HI)}{N^2}$
Agronomy	Yield of fields	Average yield of all agent-farmers	$\overline{y_t} = \frac{\sum_{i=1}^{N^2}y_{i,t}}{N^2}$
		Average yield of agent-farmers with no-input farming practice	$\overline{y_t^{NI}} = \frac{\sum_{i=1}^{N^2}y_{i,t}\cdot\mathbf{1}(k_{i,t}=NI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=NI)}$
		Average yield of agent-farmers with high-input farming practice	$\overline{y_t^{HI}} = \frac{\sum_{i=1}^{N^2}y_{i,t}\cdot\mathbf{1}(k_{i,t}=HI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=HI)}$
Economy	Profit of agent-farmers	Average profit of all agent-farmers	$\overline{\pi_t} = \frac{\sum_{i=1}^{N^2}\pi_{i,t}}{N^2}$
		Average profit of agent-farmers with no-input farming practice	$\overline{\pi_t^{NI}} = \frac{\sum_{i=1}^{N^2}\pi_{i,t}\cdot\mathbf{1}(k_{i,t}=NI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=NI)}$
		Average profit of agent-farmers with high-input farming practice	$\overline{\pi_t^{HI}} = \frac{\sum_{i=1}^{N^2}\pi_{i,t}\cdot 1(k_{i,t}=HI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=HI)}$
Ecology	Disease in fields	Number of fields with disease	$\overline{e_t} = \sum_{i=1}^{N^2}e_{i,t}$
		Percentage of fields with disease	$\overline{e_t^{'}} = \frac{\sum_{i=1}^{N^2}e_{i,t}}{N}$
		Number of fields with disease among no-input farming practice	$\overline{e_t^{NI}} = \sum_{i=1}^{N^2}e_{i,t}\cdot\mathbf{1}(k_{i,t}=NI)$
		Percentage of fields with disease among no-input farming practice	$\overline{e_t^{'NI}} = \frac{\sum_{i=1}^{N^2}e_{i,t}\cdot\mathbf{1}(k_{i,t}=NI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=NI)}$
		Number of fields with disease among high-input farming practice	$\overline{e_t^{HI}} = \sum_{i=1}^{N^2}e_{i,t}\cdot\mathbf{1}(k_{i,t}=HI)$
		Percentage of fields with disease among high-input farming practice	$\overline{e_t^{'HI}} = \frac{\sum_{i=1}^{N^2}e_{i,t}\cdot\mathbf{1}(k_{i,t}=HI)}{\sum_{i=1}^{N^2}\mathbf{1}(k_{i,t}=HI)}$
Environment	Pesticides used by agent-farmers	Total number of agent-farmers using one pesticide treatment	$Q_t^1 = \sum_{i=1}^{N^2}q_{i,t}\cdot\mathbf{1}(e_{i,t}=0)$
		Total number of agent-farmers using two pesticide treatments	$Q_t^2 = \sum_{i=1}^{N^2}q_{i,t}\cdot\mathbf{1}(e_{i,t}=1)$

choose the HI practice (Fig. 3A1). Indeed, the low cost of pesticides ($c = 0.05$) used in the simulation means that the HI practice is always more profitable than the NI practice (Fig. 3). Around 50 % of the fields are infected (Fig. 3A4), with the consequent use of around 1250 pesticide treatments for preventive and curative control (Fig. 3A5). Therefore, the average yield remains at around ~0.97 (Fig. 3A2) and the average profit at ~0.9 (Fig. 3A3).

In the scenario *MedCost-LowDispersal* (Fig. 3B), we increase the cost of pesticides to 0.075 compared with 0.05 in scenario *LowCost-Low-Dispersal* (Fig. 3A). At time step 60, 70 % of the farmers use the NI practice. Some agent-farmers using the HI practice with infected fields change to the NI practice (Fig. 3. B1). Over time, as more and more farmers adopt the NI practice, the number of infected fields (Fig. 3B4) and the quantity of pesticide treatments used (Fig. 3B5) decrease in the territory. For this set of parameters, the profit from the NI practice in a healthy field ($\pi_{i,t} = 0.8$) is greater than the profit from the HI practice in an infected field ($\pi_{i,t} = 0.75$) but lower than the profit from the HI practice in a healthy field ($\pi_{i,t} = 0.925$) (see Fig. 1 and parameter values in Table 1). The profit and yields of the HI farmers increase as they are less and less infected, thus taking advantage of the greater number of farmers with NI practices. Indeed, because the NI practice has a higher disease escape rate than the HI, the higher proportion of NI practices decreases the proportion of infected fields. The profit and yields of the NI farmers likewise increase, because they are also less infected.

In the scenario *HighCost-LowDispersal* (Fig. 3C), we further increased the cost of pesticides to 0.01. As in the previous scenario, agent-farmers again chose to change to the NI practice but much more rapidly than in the scenario *MedCost-LowDispersal* (Fig. 3C1 vs. Fig. 3B1). Here again, with the increase in the NI practice, the number of infected fields and pesticide treatments decreased. The average yield in the territory also decreased, because the NI practice has a general lower yield than the HI practice. The profit of agent-farmers performing the NI practice was the same as in the other scenarios. However, the profit of those performing the HI practice was lower (Fig. 3C3 vs. Fig. 3B3). For this set of parameters, as in the set of parameters for the scenario *MedCost-Low-Dispersal*, the profits from the NI practice in a healthy field ($\pi_{i,t} = 0.8$) are higher than those from the HI practice in an infected field ($\pi_{i,t} = 0.7$) but lower than those from the HI practice in a healthy field ($\pi_{i,t} = 0.9$). Moreover, the profits from the NI practice in an infected field ($\pi_{i,t} = 0.75$) are situated between those of the HI practice in infected and healthy fields. It is interesting to note that in the model, the higher cost of pesticides generates various changes in farming practices (first column in Fig. 3) ranging from stationary behaviors (Fig. 3A1) to almost linear changes (Fig. 3B1) and even exponential changes over time (Fig. 3C1).

In the scenario *MedCost-HighDispersal* (Fig. 3D), we changed the disease intensity in the territory by increasing the disease pressure compared with the scenario *MedCost-LowDispersal* (Fig. 3B). The scenario *MedCost-HighDispersal* thus has a higher disease dispersal capacity compared with the scenario *MedCost-LowDispersal*. This higher disease pressure leads to a higher proportion of infected fields (Fig. 3D4). The higher proportion of infected fields for farmers with HI practice suggests a greater likelihood of them transitioning to NI practice. Indeed, for this set of parameters, infected fields with the HI practice have a lower yield and are less profitable than the NI practice on average. Therefore, the higher disease pressure encourages farmers to change to the NI practice (Fig. 3D1). Even more remarkable, at the end of the simulation, more farmers used two pesticide treatments instead of one, whereas it was the contrary in the scenario *MedCost-LowDispersal*. It should also be noted that of the agent-farmers using the HI practice at the end of the simulation, 7.5 % were the ones that have changed their practice once, from NI at initialization to HI practice (Fig. 3D1). They were then prevented from returning to NI, as it was only possible to change practice once during the simulation. They chose to change practice at the start of the simulation, because a high proportion of the field was infected and did not represent an equilibrium state.

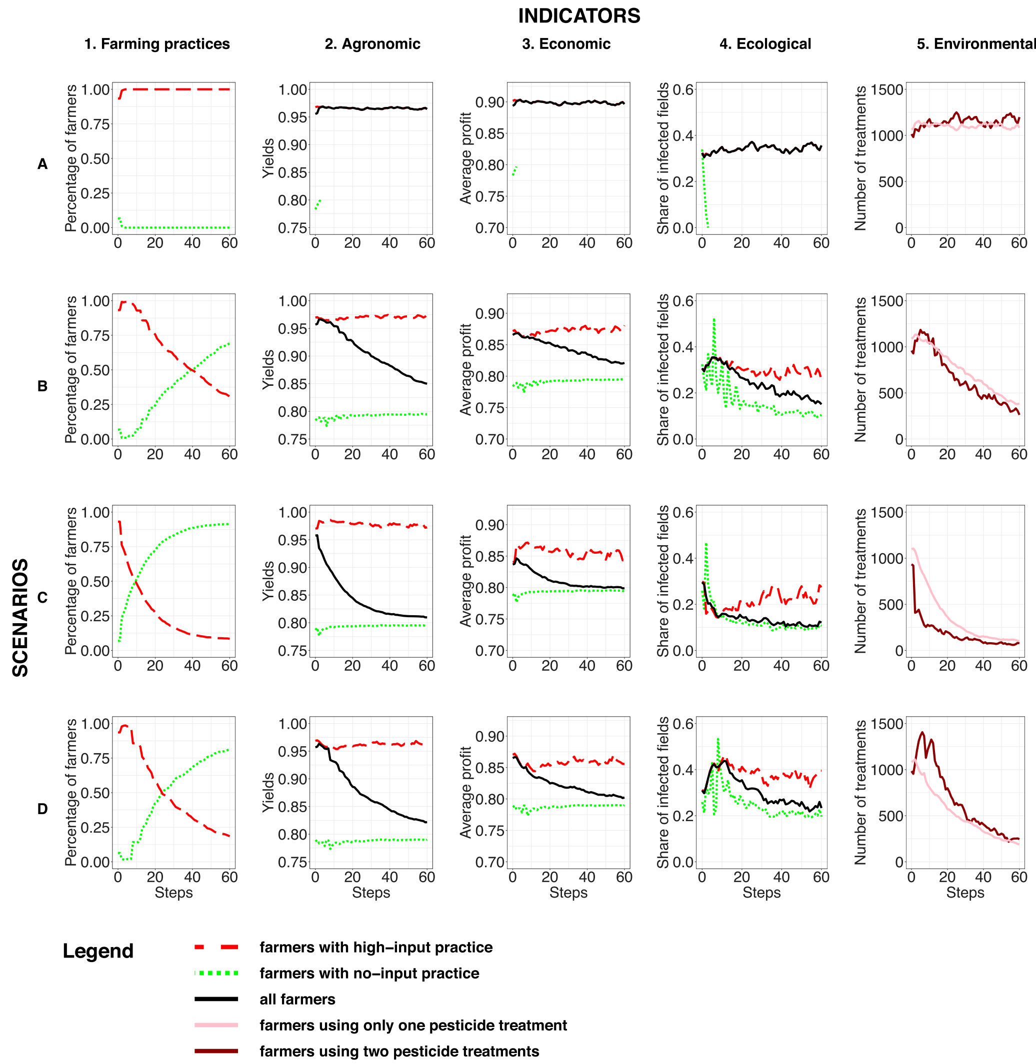

Fig. 3. Each row (A, B, C, and D) represents the simulated territorial trajectory in a particular scenario: A – *LowCost-LowDispersal*; B – *MedCost-LowDispersal*; C – *HighCost-LowDispersal*; D – *MedCost-HighDispersal*. Each column (from 1 to 5) represents calculated indicator: column 1 – proportion of agent-farmers with different farming practices in the landscape ($\overline{k_t^{HI}}$ and $\overline{k_t^{NI}}$); column 2 – agronomic (average yields of agent-farmers with different farming practice) ($\overline{y_t^{HI}}$ and $\overline{y_t^{NI}}$); column 3 – economic: average profit of the farmers ($\overline{\pi_t^{HI}}$ and $\overline{\pi_t^{NI}}$); column 4 – ecological: number of infected fields in the landscape ($\overline{e_t^{HI}}$ and $\overline{e_t^{NI}}$); column 5 - environmental: number of pesticide treatments used in the landscape (Q_t^1 and Q_t^2). Line colors in the plots represent the type of farmer's practices (HI in red, NI in green).

The scenarios *MedCost-LowDispersal* and *MedCost-HighDispersal* illustrate a different speed of transition (the number of steps required to reach the equilibrium state). The equilibrium states for both contexts are the same but with a higher transition speed for *MedCost-HighDispersal* than for *MedCost-LowDispersal*. Moreover, even though the same number of farmers changed their practice by the end of the two simulations, the share of infected fields was different.

3.2. Sensitivity of the model to the three parameters: pesticide cost, disease dispersal capacity, and efficacy of disease escape with the agroecological no-input practice

In Fig. 4, we show how the territorial indicators at the pseudo-equilibrium varied along with the ranges of pesticide costs (row A), disease dispersal capacities (row B), and probabilities of disease escape for the NI practice (row C). We used four types of indicators to characterize the territory, from left to right: proportion of agent-farmers applying *NI* and *HI* practices in the territory, average profits for both types of practices (economic indicators), number of infected fields for both types of practices (ecological indicators), and number of pesticide treatments for *HI* practices (environmental indicators). The percentage of infected fields per practice corresponds to the number of fields infected with the practice (the ecological indicator, column 3) out of the number of agent-farmers performing the practice (column 1).

The pesticide cost has a strong "threshold" effect on the number of agent-farmers performing each type of practice in the territory (Fig. 4A1). When the pesticide cost increases from 0.07 to 0.075 (tipping point), the number of agent-farmers with the HI practice drops abruptly from 100 % to 7.5 % (and thus inverses with the NI practice). The pesticide cost of 0.075 corresponds to a point where the profits from the NI practice in a healthy field ($y_{NI,0} = 0.8$) and infected field ($y_{NI,0} = 0.75$) are equal to or higher than those from the HI practice in an infected field ($y_{HI,1} = 0.75$) (Fig. 2). Hence, this is the cost at which agent-farmers performing the HI practice in an infected field decide to switch to the NI practice. At a pesticide cost $c = 0.2$, regardless of whether the fields were infected, the agent-farmers with the NI practice have a higher profit (Fig. 2). Therefore, from this price onwards, agent-farmers who perform the NI practice at initialization never change their

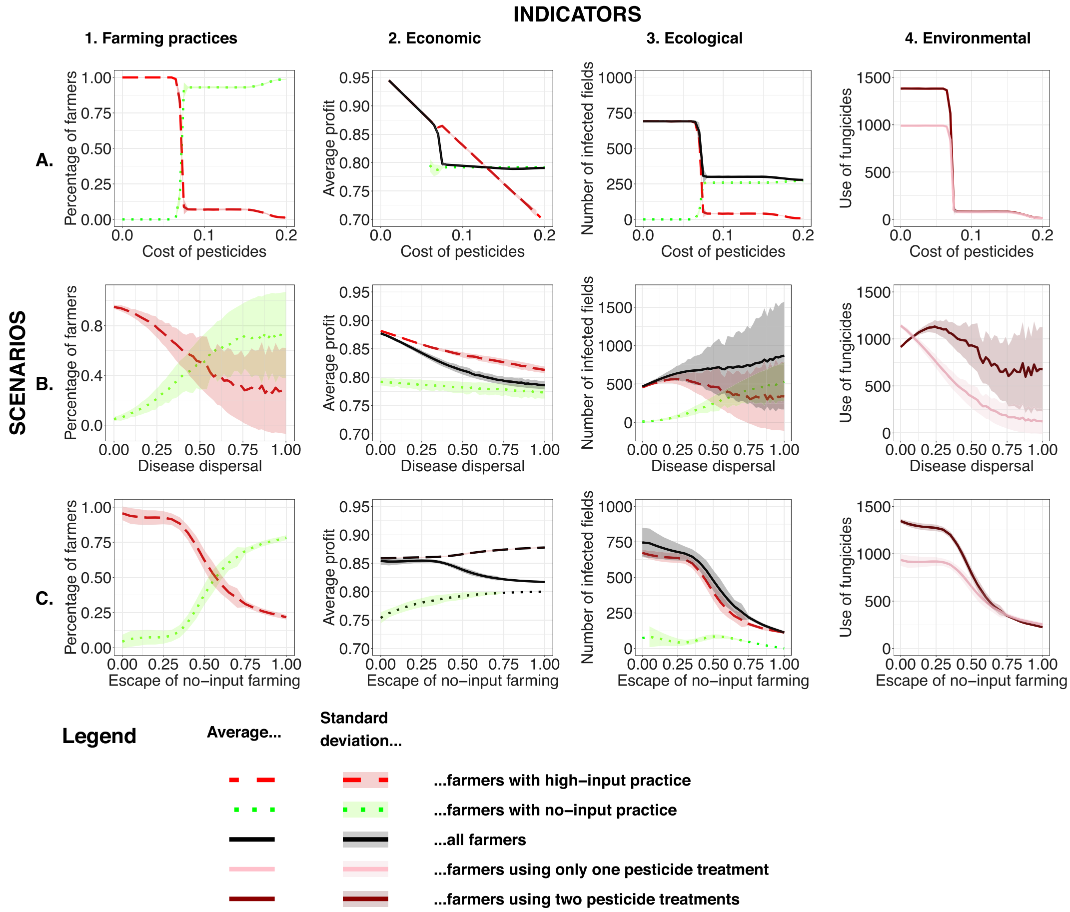

Fig. 4. Each row (A, B, and C) corresponds to simulation of territorial indicators at the equilibirum for different set of parameters: A – Economic scenario corresponding to increase in pesticide cost; B – Ecological scenario corresponding to disease dispersal capacity; C – Practice efficiency scenario, corresponding to the ability of the agroecological NI practice to escape disease. Each column (from 1 to 4) represents calculated territorial indicator: 1 – proportion of different types of farming practices in the landscape ($\overline{k_t^{HI}}$ and $\overline{k_t^{NI}}$); 2 – economic: average profit of the farmers ($\overline{\pi_t^{HI}}$ and $\overline{\pi_t^{NI}}$); 3 – ecological: number of infected fields in the landscape ($\overline{e_t^{HI}}$ and $\overline{e_t^{NI}}$); 4 – environmental: number of pesticide treatments used in the landscape (Q_t^1 and Q_t^2). Line colors in the plots represent the type of farmer's practices (HI in red, NI in green). All mathematical symbols are defined in Table 2.

practice and therefore all agent-farmers end up using the NI practice. The number of infected fields and the number of treatments follow the threshold effect of the percentage of practices. The total number of infected fields decreases in line with the threshold. Nevertheless, some fields are still infected. The effect of pesticide costs on average profits is not the same as the threshold effect of the percentage of practices. The average income of agent-farmers performing the NI practice, which is not linked to the cost of pesticides, remains stable, slightly less than 0.8. The income of agent-farmers performing the HI practice is rather linear, decreasing in line with the increasing pesticide cost.

Fig. 4B shows the average indicators at the pseudo-equilibrium along a range of disease dispersal capacities. The number of agent-farmers performing the NI practice increases almost linearly with the increase in disease dispersal probability (Fig. 4B1). The total number of infected fields increases slowly. Nevertheless, the disease dispersal capacity has a different effect on the number of NI and HI infected fields. The former increase substantially, whereas the latter decrease (Fig. 4B3). However, as the number of HI infected fields decreases less quickly than the number of agent-farmers performing HI, the share of HI infected fields increases (Fig. A2). Conversely, as the number of NI infected fields increases less quickly than the number of agent-farmers performing NI, the share of NI infected fields increases (Fig. A2). As the number of HI infected fields decreases, the number of pesticide treatments decreases. The use of two treatments is almost always higher than one treatment, with the ratio between the use of two treatments and one treatment increasing (Fig. 4B4). Due to the increase in the proportion of infected fields for both practices, the average incomes decrease whether for agent-farmers performing HI or NI practices (Fig. 4B2). The simulations show that disease pressure in the area has a major impact on the type of practices implemented by farmers or at least with regard to the pathogens' capacity to spread. In the simulation, areas with high disease dispersal will lead to areas with more NI practices. This is for two reasons in the model: NI practices help reduce disease pressure, and when disease pressure is high, pesticide treatments for agent-farmers performing the HI practice become too costly.

The effect of variation of the disease escape probability h of NI practices differs from the threshold effect of the pesticide cost or the linear effect of the disease dispersal capacity. For a low disease escape capacity of NI practices, between $h = 0$ and $h = 0.3$ of the NI practice, there is a plateau followed by a quick decrease. From $h = 0$ to $h = 0.2$, the probability of escape with the NI practice is lower than with the HI practice (as a reminder, the probability of escape with the HI practice is 0.2). Therefore, the number of infected fields of agent-farmers performing the NI practice is considerably larger than that of those performing the HI practice. Consequently, the profits of the agent-farmers performing the NI practice is low. From 0.2, the proportion of infected fields is lower for agent-farmers performing the NI practice, although their profits remain stable (Fig. 4C2). In the plateau, the number of each type of practice remains the same (high for HI and low for NI) (Fig. 4C1). It is only from $h = 0.3$ onwards that some agent-farmers start to change their practices. Afterwards, when increasing the disease escape of NI practices ($h > 0.3$), the number of agent-farmers performing the NI practice increases more than linearly with the increase in the disease escape probability. By contrast, the number of agent-farmers performing the HI practice decreases. The increase in the probability of escape leads to a decrease in the number of infected fields (Fig. 4C3). HI farmers have the greatest decrease in the number of infected fields. They benefit from increasing disease escape of the NI practices that decreases the disease inoculum in the landscape. The number of treatments follows the number of infected fields and then decreases after the plateau (Fig. 4C4). Here, we test the efficacy of agroecological practices to prevent the disease. In other words, the performance of these practices in terms of disease escape. In the simulations, the more effective these practices are, the more the territories adopt agroecological practices. It is interesting to note that all the fields in the territory (for both practices) benefit from the performance of the NI practices because of the transport of spores from field to field that is decreased in all the landscape.

4. Discussion

In this study, we built an agent-based model of an agricultural territory to analyze how economic, ecological, and agronomic factors impact pesticide use and how they can be a potential lever to reduce them. We explored how the economic and ecological characteristics of an agricultural territory influence the trajectory of change in the territory and its final status. Our results show that (1) the ecological dynamics and farmers' decision-making dynamics interact in a complex way to determine the practices; (2) the agroecosystems are subject to threshold, linear, and more-than-linear trajectories according to different factors variation; and (3) various trade-offs exist between ecological, economic, and agronomic indicators.

4.1. Feedbacks between ecological and economic systems

One key aspect of our approach is its ability to simulate the interactions between ecological variables, economic variables and farmers' decision-making variables. Our findings are in line with the literature that emphasizes the need to simultaneously address ecological, economic and social components as well as their interaction in order to manage nature reserves (Chen et al. 2023) and to effectively reduce pesticide use in territories (Lescourret et al., 2015; Rebaudo and Dangles, 2013). The model of Chien et al. (2023) highlights the integration of various mechanisms of two-way human-nature interaction through an agent-based model. Lescouret et al. (2013) proposed a social-ecological conceptual framework including successive loops between management, ecosystem, multiple services and social system. They illustrated it with a cereal-growing area where the limitation of pesticides is one of the elements of this loop. Rebaudo And Dangles (2013) stressed the need to develop a comprehensive and empirically based framework for linking the social and ecological disciplines across space and time in pest management.

In our model, a territory with a high cost of pesticides is favorable to transition to agroecological no-pesticide-use practices (NI). As the cost of pesticide treatments increases, it reaches a point where the income of agent-farmers performing the intensive high-pesticide-use (HI) practice falls below that of agent-farmers performing the agroecological practice. This threshold marks a change in the decision-making of agent-farmers who subsequently choose to change their practice. In terms of public action, the cost of pesticides can be raised through levers such as taxes and fees, although their effectiveness is not clear in the literature. In their model, Grovermann et al. (2017) showed that a pesticide tax alone has little effect on synthetic pesticide use. Although Böcker and Finger (2016) found that an additional tax does not necessarily lead to a pesticide reduction, Zilberman et al. (1991) demonstrated that pesticide fees encourage farmers to become more selective in their choices and to reduce pesticide use. Fernandez-Cornejo et al. (1998) found the same results but stressed that substantial taxes would be needed to achieve moderate reductions in pesticide use. One explanation for the different results on the effect of higher pesticide costs is the environmental circumstances (Böcker and Finger, 2016), which was confirmed by our model. Two territories with the same average cost of pesticides but with a different level of disease can be more or less favorable to agroecological practices.

For the agroecological NI practice, the higher probability of not being infected by the disease contributes to the overall reduction in disease pressure in the territory, and especially for the agent-farmers with the NI practice. These agent-farmers have a high probability of having healthy fields, and thus their average yield and income increase, surpassing those of the intensive HI practice in an infected field. Farmers performing the HI practice therefore have an increasing incentive to change their practice. Following Malézieux et al. (2009), the higher disease escape rate is the advantage of an agroecological practice: it reduces the impact of pests and diseases and increases land productivity. Other studies (Kleemann and Abdulai, 2013; Milheiras et al., 2022) show a positive relationship between the intensity of agroecological practices and income or yield. In the territories favorable to the agroecological NI practice, the number of infected fields and treatments used decrease. As shown by Scholberg et al. (2010) or Deike et al. (2008), alternative agroecological practices have the advantage of reducing weeds and pest infestation and thus reducing the quantity of pesticide treatments used. It is interesting to note that in the simulation, all the fields in the territory (for both practices) benefit from the disease escape of the agroecological practices because of a general limited transport of spores from field to field in the landscape.

4.2. Threshold, linear, and non-linear effects

The interactions between ecological and economic variables cause a non-linear response of the simulated indicators characterizing the territory. This result is in line with studies on the socio-ecosystems of agricultural territories: environmental, economic, and social components are closely linked and interact in a non-linear and complex way (Chen et al., 2023; Levin et al., 2013; Paz et al., 2020; Tittonell, 2014). In the model, the increase in the cost of pesticides has a threshold effect on the simulated proportion of agent-farmers in each type of practice in the territory, the increase in the disease dispersal capacity has a linear effect, and the increase in the probability of disease escape with the agroecological practice has a more-than-linear effect in the simulated proportion. These factors do not induce the same trajectory territorial for the varied economic, ecological, and environmental indicators. For instance, for the increase in the dispersal capacity, we observe a linear effect for the proportion of farming practices and for the economic indicators, but we did not observe the linear effect for the ecological and environmental indicators. These results are in line with the model of Sabatier et al. (2013) in which pesticide use has a non-linear effect on biodiversity and ecosystem services, leading to a negative effect on yield.

4.3. Trade-offs

The simulations highlight the trade-offs between the different indicators characterizing the territory. These trade-offs are not linear and vary depending on the initial parameters of the simulated territory.

There is a trade-off between the desire for a high average income and a reduction in the amount of pesticide treatments used. Higher pesticide use is associated with higher average incomes. This is in line with the negative relationships observed between production and ecology in conventional systems (Barraquand and Martinet, 2011; Drechsler et al., 2007; Mouysset et al., 2015; Polasky et al., 2008; Sabatier et al., 2015). However, the model shows that the strength of this trade-off depends on the initial conditions. Indeed, Seufert et al. (2012) highlight that the differences between organic and conventional yields are highly contextual, depending on both system and site characteristics. In a recent study about tropical farming systems, Wies et al. (2023) shows a similar result. They found a strong trade-off between conservation and economic profits that are depending on the total farming area, initial configurations and the number of external inputs used. This result encourages the proposal of payment for environmental services (Jayachandran, 2023), in this case environmental health (through reduced use of pesticides), to compensate for this trade-off.

However, the number of NI agroecological farmers and the number of infected fields do not always have the same relationship. A trade-off occurs when the cost of pesticides and the probability of desease escape increase, whereas the trade-off disappears when the disease dispersal capacity increases. The number of infected fields may also depend on the type of diseases. The study of Meunier et al. (2018) showed that organic farming has lower pathogen infestation, similar levels of animal pest infestation, and much higher levels of weed infestation relative to conventional farming. This result is also highlighted by Falconer and Hodge (2001) who showed that different pesticide tax specifications vary in terms of the magnitude and direction of their impacts and can have negative side effects.

4.4. Refining policy formulation: suggestions based on research findings

The model was built in order to allow simulating impacts of various levers across territories, considering their intensity, location, and impact proportions. In its current version however, the model does not explicitly incorporate policy instruments, but the simulations emphasize the importance of several types of incentives. Financial incentives (the introduction of taxes on pesticides or subsidies for alternative practices) or increasing the efficacy of alternative crop protection practices have quite a strong impact in changing practices in the simulated territory. Other incentives such as providing a safety net income earned in agroecological farming or prevent any reversal to traditional farming in bad periods would be interesting to test with the model. The model also makes clear that policies that would reduce the external pressure of pests would significantly contribute to reducing the use of pesticides. It could be incentivizing ecological practices or agroecological infrastructures that would reduce pathogen pressure (*i.e.* the introduction of hedgerows (Ministère de l'Agriculture, 2023)).

Additionally, the model lends itself to extensions and enrichments which can provide a deeper understanding of possible policies. While these are not developed in this paper, we now mention these possible extensions: a richer description of farmers' beliefs and perceptions, the additional influence of non-pecuniary considerations on their decisions (Honoré et al., 2024), and social variables such as the introduction of local training or the creation and strengthening of networks of farmers committed to change (Meunier et al. 2024).

4.5. Limits and perspectives

In our model, we based our assumptions about decision-making on the bounded rationality theory (Simon, 1984), considering that (1) farmers consider the possibility of change if it exceeds a change-practice-threshold and that (2) the change is modeled as a stochastic event with a certain probability. In this version of the model, the key factor is economic and based on both the profit of individual farmers and the average profits of farmers in the territory depending on the farming practices. Many studies have highlighted the role played by economic factors such as farm size, farm area, farm capital, land tenure, and income level in farmers' decision-making to engage in agri-environmental practices (Baumgart-Getz et al., 2012; Floress et al., 2017; Gachango et al., 2015; Mettepenningen et al., 2013; Mzoughi, 2011; Toma and Mathijs, 2007). Nevertheless, several studies have shown that farmers' decision-making process about their farming practice is also influenced by non-economic factors (Dessart et al., 2019; Lastra-Bravo et al., 2015) such as social (*e.g.*, social norms in Le Coent et al. (2021)), dispositional (*e.g.*, sense of responsibility in Walder and Kantelhardt, 2018), environmental factors (*e.g.*, environmental concern in Amblard (2019) and Giovanopoulou et al. (2011) or the perception of environmental risk in Toma and Mathijs (2007)) and individual behavioral factor (Meunier et al., 2024). This is why we have a parameter in the model accounting for the farmer resistance to change but that we have not varied in the presented simulations (data not shown). Other factors have also been highlighted as influencing pesticide use, as traditional culture (*e.g.,* Zhang and Li (2016) where farmers excessively use pesticides due to traditional culture), farmers' classification and proportion of each class (*e.g.*, Bourceret et al., 2023). The framework of the model has been done to make it easy to take into account other factors in the decision-making rule such as individual sensitivity (a parameter is in the model) or social interactions (with the knowledge for each farmer of the location of other farmers and the possibility of creating networks of connected farmers). Participation in farmers' groups has been shown to be important for change (Karaya et al., 2020). This is an important perspective for our work.

Second, in the model, we have considered social interaction between farmers, but in this version, we assumed that it is focused on knowledge of other farmers' profits. Nevertheless, other various social interactions could have been used as revealed in the literature. Several studies have highlighted the role of social factors, specifically various social norms. Le Coent et al. (2021) and Kuhfuss et al. (2016) demonstrated that farmers' decision to participate in an agri-environmental program was influenced by an injunctive norm (*i.e.,* the desire to comply with the rule) and a descriptive norm (*i.e.,* the desire to behave like the group). Showing one's environmental commitment to others can also influence farmers' adoption of pro-environment practices (Mzoughi, 2011). One perspective of the current work would be to improve the model with a factor relating to the social norm. For example, the farmers would be aware of the practices of other farmers in their social network (Bourceret et al., 2022).

Finally, one remaining challenge is to perform empirical studies to 1) calibrate our model on a territory with real-world data on the characteristics of the farmers, environment, and decision-making processes; 2) refine the model so that it is closer to certain dynamics that we want to study specifically. The model could be applied with empirical data to different territories, provided that the necessary calibration data are available. For instance, the agricultural characteristics (*e.g.*, size, location, type of farming systems) could be defined using data from the French agricultural census (*e.g.*, Xu et al., 2018). Decision-making processes, with the choice of different factors influencing the farmers and the decision model, could be determined using serious games (*e.g.*, Noeldeke et al., 2022) or surveys. The territories may be different in term of types of farmers, yield profiles, technical coefficients of practices, types of pathogens. Climatic data such as temperature, humidity and wind could be taken into account. These variables can be integrated using geographic information system (Tveito et al., 2005). They would provide a better simulation of both disease development and yield. The advantage of using this model applied to a particular territory would be to apply levers that are of interest to local farmers obtaining results linked to the territory. . We think an interesting prospect would be to carry out the model calibration, scenario definition and simulation analyses with local stakeholders (Lacombe et al. 2018).

5. Conclusion

We presented a modeling framework of a territorial socio-ecosystem that takes spatial and temporal dimensions into account. This ecological-social model enabled us to explore the impact of economic, ecological, and agronomic factors on the trajectory and equilibrium of territories agroecological transition. Our results show the following: (1) policies for pesticide reduction should take into consideration the complex interactions between ecological dynamics and farmers' decision-making in terms of practices; (2) agroecosystems are subject to threshold, linear, and more-than-linear trajectories according to different factors variation; and (3) various trade-offs exist between ecological, economic, and agronomic indicators. Next important steps would be to calibrate and discuss territorial levers in a territorial context with farmers (Lacombe et al., 2018) and to take into account diversity of farmers in the model (Meunier et al., 2024) and specificity of the territories (Honoré et al., 2024).

CRediT authorship contribution statement

Amélie Bourceret: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Francesco Accatino:** Writing – review & editing, Validation, Methodology, Conceptualization. **Corinne Robert:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Amelie Bourceret reports financial support was provided by French National Research Agency. Francesco Accatino reports financial support was provided by French National Research Agency. Corinne Robert reports financial support was provided by French National Research Agency. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to my data.

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Appendix 1

Table of parameters and variables

* P: parameter; V: variables

Table of parameters and variables relative to agent-farmers

Type*	Name	Description	Notation	Domain	Unit
P	Domain size	Number of cells	N		w.u.
P	Change-practice-threshold of farmer	Change-practice-threshold at which the farmer *i* starts to be willing to change farming practice	v_i	[0; 1]	w.u.
V	Practice	Farming practice of the farmer *i* in year *t*	$k_{i,t}$	{NI, HI}	w.u.
V	Field epidemic status	Status of the epidemic in the field of the farmer *i* in year *y*	$s_{i,\ t}$	{0; 1}	w.u.
V	Probability to be infected	Probability for the field of the farmer *i* to be infected at each year *t*.	$u_{i,\ t}$	[0; 1]	w.u.
V	Number of treatments	Number of treatments of pesticides used by the farmer *i* in year *t*	$q_{i,\ t}$	[0, 1, 2]	w.u.
V	Yield	Relative proportion of the maximum potential yield of the field of the farmer *i* in year *t*	$y_{i,t}$	[0; 1]	w.u.
V	Relative proportion of profit	Relative proportion of the maximum potential profit of the field of the farmer *i* in year *t*	$\pi_{i,t}$	[0; 1]	w.u.
V	Escape probability	The probability of the field of the farmer *i* in year *t* to escape from the disease and be healthy	$h_{i,t}$	[0; 1]	w.u.
V	*Profit comparison metric*	*The willingness of the agent-farmer* i *in year* t to have *a profit higher than the average profit of other farmers performing the same practice* a.	$\chi_{i,t}^{a\to b}$	[0; 1]	w.u.
V	Probability of change	Probability of change of farmer *i* from its practice *a* to the farming practice *b* in year *t*	$p_{i,t}^{a\to b}$	[0; 1]	w.u.

Table of parameters and variables relative to practices

Type*	Name	Description	Notation	Domain	Unit
P	Number of treatments of the practice *a*	Number of treatments of pesticides for each practice *a*	$q^{a,s}$	[0; +infinity [	treatment
P	Relative proportion of yield of the practice a	Level of yield of the practice a with the epidemic status s (proportion relative to the maximum yield)	$y^{a,s}$	[0; 1]	w.u.
P	Maximal potential yield	Maximal potential yield	$y^{max,a}$	[0; +infinity [	T/ha
P	Escape probability for the practice *a*	Probability of escape of the farming practice *a*	h^a	[0; 1]	%

Table of parameters and variables relative to economy

Type*	Name	Description	Notation	Domain	Unit
P	Maximal potential profit	Maximal potential profit	π^{max}	[0; +infinity [	€
P	Selling price	Selling price per yield	w	[0; 1]	w.u.
P	Cost per treatment	Cost per treatment of pesticides	c	[0; 1]	w.u.

Table of parameters and variables relative to pathogen

Type*	Name	Description	Notation	Domain	Unit
P	Dispersal capacity	Probability of infected fields infecting the field	d	[0; 1]	%
P	Radius of dispersal	Maximum distance at which the disease can disperse	r	[0; N/2]	?
P	Inoculum	Additional probability to be infected at each year	I	[0; 1]	%

Appendix 2

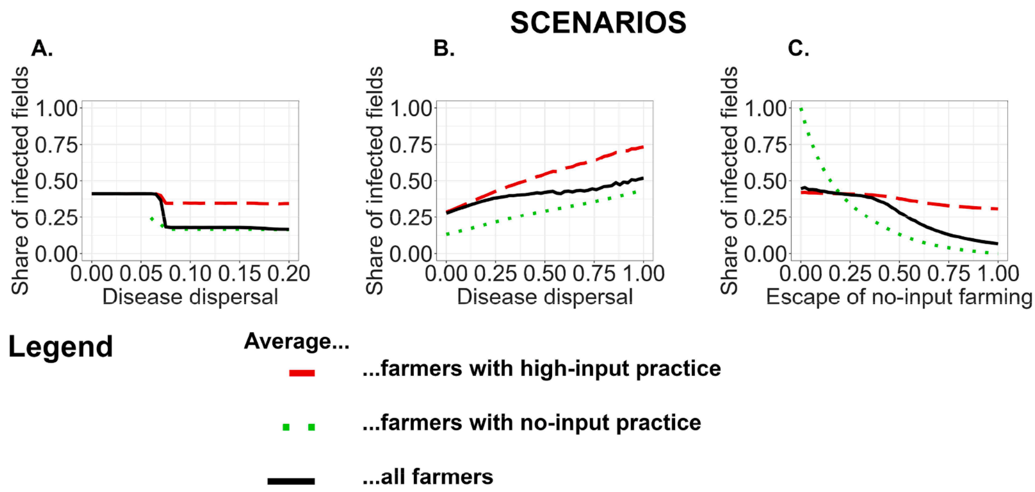

Fig. A2. Share of infected fields (*i.e.,* number of infected fields in the landscape ($\overline{e_t^{HI}}$ and $\overline{e_t^{NI}}$) divided by the proportion of different types of farming practices in the landscape ($\overline{k_t^{HI}}$ and $\overline{k_t^{NI}}$)). Each column (A, B, and C) corresponds to simulation for different set of parameters: A – Economic scenario corresponding to increase in pesticide cost; B – Ecological scenario corresponding to spore dispersal capacity; C – Practice efficiency scenario, corresponding to the ability of the agroecological NI practice to escape disease. All mathematical symbols are defined in Table 2.

References

Agence Bio, 2019. Les chiffres 2018 du secteur bio, Dossier de presse. Agence Française pour le Développement et la Promotion de l'Agriculture Biologique.

Aktar, W., Sengupta, D., Chowdhury, A., 2009. Impact of pesticides use in agriculture: their benefits and hazards. Interdiscip. Toxicol. 2, 1–12. https://doi.org/10.2478/v10102-009-0001-7.

Altieri, M.A., 2018. Agroecology: the Science of Sustainable Agriculture. CRC Press.

Altieri, M.A., Nicholls, C.I., Henao, A., Lana, M.A., 2015. Agroecology and the design of climate change-resilient farming systems. Agron. Sustain. Dev. 35, 869–890. https://doi.org/10.1007/s13593-015-0285-2.

Alvarez, R., 2022. Comparing productivity of organic and conventional farming systems: a quantitative review. Arch. Agron. Soil Sci. 68, 1947–1958. https://doi.org/10.1080/03650340.2021.1946040.

Amblard, L., 2019. Collective action for water quality management in agriculture: the case of drinking water source protection in France. Glob. Environ. Change 58, 101970. https://doi.org/10.1016/j.gloenvcha.2019.101970.

Anastasiadis, S., Chukova, S., 2019. An inertia model for the adoption of new farming practices. Int. Trans. Oper. Res. 26, 667–685. https://doi.org/10.1111/itor.12336.

Bannon, F.J., Cooke, B.M., 1998. Studies on dispersal of Septoria tritici pycnidiospores in wheat–clover intercrops. Plant Pathol 47, 49–56. https://doi.org/10.1046/j.1365-3059.1998.00200.x.

Barberi, P., 2002. Weed management in organic agriculture: are we addressing the right issues? Weed Res 42, 177–193. https://doi.org/10.1046/j.1365-3180.2002.00277.x.

Barraquand, F., Martinet, V., 2011. Biological conservation in dynamic agricultural landscapes: effectiveness of public policies and trade-offs with agricultural production. Ecol. Econ. 70, 910–920.

Baumgart-Getz, A., Prokopy, L.S., Floress, K., 2012. Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. J. Environ. Manage. 96, 17–25. https://doi.org/10.1016/j.jenvman.2011.10.006.

Bebber, D.P., Holmes, T., Gurr, S.J., 2014. The global spread of crop pests and pathogens. Glob. Ecol. Biogeogr. 23, 1398–1407. https://doi.org/10.1111/geb.12214.

Begg, G.S., Cook, S.M., Dye, R., Ferrante, M., Franck, P., Lavigne, C., Lövei, G.L., Mansion-Vaquie, A., Pell, J.K., Petit, S., Quesada, N., Ricci, B., Wratten, S.D., Birch, A.N.E., 2017. A functional overview of conservation biological control. Crop Prot 97, 145–158. https://doi.org/10.1016/j.cropro.2016.11.008.

Beillouin, D., Ben-Ari, T., Malézieux, E., Seufert, V., Makowski, D., 2021. Positive but variable effects of crop diversification on biodiversity and ecosystem services. Glob. Change Biol. 27, 4697–4710. https://doi.org/10.1111/gcb.15747.

Böcker, T., Finger, R., 2016. European pesticide tax schemes in comparison: an analysis of experiences and developments. sustainability 8, 378. https://doi.org/10.3390/su8040378.

Boudreau, M.A., 2013. Diseases in Intercropping Systems. Annu. Rev. Phytopathol. 51, 499–519. https://doi.org/10.1146/annurev-phyto-082712-102246.

Bourceret, A., Amblard, L., Mathias, J.-D., 2022. Adapting the governance of social–ecological systems to behavioural dynamics: an agent-based model for water quality management using the theory of planned behaviour. Ecol. Econ. 194, 107338.

Bourceret, A., Amblard, L., Mathias, J.D., 2023. How do farmers' environmental preferences influence the efficiency of information instruments for water quality management? Evidence from a social-ecological agent-based model. Ecol. Mode. 478, 110300.

Catalogna, M., Dubois, M., Navarrete, M., 2018. Diversity of experimentation by farmers engaged in agroecology. Agron. Sustain. Dev. 38, 50. https://doi.org/10.1007/s13593-018-0526-2.

Chen, Y., Xu, L., Zhang, X., Wang, Z., Li, H., Yang, Y., You, H., Li, D., 2023. Socio-econ-ecosystem multipurpose simulator (SEEMS): an easy-to-apply agent-based model for simulating small-scale coupled human and nature systems in biological conservation hotspots. Ecol. Model. 476, 110232 https://doi.org/10.1016/j.ecolmodel.2022.110232.

Crase, L., Maybery, D., 2004. Personality and landholders' management of remnant bush and revegetation in the murray catchment. Australas. J. Environ. Manag. 11, 21–33. https://doi.org/10.1080/14486563.2004.10648595.

Darnhofer, I., Fairweather, J., Moller, H., 2010. Assessing a farm's sustainability: insights from resilience thinking. Int. J. Agric. Sustain. 8, 186–198. https://doi.org/10.3763/ijas.2010.0480.

David, P., Roemer, C., Anibaldi, R., Rundle-Thiele, S., 2022. Factors enabling and preventing farming practice change: an evidence review. J. Environ. Manage. 322, 115789 https://doi.org/10.1016/j.jenvman.2022.115789.

De Ponti, T., Rijk, B., Van Ittersum, M.K., 2012. The crop yield gap between organic and conventional agriculture. Agric. Syst. 108, 1–9. https://doi.org/10.1016/j.agsy.2011.12.004.

De Schutter, O., 2012. Agroecology, a tool for the realization of the right to food (Ed.). In: Lichtfouse, E. (Ed.), Agroecology and Strategies for Climate Change. Springer Netherlands, Dordrecht, pp. 1–16. https://doi.org/10.1007/978-94-007-1905-7_1.

Defrancesco, E., Gatto, P., Runge, F., Trestini, S., 2007. Factors Affecting Farmers? Participation in Agri-environmental Measures: a Northern Italian Perspective. J. Agric. Econ. 0 https://doi.org/10.1111/j.1477-9552.2007.00134.x, 071003055534001-???

Deike, S., Pallutt, B., Melander, B., Strassemeyer, J., Christen, O., 2008. Long-term productivity and environmental effects of arable farming as affected by crop rotation, soil tillage intensity and strategy of pesticide use: a case-study of two long-term field experiments in Germany and Denmark. Eur. J. Agron. 29, 191–199.

Dessart, F.J., Barreiro-Hurlé, J., van Bavel, R., 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Eur. Rev. Agric. Econ. 46, 417–471. https://doi.org/10.1093/erae/jbz019.

Drechsler, M., Wätzold, F., Johst, K., Bergmann, H., Settele, J., 2007. A model-based approach for designing cost-effective compensation payments for conservation of endangered species in real landscapes. Biol. Conserv. 140, 174–186.

Ekroth, A.K.E., Rafaluk-Mohr, C., King, K.C., 2019. Host genetic diversity limits parasite success beyond agricultural systems: a meta-analysis. Proc. R. Soc. B Biol. Sci. 286, 20191811 https://doi.org/10.1098/rspb.2019.1811.

European parliament, Council, 2009. Directive establishing a framework for Community action to achieve the sustainable use of pesticides.

Falconer, K., Hodge, I., 2001. Pesticide taxation and multi-objective policy-making: farm modelling to evaluate profit/environment trade-offs. Ecol. Econ. 36, 263–279. https://doi.org/10.1016/S0921-8009(00)00236-6.

FAO, 2022. Pesticides use, Pesticides Trade and Pesticides Indicators Global, Regional and Country trends, 1990–2020. !FAOSTAT Analytical Brief.

Faraldo, C., Bernard, H., Lebreton, A., Puisieux, K., 2022. Réduction des peseticides en France : pourquoi un tel échec ?, Agriculture. Fondation pour la NAture et l'Homme Think Tank.

Feola, G., Binder, C.R., 2010. Towards an improved understanding of farmers' behaviour: the integrative agent-centred (IAC) framework. Ecol. Econ. 69, 2323–2333. https://doi.org/10.1016/j.ecolecon.2010.07.023.

Fernandez-Cornejo, J., Jans, S., Smith, M., 1998. Issues in the economics of pesticide use in agriculture: a review of the empirical evidence. Appl. Econ. Perspect. Policy 20, 462–488. https://doi.org/10.2307/1350002.

Floress, K., García de Jalón, S., Church, S.P., Babin, N., Ulrich-Schad, J.D., Prokopy, L.S., 2017. Toward a theory of farmer conservation attitudes: dual interests and willingness to take action to protect water quality. J. Environ. Psychol. 53, 73–80. https://doi.org/10.1016/j.jenvp.2017.06.009.

Frische, T., Egerer, S., Matezki, S., Pickl, C., Wogram, J., 2018. 5-Point programme for sustainable plant protection. Environ. Sci. Eur. 30, 8. https://doi.org/10.1186/s12302-018-0136-2.

Frison, E.A., Cherfas, J., Hodgkin, T., 2011. Agricultural biodiversity is essential for a sustainable improvement in food and nutrition security. Sustainability 3, 238–253. https://doi.org/10.3390/su3010238.

Gachango, F.G., Andersen, L.M., Pedersen, S.M., 2015. Adoption of voluntary water-pollution reduction technologies and water quality perception among Danish farmers. Agric. Water Manag. 158, 235–244. https://doi.org/10.1016/j.agwat.2015.04.014.

Gahlot, S., Lin, T.S., Jain, A.K., Baidya Roy, S., Sehgal, V.K., Dhakar, R., 2020. Impact of environmental changes and land management practices on wheat production in India. Earth Syst. Dyn. 11, 641–652. https://doi.org/10.5194/esd-11-641-2020.

Gaudio, N., Louarn, G., Barillot, R., Meunier, C., Vezy, R., Launay, M., 2022. Exploring complementarities between modelling approaches that enable upscaling from plant community functioning to ecosystem services as a way to support agroecological transition. Silico Plants 4, diab037. https://doi.org/10.1093/insilicoplants/diab037.

Giovanopoulou, E., Nastis, S.A., Papanagiotou, E., 2011. Modeling farmer participation in agri-environmental nitrate pollution reducing schemes. Ecol. Econ. 70, 2175–2180.

Gliessman, S., 2018. Defining Agroecology. Agroecol. Sustain. Food Syst. 42, 599–600. https://doi.org/10.1080/21683565.2018.1432329.

Greiner, B., 2015. Subject pool recruitment procedures: organizing experiments with ORSEE. J. Econ. Sci. Assoc. 1, 114–125. https://doi.org/10.1007/s40881-015-0004-4.

Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol: a review and first update. Ecol. Model. 221, 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019.

Grovermann, C., Schreinemachers, P., Riwthong, S., Berger, T., 2017. 'Smart' policies to reduce pesticide use and avoid income trade-offs: an agent-based model applied to Thai agriculture. Ecol. Econ. 132, 91–103. https://doi.org/10.1016/j.ecolecon.2016.09.031.

Gunderson, L.H., Holling, C.S., 2002. Panarchy: Understanding Transformations in Human and Natural Systems. Island Press.

Guo, Z., Dong, Y., Dong, K., Zhu, J., Ma, L., 2020. Effects of nitrogen management and intercropping on faba bean chocolate spot disease development. Crop Prot. 127, 104972 https://doi.org/10.1016/j.cropro.2019.104972.

Holt-Giménez, E., Altieri, M.A., 2012. Agroecology, food sovereignty and the new green revolution. J. Sustain. Agric, 120904081412003. https://doi.org/10.1080/10440046.2012.716388.

Honlonkou, A.N., 2004. Modelling adoption of natural resources management technologies: the case of fallow systems. Environ. Dev. Econ. 9, 289–314. https://doi.org/10.1017/S1355770×03001128.

Honoré, F., Carré, C., Robert, C., 2024. Entre Rupture Et Inscription Dans Un territoire : Saisir Les Expériences Paysannes En Agroécologie Forte. Géographie Économie Société.

INSEE, 2020. Exploitations agricoles. https://www.insee.fr/fr/statistiques/4277860?sommaire=4318291 (accessed 3.12.24).

Jayachandran, S., 2023. The inherent trade-off between the environmental and anti-poverty goals of payments for ecosystem services. Environ. Res. Lett. 18, 025003 https://doi.org/10.1088/1748-9326/acb1a7.

Karaya, R.N., Onyango, C.A., Ogendi, G.M., 2020. The Effect of Participation in Farmer Groups on Household Adoption of Sustainable Land Management Practices in Kenyan Drylands. Asian J. Agric. Ext. Econ. Sociol. 66–80. https://doi.org/10.9734/ajaees/2020/v38i1130454.

Kleemann, L., Abdulai, A., 2013. Organic certification, agro-ecological practices and return on investment: evidence from pineapple producers in Ghana. Ecol. Econ. 93, 330–341.

Knapp, S., Van Der Heijden, M.G.A., 2018. A global meta-analysis of yield stability in organic and conservation agriculture. Nat. Commun. 9, 3632. https://doi.org/10.1038/s41467-018-05956-1.

Kuhfuss, L., Préget, R., Thoyer, S., Hanley, N., Coent, P.L., Désolé, M., 2016. Nudges, Social Norms, and Permanence in Agri-environmental Schemes. Land Econ 92, 641–655. https://doi.org/10.3368/le.92.4.641.

Lacombe, C., Couix, N., Hazard, N., 2018. Fesigning agroecological farming systems with farmers: A review. Agricultural Systems 165, 208–220. https://doi.org/10.1016/j.agsy.2018.06.014.

Läpple, D., Kelley, H., 2013. Understanding the uptake of organic farming: accounting for heterogeneities among Irish farmers. Ecol. Econ. 88, 11–19. https://doi.org/10.1016/j.ecolecon.2012.12.025.

Lastra-Bravo, X.B., Hubbard, C., Garrod, G., Tolón-Becerra, A., 2015. What drives farmers' participation in EU agri-environmental schemes?: results from a qualitative meta-analysis. Environ. Sci. Policy 54, 1–9. https://doi.org/10.1016/j.envsci.2015.06.002.

Le Coent, P., Préget, R., Thoyer, S., 2021. Farmers follow the herd: a theoretical model on social norms and payments for environmental services. Environ. Resour. Econ. 78, 287–306.

Le Gal, A., Robert, C., Accatino, F., Claessen, D., Lecomte, J., 2020. Modelling the interactions between landscape structure and spatio-temporal dynamics of pest natural enemies: implications for conservation biological control. Ecol. Model. 420, 108912 https://doi.org/10.1016/j.ecolmodel.2019.108912.

Lescourret, F., Magda, D., Richard, G., Adam-Blondon, A.F., Bardy, M., Baudry, J., Doussan, I., Dumont, B., Lefèvre, F., Litrico, I., Martin-Clouaire, R., Montuelle, B., Pellerin, S., Plantegenest, M., Tancoigne, E., Thomas, A., Guyomard, H., Soussana, J. F., 2015. A social–ecological approach to managing multiple agro-ecosystem services. Curr. Opin. Environ. Sustain. 14, 68–75. https://doi.org/10.1016/j.cosust.2015.04.001.

Levin, S., Xepapadeas, T., Crépin, A.-S., Norberg, J., De Zeeuw, A., Folke, C., Hughes, T., Arrow, K., Barrett, S., Daily, G., 2013. Social-ecological systems as complex adaptive systems: modeling and policy implications. Environ. Dev. Econ. 18, 111–132.

Levionnois, S., Pradal, C., Fournier, C., Sanner, J., Robert, C., 2023. Modeling the Impact of Proportion, Sowing Date, and Architectural Traits of a Companion Crop on Foliar Fungal Pathogens of Wheat in Crop Mixtures. Phytopathology® PHYTO-06-22-0197-R. https://doi.org/10.1094/PHYTO-06-22-0197-R.

Luo, C., Lv, J., Guo, Z., Dong, Y., 2022. Intercropping of faba bean with wheat under different nitrogen levels reduces faba bean rust and consequent yield loss. Plant Dis. 106, 2370–2379. https://doi.org/10.1094/PDIS-11-21-2451-RE.

Malard, J.J., Adamowski, J.F., Rojas Díaz, M., Nassar, J.B., Anandaraja, N., Tuy, H., Arévalo-Rodriguez, L.A., Melgar-Quiñonez, H.R., 2020. Agroecological food web modelling to evaluate and design organic and conventional agricultural systems. Ecol. Model. 421, 108961 https://doi.org/10.1016/j.ecolmodel.2020.108961.

Malézieux, E., Crozat, Y., Dupraz, C., Laurans, M., Makowski, D., Ozier-Lafontaine, H., Rapidel, B., De Tourdonnet, S., Valantin-Morison, M., 2009. Mixing plant species in cropping systems: concepts, tools and models: a review (Eds.). In: Lichtfouse, E., Navarrete, M., Debaeke, P., Véronique, S., Alberola, C. (Eds.), Sustainable Agriculture. Springer Netherlands, Dordrecht, pp. 329–353. https://doi.org/10.1007/978-90-481-2666-8_22.

Mesnage, R., Séralini, G.E., 2018. Editorial: toxicity of pesticides on health and environment. Front. Public Health 6, 268. https://doi.org/10.3389/fpubh.2018.00268.

Mettepenningen, E., Vandermeulen, V., Delaet, K., Van Huylenbroeck, G., Wailes, E.J., 2013. Investigating the influence of the institutional organisation of agri-environmental schemes on scheme adoption. Land Use Policy 33, 20–30. https://doi.org/10.1016/j.landusepol.2012.12.004.

Meunier, E., Smith, P., Grissienger, T., Robert, C., 2024. Understanding changes in reducing pesticide use by farmers: contribution of the behavioural sciences. Agric. Syst.

Milheiras, S.G., Sallu, S.M., Loveridge, R., Nnyiti, P., Mwanga, L., Baraka, E., Lala, M., Moore, E., Shirima, D.D., Kioko, E.N., 2022. Agroecological practices increase farmers' well-being in an agricultural growth corridor in Tanzania. Agron. Sustain. Dev. 42, 56.

Ministère de l'Agriculture, 2023. Pacte en faveur de la haie. https://agriculture.gouv.fr/pacte-en-faveur-de-la-haie.

Montgomery, I., Caruso, T., Reid, N., 2020. Hedgerows as ecosystems: service delivery, management, and restoration. Annual Review of Ecology, Evolution, and Systematics 51, 81–102.

Mouysset, L., Doyen, L., Pereau, J.-C., Jiguet, F., 2015. Benefits and costs of biodiversity in agricultural public policies. Eur. Rev. Agric. Econ. 42, 51–76.

Müller-Hansen, F., Schlüter, M., Mäs, M., Donges, J.F., Kolb, J.J., Thonicke, K., Heitzig, J., 2017. Towards representing human behavior and decision making in Earth system models – an overview of techniques and approaches. Earth Syst. Dyn. 8, 977–1007. https://doi.org/10.5194/esd-8-977-2017.

Mzoughi, N., 2011. Farmers adoption of integrated crop protection and organic farming: do moral and social concerns matter? Ecol. Econ. 70, 1536–1545. https://doi.org/10.1016/j.ecolecon.2011.03.016.

Neumann, K., Verburg, P.H., Elbersen, B., Stehfest, E., Woltjer, G.B., 2011. Multi-scale scenarios of spatial-temporal dynamics in the European livestock sector. Agric. Ecosyst. Environ. 140, 88–101. https://doi.org/10.1016/j.agee.2010.11.015.

Noeldeke, B., Winter, E., Ntawuhiganayo, E.B., 2022. Representing human decision-making in agent-based simulation models: agroforestry adoption in rural Rwanda. Ecol. Econ. 200, 107529 https://doi.org/10.1016/j.ecolecon.2022.107529.

Obrycki, J.J., Harwood, J.D., Kring, T.J., O'Neil, R.J., 2009. Aphidophagy by Coccinellidae: application of biological control in agroecosystems. Biol. Control 51, 244–254. https://doi.org/10.1016/j.biocontrol.2009.05.009.

Özkara, A., Akyil, D., Konuk, M., 2016. Pesticides, Environmental pollution, and health, Environmental health Risk-Hazardous Factors to Living Species. IntechOpen ed.

Paz, D.B., Henderson, K., Loreau, M., 2020. Agricultural land use and the sustainability of social-ecological systems. Ecol. Model. 437, 109312.

Polasky, S., Nelson, E., Camm, J., Csuti, B., Fackler, P., Lonsdorf, E., Montgomery, C., White, D., Arthur, J., Garber-Yonts, B., 2008. Where to put things? Spatial land management to sustain biodiversity and economic returns. Biol. Conserv. 141, 1505–1524.

Précigout, P.A., Renard, D., Sanner, J., Claessen, D., Robert, C., 2023. Crop mixtures outperform rotations and landscape mosaics in regulation of two fungal wheat pathogens: a simulation study. Landsc. Ecol. 38, 77–97. https://doi.org/10.1007/s10980-022-01545-2.

Précigout, P.A., Robert, C., 2022. Effects of hedgerows on the preservation of spontaneous biodiversity and the promotion of biotic regulation services in agriculture: towards a more constructive relationships between agriculture and biodiversity. Bot. Lett. 169, 176–204. https://doi.org/10.1080/23818107.2022.2053205.

Qiu, J., Carpenter, S.R., Booth, E.G., Motew, M., Kucharik, C.J., 2020. Spatial and temporal variability of future ecosystem services in an agricultural landscape. Landsc. Ecol. 35, 2569–2586. https://doi.org/10.1007/s10980-020-01045-1.

Ratnadass, A., Fernandes, P., Avelino, J., Habib, R., 2012. Plant species diversity for sustainable management of crop pests and diseases in agroecosystems: a review. Agron. Sustain. Dev. 32, 273–303. https://doi.org/10.1007/s13593-011-0022-4.

Rebaudo, F., Dangles, O., 2013. An agent-based modeling framework for integrated pest management dissemination programs. Environ. Model. Softw. 45, 141–149. https://doi.org/10.1016/j.envsoft.2012.06.014.

Rusch, A., Chaplin-Kramer, R., Gardiner, M.M., Hawro, V., Holland, J., Landis, D., Thies, C., Tscharntke, T., Weisser, W.W., Winqvist, C., Woltz, M., Bommarco, R., 2016. Agricultural landscape simplification reduces natural pest control: a quantitative synthesis. Agric. Ecosyst. Environ. 221, 198–204. https://doi.org/10.1016/j.agee.2016.01.039.

Sabatier, R., Meyer, K., Wiegand, K., Clough, Y., 2013. Non-linear effects of pesticide application on biodiversity-driven ecosystem services and disservices in a cacao agroecosystem: a modeling study. Basic Appl. Ecol. 14, 115–125.

Sabatier, R., Teillard, F., Rossing, W.A., Doyen, L., Tichit, M., 2015. Trade-offs between pasture production and farmland bird conservation: exploration of options using a dynamic farm model. Animal 9, 899–907.

Schoeny, A., Jumel, S., Rouault, F., Lemarchand, E., Tivoli, B., 2010. Effect and underlying mechanisms of pea-cereal intercropping on the epidemic development of ascochyta blight. Eur. J. Plant Pathol. 126, 317–331. https://doi.org/10.1007/s10658-009-9548-6.

Scholberg, J.M., Dogliotti, S., Leoni, C., Cherr, C.M., Zotarelli, L., Rossing, W.A., 2010. Cover crops for sustainable agrosystems in the Americas. Genet. Eng. Biofertilisation Soil Qual. Org. Farming 23–58.

Schulze, J., Müller, B., Groeneveld, J., Grimm, V., 2017. Agent-based modelling of social-ecological systems: achievements, challenges, and a way forward. J. Artif. Soc. Soc. Simul. 20 https://doi.org/10.18564/jasss.3423.

Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 485, 229–232. https://doi.org/10.1038/nature11069.

Simon, H.A., 1984. Models of Bounded rationality, Volume 1: Economic Analysis and Public Policy. MIT Press Books 1.

Tittonell, P., 2014. Livelihood strategies, resilience and transformability in African agroecosystems. Agric. Syst. 126, 3–14.

Tixier, P., 2020. Modelling in agroecology: from simple to complex models, and vice versa.

Toma, L., Mathijs, E., 2007. Environmental risk perception, environmental concern and propensity to participate in organic farming programmes. J. Environ. Manage. 83, 145–157. https://doi.org/10.1016/j.jenvman.2006.02.004.

Tveito, O.E., Bjørdal, I., Skjelvåg, A.O., Aune, B., 2005. A GIS-based agro-ecological decision system based on gridded climatology. Meteorol. Appl. 12, 57–68. https://doi.org/10.1017/S1350482705001490.

Visser, B., Meyer, M., Park, R.F., Gilligan, C.A., Burgin, L.E., Hort, M.C., Hodson, D.P., Pretorius, Z.A., 2019. Microsatellite Analysis and urediniospore dispersal simulations support the movement of puccinia graminis f. sp. tritici from Southern Africa to Australia. Phytopathology® 109, 133–144. https://doi.org/10.1094/PHYTO-04-18-0110-R.

Walder, P., Kantelhardt, J., 2018. The environmental behaviour of farmers–capturing the diversity of perspectives with a Q methodological approach. Ecol. Econ. 143, 55–63.

Wan, C., Dang, P., Gao, L., Wang, J., Tao, J., Qin, X., Feng, B., Gao, J., 2022. How Does the environment affect wheat yield and protein content response to drought? A Meta-Analysis. Front. Plant Sci. 13, 896985 https://doi.org/10.3389/fpls.2022.896985.

Wezel, A., Casagrande, M., Celette, F., Vian, J.F., Ferrer, A., Peigné, J., 2014. Agroecological practices for sustainable agriculture. A review. Agron. Sustain. Dev. 34, 1–20. https://doi.org/10.1007/s13593-013-0180-7.

Wezel, A., Herren, B.G., Kerr, R.B., Barrios, E., Gonçalves, A.L.R., Sinclair, F., 2020. Agroecological principles and elements and their implications for transitioning to sustainable food systems. A review. Agron. Sustain. Dev. 40, 40. https://doi.org/10.1007/s13593-020-00646-z.

Wilensky, U., 1999. NetLogo.

Wilson, G.A., 1992. A survey on attitudes of landholders to native forest on farmland. J. Environ. Manage. 34, 117–136. https://doi.org/10.1016/S0301-4797(06)80018-6.

Xu, Q., Huet, S., Poix, C., Boisdon, I., Deffuant, G., 2018. Why do farmers not convert to organic farming? Modeling conversion to organic farming as a major change: XU \textlessspan style="font-variant:small-caps;"\textgreateret al.\textless/span \textgreater. Nat. Resour. Model. 31, e12171. https://doi.org/10.1111/nrm.12171.

Zhang, C., Dong, Y., Tang, L., Zheng, Y., Makowski, D., Yu, Y., Zhang, F., Van Der Werf, W., 2019. Intercropping cereals with faba bean reduces plant disease incidence regardless of fertilizer input; a meta-analysis. Eur. J. Plant Pathol. 154, 931–942. https://doi.org/10.1007/s10658-019-01711-4.

Zhang, L., Li, X., 2016. The Impact of Traditional Culture on Farmers' Moral Hazard Behavior in Crop Production: Evidence from China. Sustainability 8, 643. https://doi.org/10.3390/su8070643.

Zilberman, D., Schmitz, A., Casterline, G., Lichtenberg, E., Siebert, J.B., 1991. The economics of pesticide use and regulation. Science 253, 518–522.