Adapting the governance of social–ecological systems to behavioural dynamics: An agent-based model for water quality management using the theory of planned behaviour

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Abstract

Nonpoint source pollution from agriculture is one of the main causes of water quality degradation. To cope with this issue, diverse policy measures have been implemented to promote farming practices that favour water quality. Among these measures, many instruments are based on the voluntary commitments of farmers. Farmers' participation is therefore important for water quality outcomes. To analyse this issue, we built an agent-based model of a drinking water catchment area using the social–ecological systems framework and the theory of planned behaviour. This model aims to better understand the impact of behavioural dynamics on the effectiveness and efficiency of policies targeting water pollution. Our model allows us to explore how the evolution of farming practices is influenced by, first, the behavioural characteristics of farmers and, second, the characteristics of the policy measures implemented. Our main results are threefold: 1) The characteristics of farmers influence policy effectiveness and efficiency; 2) taking into account farmers' behavioural characteristics in the definition of policies may improve the efficiency of policies; and 3) in situations where behavioural characteristics are unknown, policies combining both financial incentives and training measures are costlier but may be a better option than policies relying on a single measure.

Keywords

agent-based model; behavioural economics; theory of planned behaviour; social–ecological system; water management

1. INTRODUCTION

Water resources are vulnerable due to demographic pressures, climate change and human activities. Accordingly, water security has become a prominent concern (FAO 2011, Deng et al. 2018). Water pollution leads to the degradation of aquatic ecosystems, causes problems in drinking water supply and negatively affects economic activities such as fisheries and tourism. Sources of water pollution are diverse: industry effluents, discharge from urban wastewater treatment and losses from agriculture. Many European waterbodies are affected by pollutants and/or altered habitats, and more than half of the rivers and lakes in Europe are reported to have less than good ecological status (EEA 2020).

In 2000, the European Union adopted the Water Framework Directive (WFD), with the objectives of preventing and reducing water pollution, promoting the sustainable use of water, protecting the environment and improving the status of aquatic ecosystems. At the French level, the WFD has led, for example, to the identification of 1000 priority drinking water catchments as being particularly threatened by nonpoint source pollution where measures targeting farmers' practices have been implemented (MTE 2020). The measures implemented include information and advisory instruments as well as economic instruments such as the agri-environmental schemes (AES) of the EU Common Agricultural Policy (CAP), which aim to encourage the adoption of environmentally friendly farming practices.

The implementation of the various protection measures is based on the voluntary commitment of farmers. Several studies have shown that the participation rate of farmers in agri-environmental programmes is generally low, particularly for measures involving changes in farming practices (Villien and Claquin 2012, Epice and ADE 2011, Chabé-Ferret and Subervie 2013, Carvin et al. 2020). However, the participation rate plays a determinant role in the effectiveness and efficiency of agri-environmental programmes (Dupraz et al. 2007, Kuhfuss et al. 2012). Policy effectiveness corresponds to the difference between the outcomes achieved and the outcomes expected, and efficiency is the relationship between the human and financial means used and the policy outcomes. Both indicators constitute commonly used criteria for evaluating the performance of environmental policies (OECD 2008), including policy instruments for water quality protection (Shortle and Horan 2013).

Understanding the factors that affect farmers' participation in environmental programmes is crucial to enhance the effectiveness and efficiency of such programmes. These factors have been extensively studied (Lastra-Bravo et al. 2015, Dessart et al. 2019). Many studies have highlighted the role of economic factors (such as farm size, farm area, farm capital, land tenure and income level) in farmers' decisions to participate in agri-environmental programmes (Toma and Mathijs

2007, Mzoughi 2011, Baumgart-Getz et al. 2012, Mettepenningen et al. 2013, Gachango et al. 2015, Floress et al. 2017). More recently, several studies have shown that not only economic factors but also noneconomic factors, including behavioural factors and institutional factors, influence the decision-making process of farmers. The behavioural factors include social, dispositional and institutional factors.

The institutional factors that influence farmers' behaviours are diverse. Mettepenningen et al. (2013) have shown that the characteristics of agri-environmental programmes (duration, payment level) and the level of information about the programmes have an effect on farmers' intentions to participate. Prokopy et al. (2008), in a review of the literature about the adoption of agricultural best management practices, also highlighted that the level of financial compensation has a positive effect on adoption. Gachango et al. (2015) have shown that access to information and farmers' attitude towards subsidies are two factors influencing the adoption of voluntary water pollution reduction technologies.

The behavioural factors include dispositional and social factors. Dispositional factors are individual characteristics that influence an individual to behave in a certain way (Malle 2011). One factor of interest is environmental concern, which has been found to influence farmers' participation in collective action for water quality management (Amblard 2019) and their adoption of environmental practices (Giovanopoulou et al. 2011). Toma and Mathijs (2007) have shown that the perception of environmental risk regarding the health of farmers' own family as well as their crops and livestocks is a strong determinant of farmers' propensity to participate in organic farming programmes. The dispositional factors also include more general feelings of responsibility towards nature, the environment, cultural landscapes and the common good (Walder and Kantelhardt 2018).

Several studies have highlighted the role of social factors and, more specifically, social norms. Le Coent et al. (2016) and Kuhfuss et al. (2015) showed that farmers' decisions to enrol in an agri-environmental programme are influenced by an injunctive norm (the desire to comply with the rule) and a descriptive norm (the desire to behave like the group). Showing to others one's environmental commitment can also influence farmers' adoption of pro-environmental practices (Mzoughi 2011).

Ajzen and Fishbein (1980) proposed a theory that makes it possible to integrate diverse social, economic, institutional and environmental issues into behavioural analysis: the theory of reasoned action, which was later extended to the theory of planned behaviour (TPB) (Ajzen 1991). It is one of the most frequently used approaches to understanding farmers' decision-making with regard to agri-environmental policies (Falconer 2000, Toma and Mathijs 2007). Within this framework, the intention towards a behaviour is considered a trustworthy predictor as to whether the behaviour will be performed. Individual intention is influenced by three main factors: attitude, subjective norm and perceived behavioural control (PBC) (Ajzen 1991).

Previous work has shown that each factor has a relative importance in the intention that is highly dependent on the investigated behaviour and population (Ajzen and Fishbein 2005, Fife-Schaw et al. 2007, Ajzen 2011). The relative effects of the TPB factors on intention can vary among different populations, depending on the cultural and institutional contexts (e.g., Ajzen and Klobas 2013). Previous studies have highlighted that the relative importance of factors can differ between countries in the European context (Kaufman et al. 2009, Mettepenningen et al. 2013). However, the specific effect of these relative weights has not been widely studied, especially in the case of farmers' behaviour. This article contributes to this literature by focusing on TPB factors and their relative importance, as they influence farmers' participation in a water protection programme and therefore the efficiency and effectiveness of protection programmes.

The objective of our study has been to analyse how the characteristics of farmers and the policies implemented jointly influence the evolution of agricultural practices and, therefore, the concentration of pollutants in drinking water catchment areas. For this purpose, we use a conceptual framework based on the social–ecological system (SES) framework developed by Ostrom (Ostrom 2009, McGinnis and Ostrom 2014) and the TPB (Section 2). We built an agent-based model of a water catchment area, which is described in the third section. This model allowed us to analyse how water quality management is influenced by the governance system and actor characteristics and dynamics (Section 4). More particularly: (1) We identified how the characteristics of farmers in a catchment area affect policy effectiveness. We focused on the relative importance of the factors and on the characteristics of the population in the catchment area and the interactions between them (Section 4.1). (2) We characterised the effectiveness of different water quality protection programmes. We analysed the marginal effect of different policy measures targeting different farmer populations and have shown that their effectiveness is influenced by the interaction between the characteristics of the measures implemented and farmers' behavioural characteristics (Section 4.2). (3) We assessed the efficiency of different water quality protection programmes that are also influenced by both the characteristics of the policy measures implemented and farmers' behavioural characteristics (Section 4.3). Finally, Section 5 offers a discussion of the findings and a conclusion.

2. CONCEPTUAL FRAMEWORK

2.1. Agent-based models of social–ecological water systems

Water catchments are areas where rainfall feeds the aquifer and thus contribute to the renewal of the resource. In these areas, different actors interact with each other and with the water system. To explore such interactions, we built a model based on the SES framework (Ostrom 2009, McGinnis and Ostrom 2014).

The SES framework was developed from the Institutional Analysis and Development approach (Ostrom 2011) for analysing the governance of common-pool resources (Ostrom 2007, 2009). It is now being used more widely, including for the analysis of the various public goods and services generated by SESs (McGinnis and Ostrom 2014, Ban et al. 2015, Bennett and Gosnell 2015). Regarding water quality management, several studies have used the SES framework to underline the factors affecting the emergence and performance of collaborative water quality management (e.g., Lubell et al. 2002, Madrigal et al. 2011, Montenegro and Hack 2020) or to assess the effect of multilevel or polycentric governance on sustainable water use (Nagendra and Ostrom 2014, Naiga et al. 2015). However, to the best of our knowledge, only one study has applied the SES framework to the protection of drinking water catchments (Amblard 2019).

The IAD and subsequently the SES framework were built incrementally through the empirical analysis of a large number of case studies, which led to a multitier collection of concepts and variables (Hinkel et al. 2014). As first-tier variables, the framework conceptualises SESs into resource systems, resource units, governance systems, actors, interactions, and outcomes. In this paper, we use the framework to model the SES considered, a water catchment where a programme targets farming practices to control nonpoint source pollution (see Figure 1). The resource system considered is the catchment area, from which groundwater, as a resource unit, is abstracted for drinking water production. The social system involves actors – farmers – and a governance system – a protection programme that includes different types of measures such as financial incentives and training. The objective of the governance system is to reduce water pollution; thus, the outcome of interest in the study is the restoration of water quality.

Among the different modelling approaches, agent-based modelling is particularly relevant for understanding social–ecological phenomena because of its capacity to simulate the emergence of macroscopic patterns, the embeddedness of spatial and temporal scales, and the integration of agents in ecological and social environments (Schlüter et al. 2019). Indeed, in agent-based models (ABMs), agents with heterogeneous characteristics are represented in a given environment. ABMs have already been used for analysing SESs or predicting management results (see reviews by Rounsevell et al. 2012, Schulze et al. 2017). Regarding the governance of SESs, ABMs have been used to explore the impact of formal institutions, informal institutions or different modes of governance on resource management (Bourceret et al. 2021*)*. For example, Akapov et al. propose models that may serve as decision support tools for the ecological modernisation of enterprises (Akapov et al. 2017) or to identify optimal urban greenery strategies under budget constraints (Akapov et al. 2019). Moreover, ABMs have been used to analyse the effectiveness of economic instruments (taxes and subsidies) to control pollution emissions (Deng et al. 2018) or the potential of hybrid mechanisms with 'social engagement' and 'legal enforcement' for lake restorations (Martin and Schlüter 2015).

2.2. Theory of planned behaviour: Background and application to farmers' decision-making in a water system

In agent-based modelling of SESs, representing human decision-making is a key element (Schulze et al. 2017). Models of decision-making processes can be framed by empirical studies or by existing theories (e.g., rational choice theory, TPB (Ajzen 1991), prosocial behaviour theory (Bénabou and Tirole 2006) or norm activation theory (Schwartz 1977)). In most ABMs, the decision-making model has been grounded in rational choice theory (An 2012) and based on simple assumptions (Jager et al. 2000).

The TPB is a social–psychological theory commonly used for representing decision-making processes in the field of environmental and natural resource management (Grilli and Notaro 2019, Si et al. 2019). For example, it has been used to describe recycling behaviour (e.g., Aguiliar-Luzon et al. 2012, Chan and Bishop 2013, Ahmad et al. 2016), green purchasing behaviour (e.g., Albayrak et al. 2013) and transportation choices (e.g., Bamberg and Schmidt 2001, De Groot and Steg 2007). More particularly, this theory has frequently been used for understanding farmers' decision-making with regard to agri-environmental policies and the adoption of sustainable farming practices. For instance, it has been used to study farmers' conservation behaviour (Lynne et al. 1995, Beedell and Rehman 1999, 2000, Fielding et al. 2005) or to assess the influence of institutions on farmers' participation in conservation schemes (Mettepenningen et al. 2013).

The TPB suggests that a given behaviour is influenced by the intention to perform this behaviour (Ajzen 1991). The higher the intention to engage in a behaviour is, the more likely its realisation is. According to the theory, someone's intention towards a behaviour is a reliable predictor of whether or not they will perform the behaviour. In the case of farming practices in a water catchment area, a farmer's higher intention to adopt a low-input practice promoted by a policy is assumed to lead to a higher chance of adopting this practice.

The concept of intention captures the motivations to perform the behaviour through three conceptually independent factors: attitude towards the behaviour, subjective norm and PBC (actors' decision-making box in Figure 1). Attitude is the judgement about the desirability of the behaviour and its consequences. The considerations of the influence of others' opinions on the behaviour of interest define the subjective norm. Others can be neighbours, friends, family or other important persons who may influence the farmer (link 2 in Figure 1). PBC encompasses beliefs about the individual's ability to succeed in behaviour.

The relative importance of factors in the intention is highly dependent on the specific behaviour and population being studied (Ajzen and Fishbein 2005, Fife-Schaw et al. 2007, Ajzen 2011) (link 4 in Figure 1). It can differ across cultural and institutional contexts (e.g., Ajzen and Klobas 2013). Some authors used Hofstede's cultural dimension (Hofstede 2001) to test and explain differences in the relative importance of factors. For example, Engle et al. (2010), using a regional clustering of societal cultures (based on common language, geography, religion and history), highlighted that all three factors are important but not in every context and not to the same degree. Khalid (2018) compared the cultural characteristics of Japan and Pakistan to provide insights into the association of culture and cognitions relevant to entrepreneurship.

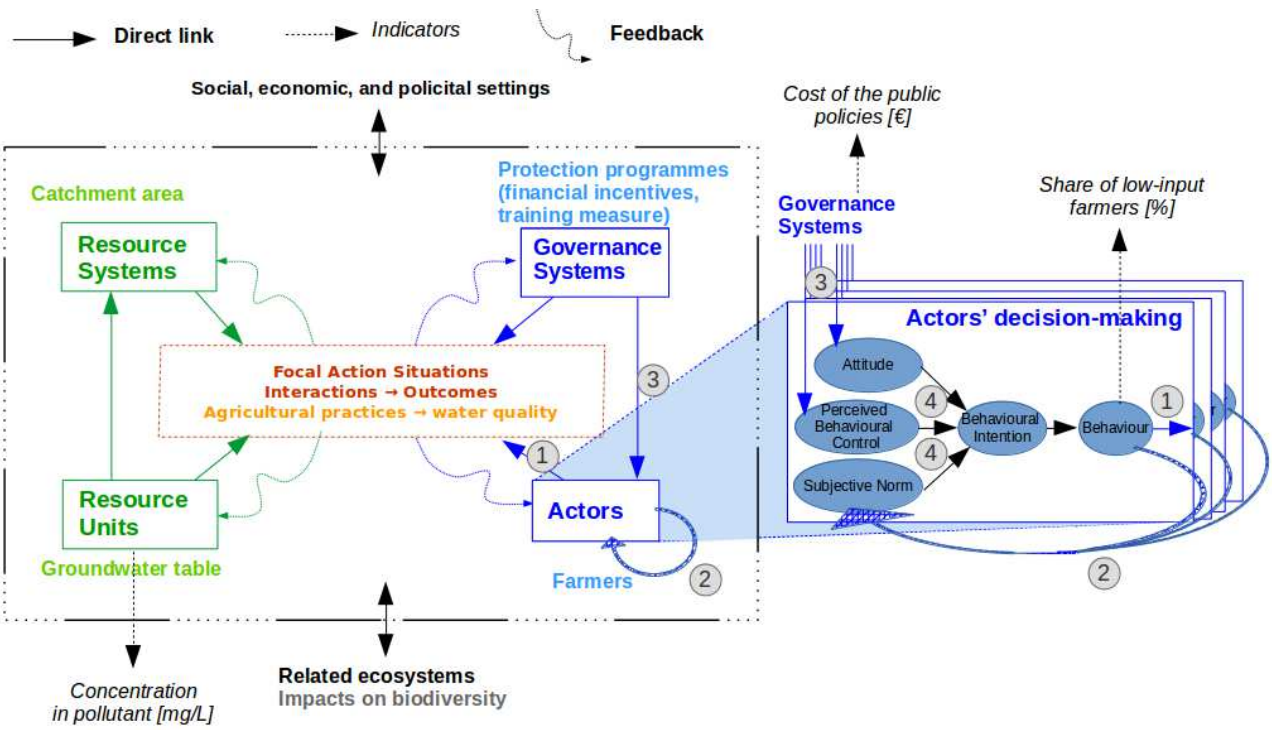

Figure 1: Representation of a drinking water catchment area based on the SES framework and the theory of planned behaviour (adapted from: Ajzen 1991, McGinnis and Ostrom 2014). Farmers' behaviours correspond to their agricultural practices (link 1). Link 2 represents the interactions between farmers affected by the subjective norm. The influence of the governance system on attitude and perceived behavioural control is highlighted by link 3. Link 4 represents the contribution of the three factors (attitude, perceived behavioural control and subjective norm) to intention.

The implementation of the TPB within an ABM has been used to study technology diffusion among households (Schwarz and Ernst 2009, Gamal Aboelmaged 2010, Robinson and Rai 2015, Schwarz et al. 2016), migration decisions (Kniveton et al. 2011, 2012, Klabunde and Willekens 2016), farmers' decision-making (Kaufmann et al. 2009), healthy lifestyle choices (Richetin et al. 2010), waste recycling (Ceschi et al. 2015), adoption of food safety measures (Verwaart and Valeeva 2011), segregation decisions (Wang and Hu 2012), traffic behaviour (Roberts and Lee 2012, Yu and Gou 2014) and ethical problem-solving (Robbins and Wallace 2007).

3. AGENT-BASED MODEL

The purpose of the proposed ABM is to explore how farmers, who are connected in a network, are influenced in their choice to join a protection programme by (1) different behavioural characteristics of the farmer populations and (2) different characteristics of the protection programme (see Appendix 1 for the Overview Design concepts and Details (ODD) protocol description).

Three subsystems are modelled:

- The resource system entity represents a groundwater catchment area that has a certain concentration of pollutants. It is described by parameters and variables.
- Actors are farmers whose farming practices have the unintended consequence of releasing pollutants into the groundwater. They decide whether to enter the protection programme or not, i.e., whether to adopt a low-input farming practice. The actors' system is represented by heterogeneous agents.
- The governance system represents the protection programme that promotes farmers' adoption of low-input practices (link 3 in Figure 1). It is described by parameters and variables.

All parameters, value ranges, and sources of values can be found in Appendix 2.

3.1. Resource system

We assume that the water used for drinking water production is abstracted from a groundwater body. The resource system submodel is a linear reservoir model. The linear reservoir model, in its simplest form, appears well adapted to quite diverse situations ranging from small, highly urbanised watersheds to watersheds of several hundred hectares (*Ministère de la transition écologique et solidaire*, 2020). This model represents a single reservoir, whose storage and discharge vary linearly as a function of the water level. We assume that agricultural activities are the only source of groundwater pollution (link 1 Figure 1). See Appendix 3 for a description of the resource system model.

3.2. Actors

Actors, here agent-farmers, are randomly distributed spatially in the environment. The environment is a discrete toric space of 10*10 patches. Each of the 80 agent farmers is located in a patch (x_i, y_i). They all have the same farm area and the same type of production. At the beginning of the simulations, they all practice high-input farming. Each year (the time step of the model), they can change their practice to low-input farming. The low-input farming practice (l) is more favourable to water quality than the high-input practice (h) but less economically profitable. Farming practices represent the state of the agent-farmer.

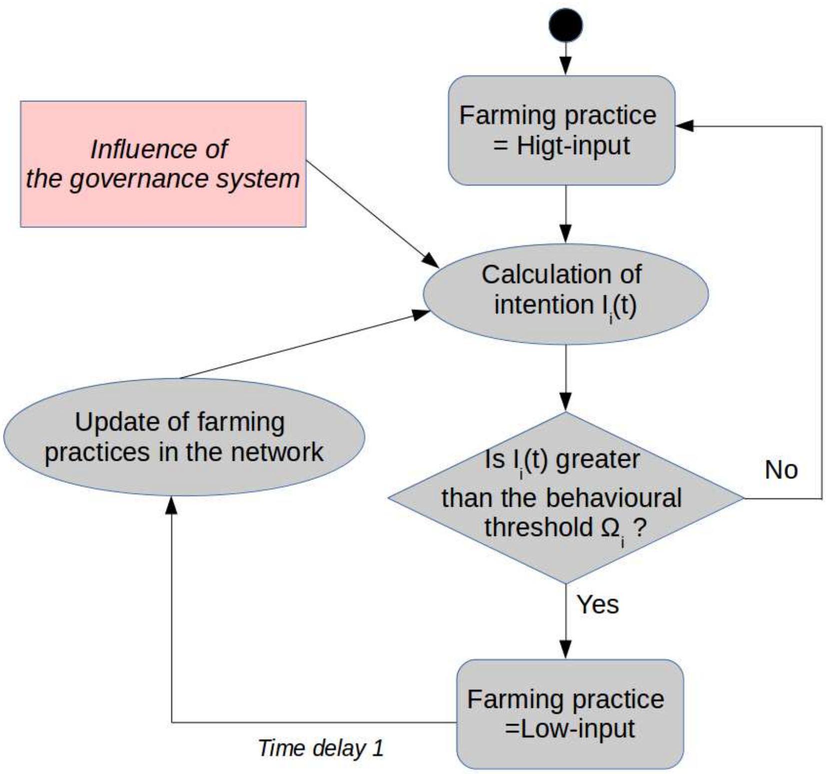

Figure 2: The states of an agent-farmer and the transition between the states. The pink box represents the influence of the protection programme. The transition between states is shown as a diamond-shaped symbol. The squircles represent the states of an agent-farmer. The ovals contain processes underlying the decision-making.

The intention of agent farmers to participate in the protection programme and therefore to change their farming practice is calculated. Intention is composed of the three factors of the TPB, namely, attitude, subjective norm and PBC, weighted by their relative importance in intention. The transition between the two states, i.e., from the high-input farming practice to the low-input farming practice, is controlled by the intention. The pattern of transition between states is represented in Figure 2. The complexity of the model lies in this transition, which represents the decision-making process of agent-farmers, and more specifically in the nature and number of interactions between agents that occur in the process (see below for more details on the nature of interactions and in Appendix 4 for the construction of the network of interactions).

3.2.1. Calculation of behavioural intention $I_i(t)$

To calculate the coefficient of intention to change to low-input farming practice, $I_i(t)$, we use a linear function of the three basic factors weighted by their importance in intention, following Beedell and Rehman (2000).

$$I_i(t) = s_i(t) * \gamma_s + a_i * \gamma_a + p * \gamma_p \qquad (1)$$

$$\gamma_a + \gamma_s + \gamma_p = 1 \qquad (2)$$

where,

- $s_i(t)$ is the subjective norm linked to the behaviour of others; it is the dynamic component of the decision process of the model.

- a_i is the attitude, i.e., the judgement of agent-farmer i on the desirability of adopting the low-input farming practice and on the consequences of this change; it is a parameter depending on the type of farmer.

- p is the PBC and represents the beliefs of the agent-farmer on their ability to adopt the low-input farming practice; it is a parameter.

- γ_s, γ_a and γ_p are the weights of $s_i(t)$, a_i and p, respectively, in intention.

We assume that the weights of the factors affecting the intention are the same among the population of agent farmers in a given water catchment area. These weights $(\gamma_s\ \gamma_a\ \gamma_p)$ characterise the population of agent farmers.

3.2.2. Calculation of the subjective norm $s_i(t)$

The subjective norm is the agent's perception of what the other important people for the agent (agent-farmers in the network of the agent) think the agent should or should not do. Agent farmers in a network can communicate their farming practice among each other (link 2 in Figure 1). Like most authors using TPB in ABM (Schwarz and Ernst 2009, Warnke et al. 2017, Muelder and Filatova 2018, Raihanian Mashhadi and Behdad 2018, Tong et al. 2018), we implement a descriptive norm in place of the subjective norm. We assume that what the agent-farmer thinks the other important people think the agent-farmer should or should not do is equivalent to what the other important people do. Thus, the subjective norm is equal to the share of low-input agent farmers in their network. This factor is dynamic and evolves during the simulation:

$$s_i(t) = m_i(t) / n_i \qquad (5)$$

where $m_i(t)$ is the percentage of agent-farmers in set S_i performing the low-input farming practice, n_i is the number of agent-farmers in set S_i, and S_i is the set of agent-farmers in agent-farmer *i*'s social network (see Appendix 4 for the construction of the social network).

3.2.3. Calculation of the attitude a_i

Mettepenningen et al. (2013) and Falconer (2000) considered two different types of attitude: attitude towards the environment and environmental management on farms and attitude towards agri-environmental policy implementation. In the model, we assume that attitude entails two aspects: a financial aspect and an environmental aspect (Eq. (3)).

$$a_i = e * (1-w_i) + f * w_i \quad (3)$$

$$f = (\pi^l - \pi^h + \varphi) / (\pi^h - \pi^l) \quad (4)$$

$$e = 1 \quad (5)$$

We assume that the financial component of the attitude is the normalised difference between the low-input and high-input farming gross margins (π_l and π_h) (Eq. (4)). Indeed, most farmers will not adopt an agro-environmental measure if the financial compensation does not cover the cost of changing to a sustainable farming practice (Wilson 1992, Defrancesco et al. 2007, Mettepenningen et al. 2013). Hence, the costs of change can be a barrier to the intention of changing farming practices. The assumed values of the gross margins of the high-input and low-input farming practices (π_h and π_l) are 900 and 600 €, respectively. Compensation (φ) can be provided to agent farmers depending on the protection programme. The financial component of attitude can be negative or positive.

The environmental component of attitude e is the judgement regarding the environmental desirability of the low-input farming practice, i.e., the environmental consequences of the low-input practice on the concentration of pollutant in the groundwater. We assume that the actors consider that the adoption of a low-input practice has a real impact on water quality and that it is completely desirable (Eq. (5)).

Financial preference (w_i) is the weight of the financial component of the attitude. We distinguish two types of agent farmers: "economicus" and "eco-friendly". The "economicus" type places more emphasis on the economic profit; hence, the financial preference is higher than for the "eco-friendly" type, which attaches more importance to the environment. w_i equals 0.9 for economicus and 0.5 for eco-friendly agent-farmers. Thus, a_i is static and differs between the two types of agent farmers.

3.2.4. Calculation of the Perceived Behavioural Control (PBC) p

The PBC (p) is the perception of the ease and the difficulty of performing the behaviour. This factor is static and the same for all agent farmers.

$$p = \theta + p_0 \qquad (6)$$

Mettepenningen et al. (2013) point out that several studies show that the adoption of an AES is influenced by the perception of its ease of implementation and its compatibility with farm characteristics. In the literature, the PBC of farmers is influenced by qualification (e.g., Kaufmann et al. 2009), past experiences (e.g., Kniveton et al. 2012, Diez-Echavarría et al. 2018), economic aspects (e.g., Verwaart and Valeeva 2011, Warnke et al. 2017) or available infrastructure or equipment (e.g., Schwarz and Ernst 2009, Labelle and Frayret 2018). In the model, we represent the PBC as the initial aggregation of past experiences, knowledge and qualification (p_0) enriched by new knowledge acquired with the protection programme (θ). We assumed that the initial PBC (p_0) is zero and the same for all agent farmers.

3.2.5. Dynamics of actors' decision-making

The link between intention and behaviour raises two interlinked issues regarding the strength of the link and its representation. Depending on the level of $I_i(t)$, the agent-farmer will choose whether to change their farming practice ($B_i(t)$). The studies that implement the TPB in an ABM suggest that three different types of links between intention and behaviour can be implemented. First, when different behaviours occur, the intentions for all of them are calculated, and the maximum is chosen (e.g., Klabunde and Willekens 2016, Raihanian Mashhadi and Behdad 2018). Second, intentions are compared with a behavioural threshold that determines whether the intended behaviour will be performed. If the behaviour is undertaken, the success of its realisation could take on different forms: systematic success (Kaufmann et al. 2009, Verwaart and Valeeva 2011), probability of success (Tong et al. 2018), and a success function (Warnke et al. 2017). Third, the intention is a probability of the behaviour (Wang and Hu 2012).

Following Kaufmann et al. (2009) and Verwaart and Valeeva (2011), we have chosen to represent the shift from intention to behaviour by using a behavioural threshold:

$$\text{If } I_i(t) \geq \Omega_i \text{ then } B_i(t+1) = 1 \qquad (7)$$

Some studies comparing multiple analyses show that the gap between intention and behaviour can be more important or less important, depending on the behaviour studied (Sheeran and Webb 2016). In the model, the value of this behavioural threshold (Ω_i) is distributed among the population according to a normal law. Thus, it is different for each simulation. This type of distribution was chosen to represent the diversity among individuals and the fact that the intention, although relatively good at predicting behaviour, is not a perfect predictor.

3.3. Governance

A programme aiming at protecting the drinking water catchment is implemented (link 3 in Figure 1). The agent-farmer may or may not choose to participate in the programme. If agent-farmers enter the process, they must change their farming practice to low-input practice. The governance submodel represents the choice of a protection programme based on the combination of the two following measures: financial compensation, individual training and technical support (Table 1). The choice also includes the "level" of the measures, i.e., the amount of financial compensation and the intensity of training. The duration of the programme is 5 years.

- *Financial compensation*. This measure is based on the agri-environmental schemes of the EU CAP. Agent farmers voluntarily commit to adopting low-input farming practices in return for financial compensation. The compensation aims at covering the costs and income losses resulting from the change in farming practices as well as the transaction costs. It influences the economic profits associated with a farming practice and hence the economic aspect of the attitude. Compensation is provided annually for 5 years. A compensation of 300€/year corresponds to the exact difference between the gross margins of the low-input and high-input farming practices (π_h and π_l). We test a range of financial compensations from zero to twice this difference, i.e., 600€/year.
- *Training*. Technical support and training are individual measures offered to support farmers in their change of practice (e.g., technical advice, meetings, tests and experiments). According to Paineau et al. (1998) and Lastra-Bravo et al. (2015), training and information for farmers are the key elements that promote a greater respect for the environment. In the model, this measure affects the perceived behavioural control by increasing the agent-farmers' knowledge of a farming practice. Knowledge persists over time. The training intensity is calibrated from 0 to 1. An intensity of 0.2 corresponds to a 1-year training course during a 5-year protection programme. We assumed that a 5-year training measure costs 2500€/programme, based on data on the costs of training in a catchment protection programme implemented in France (see Appendix 5 for the calculation).

Measure	Impact on	
	Attitude	Perceived behavioural control
Financial compensation (φ)	$f = (\pi^l - \pi^h + \varphi) / (\pi^h - \pi^l)$	
Training (θ)		$p = \theta + p_0$

Table 1: Measures and their impact on agent-farmers' decision-making (link 3 in Figure 1)

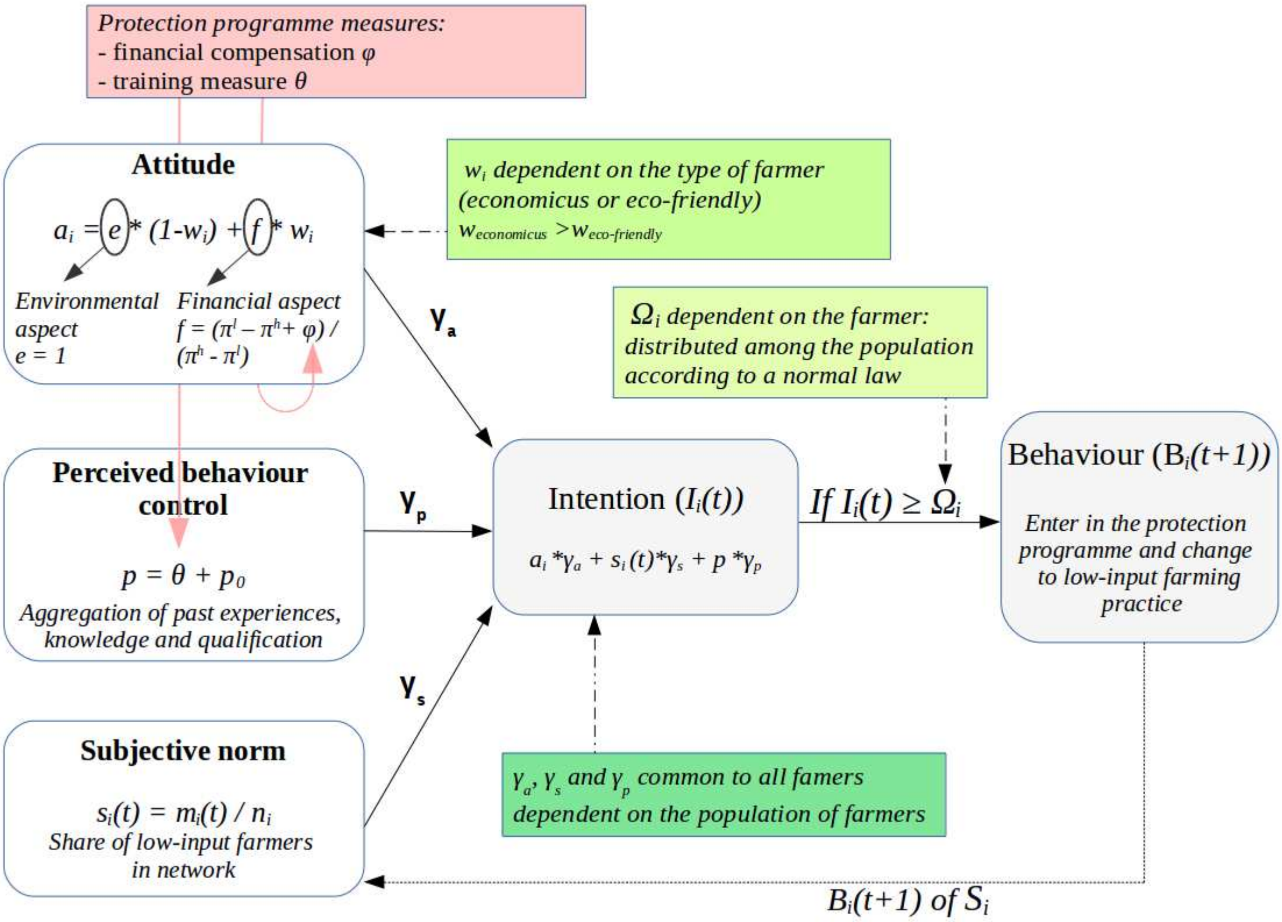

Figure 3: Decision model diagram based on the theory of planned behaviour (source: Ajzen 1991). The pink box represents the protection programme measures. The squircles represent the decision-making process. The green boxes describe parameters at the different levels: the threshold (Ω) at the individual level in light green, the financial preference (w) characterising types of farmers in green, and the weights of factors in intention at the population level (γ_a, γ_p and γ_s) in dark green. The dashed lines represent the feedback from the behaviours of the members of the social network of farmer i ($B_i(t+1)$ *of* S_i) to the subjective norm of the farmer.

3.4. Reference scenario

In what follows, we present a reference scenario with which we analyse the processes involved in the system dynamics (see Appendices 2 and 6 for all of the detailed values). We run simulations over two time horizons: 10 years, which corresponds to the policy time scale, and 500 years, to evaluate the ecological equilibrium. The results presented are representative on average. In the reference population, the three intention factors used in the TPB have equal weights ($\gamma_a = \gamma_s = \gamma_p = 1/3$); initially, there are no low-input farmers, and half of the farmers are eco-friendly. The reference protection programme includes a financial compensation of 300€/year and a training measure with an intensity of 0.5.

As explained before, the intention to change depends on three factors:

- The PBC, which is the same regardless of the type of farmer (economicus or eco-friendly). This means that training has the same effect on both types of farmers. The PBC is constant over time. Because we assumed that the initial PBC is zero, it is equal to 0.5 when the reference programme is implemented.
- The attitude in which the weight of the financial component differs according to the type of farmer. The economicus farmers exhibit a higher financial preference (0.9) than the eco-friendly farmers (0.5). This implies that economicus farmers are more sensitive to the financial compensation of a protection programme. The compensation (φ) is less than twice the difference between the gross margins of the high-input and low-input farming practices (π_h and π_l), so the ecological component is higher than the financial component. Consequently, economicus farmers have a lower attitude than eco-friendly farmers. With the reference programme, the attitude is equal to 0.5 for the eco-friendly farmers and to 0.1 for the economicus farmers. Attitude is constant over time.
- The subjective norm depends on the social network of each farmer. Each farmer is influenced by the practices of farmers in their social network. The social network evolves over time and constitutes the driver of the dynamics of the model.

In Figure 4, the dynamics of low-input practice adoption by farmers are represented in the case of the reference scenario. In the first phase, only individual effects of the implementation of the protection programme occur. Indeed, at t = 0, all farmers practice high-input farming; thus, the subjective norm is null. More eco-friendly farmers than economicus farmers adopt the low-input practice because, as explained previously, the PBC is equal for the two types of farmers, while the attitude is higher for eco-friendly farmers than for economicus farmers. The second phase represents the additional effect of the collective diffusion of the low-input practice. Only the subjective norm evolves due to the evolution of the share of low-input farmers. After 5 years, 7.2% of farmers adopted a low-input practice (see the blue line in Figure 4). Note that the dynamics of practice change towards a stable share of low-input farmers after 5 years (phase 3 in Figure 4) can be explained by the characteristics of the social network and the low number of farmers. The small percentage of low-input practice adoption has a marginal impact on the quality of water after 10 years (approx. a 1.5% decrease of the pollutant in the water) as well as in the long term (approx. a 8% decrease of the pollutant in the water). The evolution of water quality also depends on the characteristics of the water resource system, notably the water renewal rate.

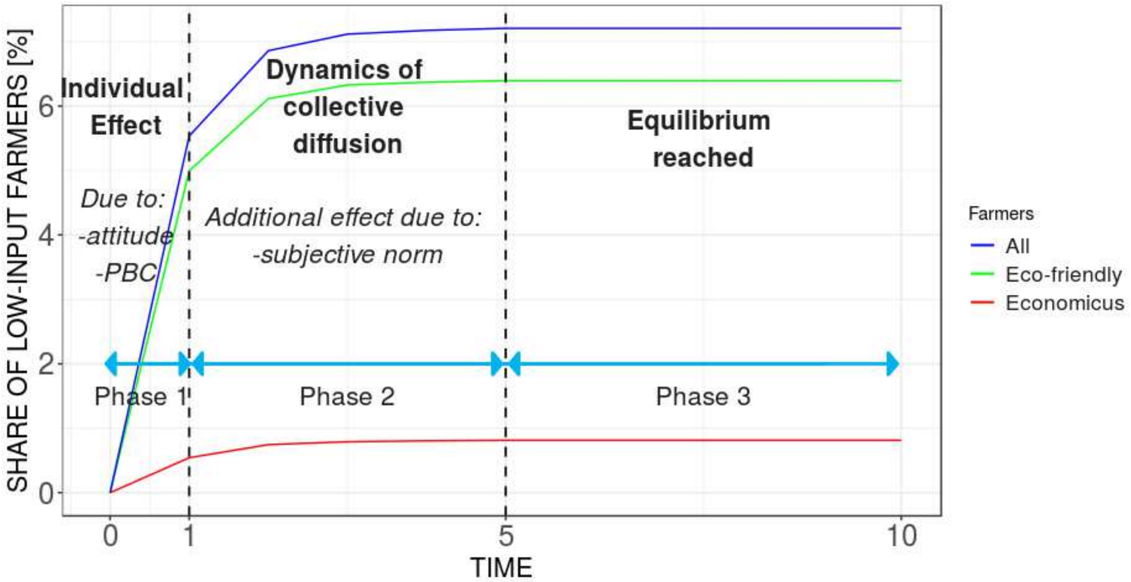

Figure 4: Share of low-input farmers [%] (in blue all farmers, in green eco-friendly farmers and in red economicus farmers) for the reference scenario (the three factors of intention are equal: $\gamma_a = \gamma_s = \gamma_p = 1/3$, the financial compensation φ is equal to 300€, and the training intensity θ equals 0.5).

4. RESULTS

Based on the reference scenario, we explore how policy effectiveness, i.e., the evolution of farmers' practices and water pollution levels, is influenced by the characteristics of the farmer population (Section 4.1). Then, we examine how the characteristics of the protection programme, interacting with the behavioural characteristics of the farmer population, impact the policy effectiveness (Section 4.2) and efficiency (Section 4.3).

4.1. Influence of the population characteristics on policy effectiveness

4.1.1. The influence of behavioural characteristics of the population

The behavioural characteristics of the populations have a strong influence on the final share of farmers adopting a low-input farming practice (see Figure 5a) and on the concentration of pollutants. In the reference scenario, the higher the weight of the subjective norm for a population is, the lower the diffusion of the low-input practice is. Indeed, the subjective norm acts as a brake because of the assumption of no low-input farmers in the population before the implementation of the protection programme.

The difference in shares of low-input farmers between the economicus and eco-friendly farmers increases with the weight of attitude. In the case of eco-friendly farmers, the weights of attitude and PBC are equal in the reference protection programme; thus, only the weight of the subjective norm in the population influences the final number of low-input farmers (see Figure 5b). In the case of economicus farmers, the attitude is lower than the PBC; therefore, a higher weight of PBC increased the final share of low-input farmers (see Figure 5c).

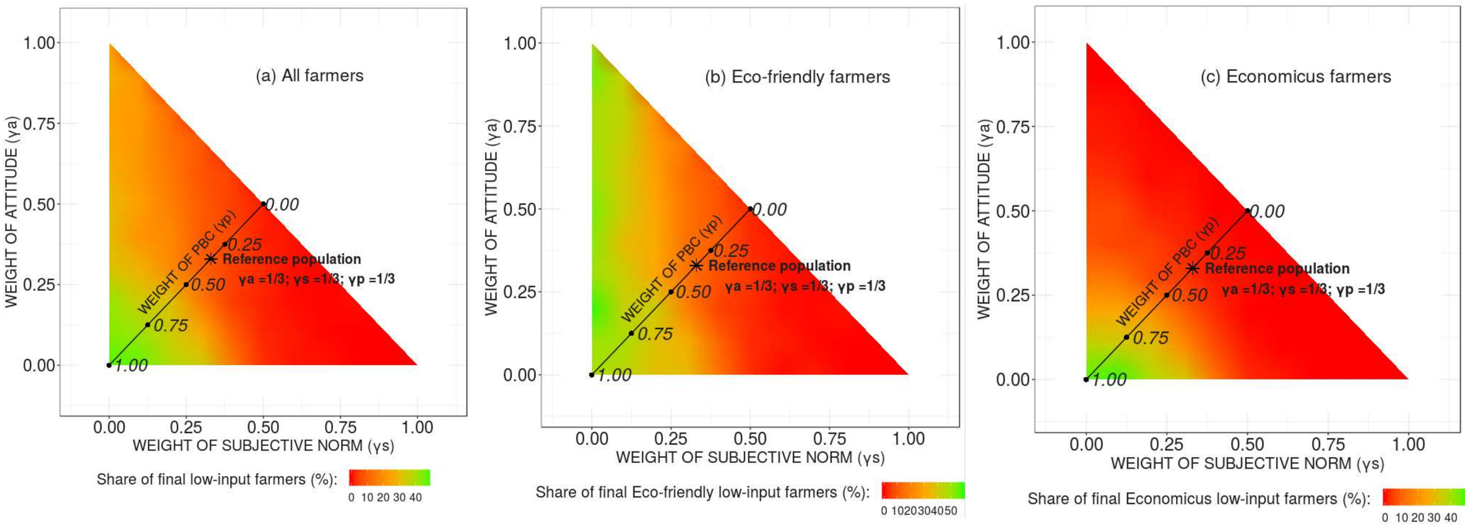

Figure 5: Heatmap of the final share of low-input farmers depending on the weights of TPB factors for (a) all farmers, (b) eco-friendly farmers and (c) economicus farmers in the reference scenario. Whereas the share of eco-friendly low-input farmers can be explained by the weight of subjective norm, the share of economically low-input farmers is influenced by all factors and was higher with a higher PBC weight.

4.1.2. The influence of the initial share of low-input farmers

In the previous section, we initially investigated the case of no low-input farmers at the start of the programme. To analyse the effect of the presence of one or many low-input farmers on policy effectiveness, we tested different initial shares of low-input farmers according to different values of the importance of the subjective norm for the population (see Figure 6). Regardless of the weight of the subjective norm for a population (γ_s), the share of low-input farmers after the implementation of a protection programme increases with the initial share of low-input farmers (see Figure 6a). However, a subjective norm with a higher weight does not necessarily lead to a higher final share of low-input farmers. In a context where there are initially few low-input farmers, the implementation of a protection programme will have a greater effect if the population gives less importance to the subjective norm. Below a threshold in terms of the initial share of low-input farmers, the subjective norm acts as a brake. Above this threshold, the final share of low-input farmers increases with the weight of the subjective norm. The subjective norm has a ripple effect on the diffusion of the adoption of the low-input farming practice (see Figure 6a).

Nevertheless, the relative increase in the share of low-input farmers is not the highest when the initial share of low-input farmers is the highest. Indeed, the highest increase can be found in populations that include approximately one-third of initial low-input farmers and that give high importance to the subjective norm (yellow area in Figure 6b). This corresponds to situations where there is both a greater possibility for a difference between the initial and final shares and a sufficiently high initial share of low-input farmers to trigger the ripple effect of the subjective norm.

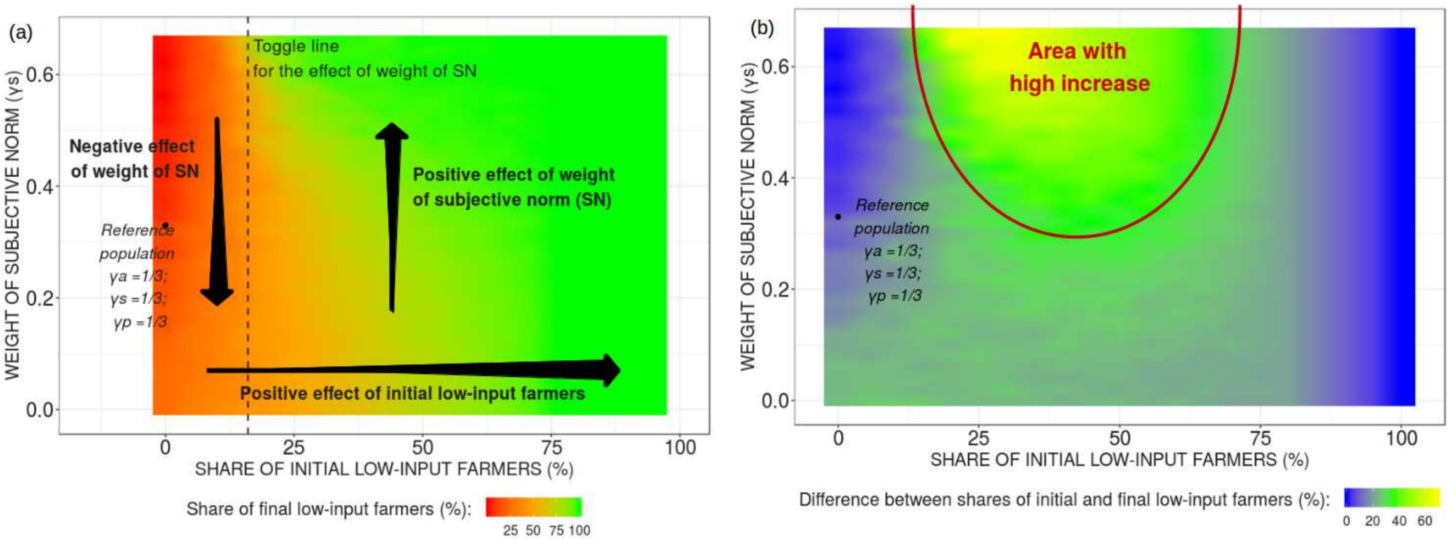

Figure 6: Heatmap of (a) the final share of low-input farmers and (b) the difference between the initial and final shares of low-input farmers, depending on the weights of the subjective norm and on the initial share of low-input farmers in the reference scenario.

4.1.3. The influence of the share of eco-friendly farmers

Because of their favourable attitude towards the adoption of the low-input farming practice, it is likely that the presence of more eco-friendly farmers improves the effectiveness of the protection programme. To analyse the effect of the number of eco-friendly farmers on policy effectiveness, we tested different shares of eco-friendly farmers according to different values of the importance of the attitude for the population (see Figure 7).

Regardless of the weights of the factors in intention or the distribution between eco-friendly and economicus farmers, the share of low-input farmers after the implementation of the protection programme increases with the share of eco-friendly farmers in the population (Figure 7). The increase is higher for eco-friendly farmers than for economicus farmers.

Eco-friendly and economicus farmers do not have the same sensitivity to an increase in the weight of attitude. The impact of the weight of attitude depends on the weights of the subjective norm and the PBC. As shown in Section 4.1.1, in the reference scenario, the subjective norm has a negative effect and the PBC has the same effect as the attitude for eco-friendly farmers. Thus, for eco-friendly farmers, a decrease in the weight of subjective norm increases the final share of low-input farmers (see Figures 7.a2, 7.b2 and 7.c2). Economicus famers have a less favourable attitude towards the low-input practice than do eco-friendly farmers. The weight of the PBC has a positive effect compared with the weight of attitude for this type of farmer. Thus, a lower weight of attitude increases the final share of low-input economicus farmers (Figures 7.a3, 7.b3 and 7.c3). This share is the highest in Figure 7.b3, where the weight of the subjective norm is fixed and the weight of PBC is the highest. With γ_s = *1/3*, a higher share of eco-friendly farmers leads to an increase in the final share of low-input farmers due to the influence of the subjective norm (see Figures 7.b2).

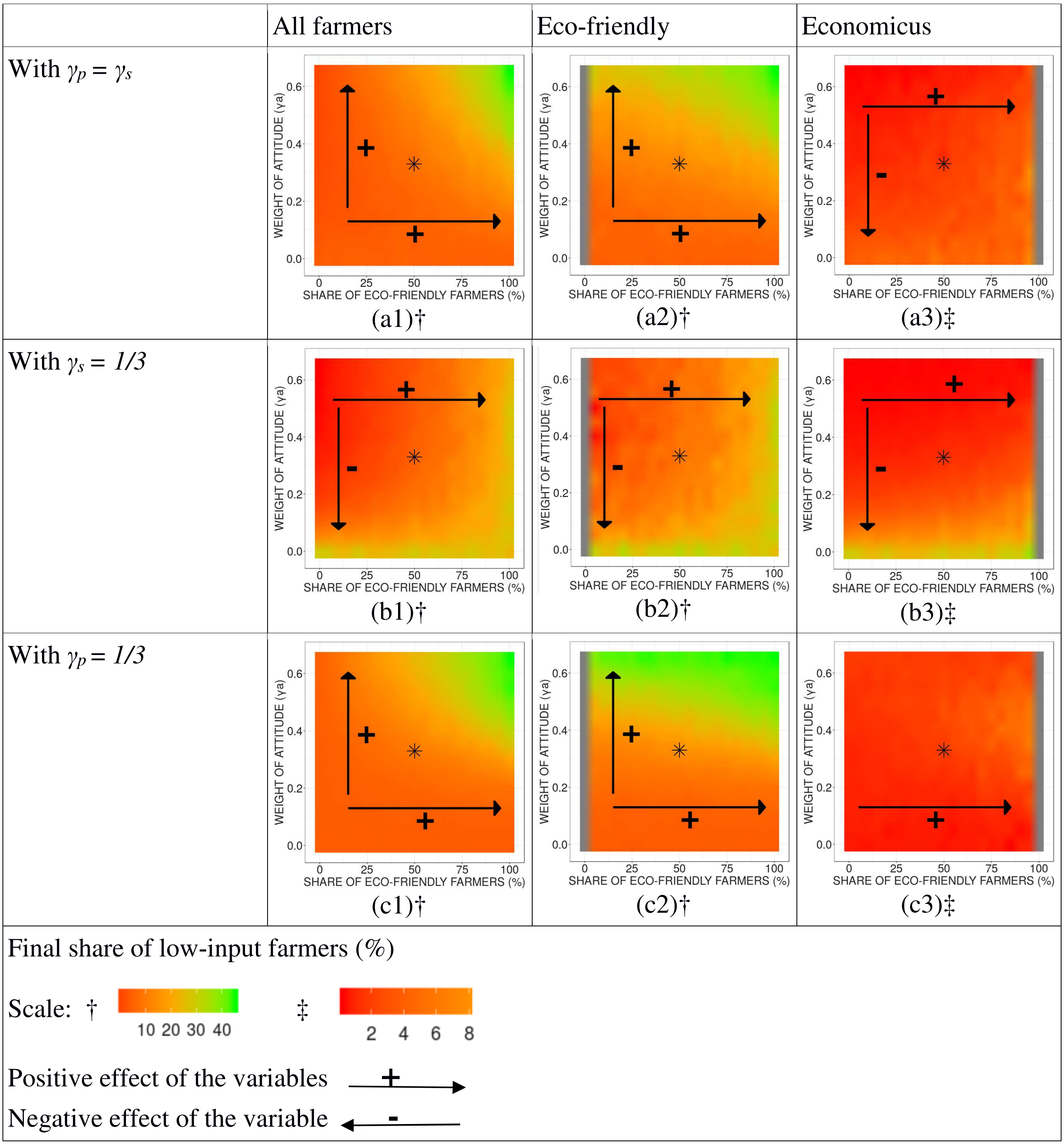

Figure 7: Heatmaps of the final share of low-input farmers: (1) all farmers, (2) eco-friendly farmers and (3) economicus farmers depending on the weight of attitude and the share of eco-friendly farmers, in the reference scenario, with (a) other weights equal ($\gamma_p = \gamma_s$), (b) a fixed weight of subjective norm ($\gamma_s = 1/3$) and (c) a fixed weight of the PBC ($\gamma_p = 1/3$). * is the reference population ($\gamma_a = 1/3$ and 50% of eco-friendly farmers). The difference between the two types of farmers in the final share of low-input farmers is a function of the weight of attitude.

4.2. Influence of the characteristics of protection programmes on policy effectiveness

As explained earlier, a protection programme is composed of two policy measures (financial compensation and individual training) that may be combined in different ways. These different combinations in interaction with the behavioural characteristics of the farmers' population may affect the effectiveness of the protection programme. We investigate this issue in this section.

4.2.1. Adapting policy measures to population characteristics

Regardless of the relative importance of the factors in the intention, the level of financial compensation or the intensity of training included in the protection programme has a positive effect on the final share of low-input farmers. However, the extent of this positive effect depends on the behavioural characteristics of the population. To analyse the coupled effects of the characteristics of the protection programme and the behavioural characteristics of the population, we compare the reference scenario population ($\gamma_a = \gamma_s = \gamma_p = 1/3$) with the three following populations:

- the attitude-influenced population that gives more importance to attitude ($\gamma_a = 0.5; \gamma_s = 0.25; \gamma_p = 0.25$); therefore, the population is more sensitive to financial compensation, especially the economicus farmers.
- the PBC-influenced population that values the PBC more ($\gamma_a = 0.25; \gamma_s = 0.25; \gamma_p = 0.5$); such a population is more sensitive to the intensity of the training offered by the protection programme.
- the subjective norm-influenced population (which values the subjective norm more, i.e., $\gamma_a = 0.25; \gamma_s = 0.5; \gamma_p = 0.25$); this population is more sensitive to the dynamic effects caused by the social network.

For each population, several combinations of measures lead to the same share of low-input farmers. A mix of minimum levels of financial compensation and training intensity is needed to trigger a high level of adoption of low-input farming. We define tipping areas as areas where a small change in initial conditions (combinations of measures) leads to a large increase in the share of low-input farmers. These areas differ from one population to another. They are linked to the social network and are not as large when the population is more sensitive to the subjective norm, which leads to the absence or full adoption of the low-input farming practice (Figure 8d).

The intention of farmers in the attitude-influenced population is more sensitive to financial compensation; nevertheless, the minimal financial compensation in the tipping area is higher than for other populations. Likewise, while the intention of farmers in the PBC-influenced population is more sensitive to training intensity, the minimal intensity triggering the population to shift to the low-input practice is higher than for other populations.

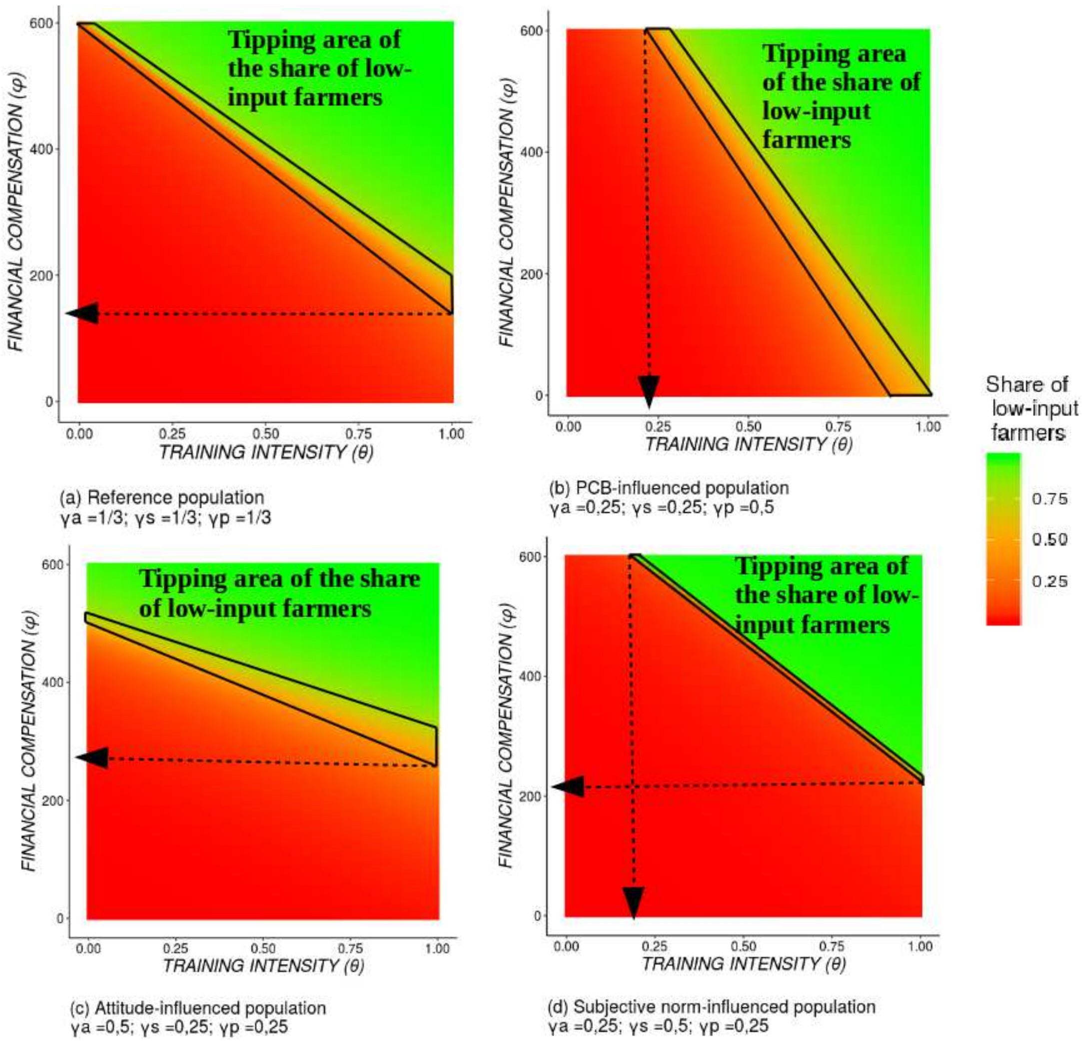

Figure 8: Heatmaps of the trade-offs between financial compensation and training measures for four populations: (a) the reference population (γ_a = *1/3;* γ_s = *1/3;* γ_p = *1/3*), (b) PBC-influenced (γ_a = 0.25; γ_s = 0.25; γ_p = 0.5), (c) attitude-influenced (γ_a = *0.5;* γ_s = *0.25;* γ_p = *0.25*) and (d) subjective norm-influenced (γ_a = *0.25;* γ_s = *0.5;* γ_p = *0.25*). The tipping areas and their orientation show the differences in the sensitivity of the populations to the measures.

Comparing the tipping areas shows that the attitude-influenced population (Figure 8c) has a higher marginal effect of financial compensation on the level of training intensity than other populations.

That is, a small decrease in the amount of financial compensation must be compensated by a greater increase in training intensity than for the other populations to lead to the same share of low-input farmers. In the case of the PBC-influenced population, a small decrease in the intensity of training must be compensated by a greater increase in the level of financial compensation than for the other populations to lead to the same proportion of low-input farmers.

4.2.2. Isolines of effectiveness of different policy measures according to populations

The isolines of involvement are curves where the combinations of measures (policy mixes) engage the same share of low-input farmers. An isoline of involvement serves as a demarcation between two areas: one area representing the set of policy mixes leading to a higher share of low-input farming and one area representing the set of policy mixes not leading to this share. The combination of isoline zones for different populations makes it possible to define an area where a given level of effectiveness is achieved for all populations and an area where this given level of effectiveness is not achieved for any population.

The results show that some policy mixes, regardless of which of the four populations described in Section 4.2.1 are considered, do not lead to the achievement of the target of 90% of farmers adopting low-input farming (area B in Figure 9). In contrast, some policy mixes make it possible to reach the target for all four populations (area A in Figure 9). However, depending on the actual population, financial compensation and/or training intensity could have been less important; thus, the total cost of the programme could have been lower to reach the same result (area C in Figure 9).

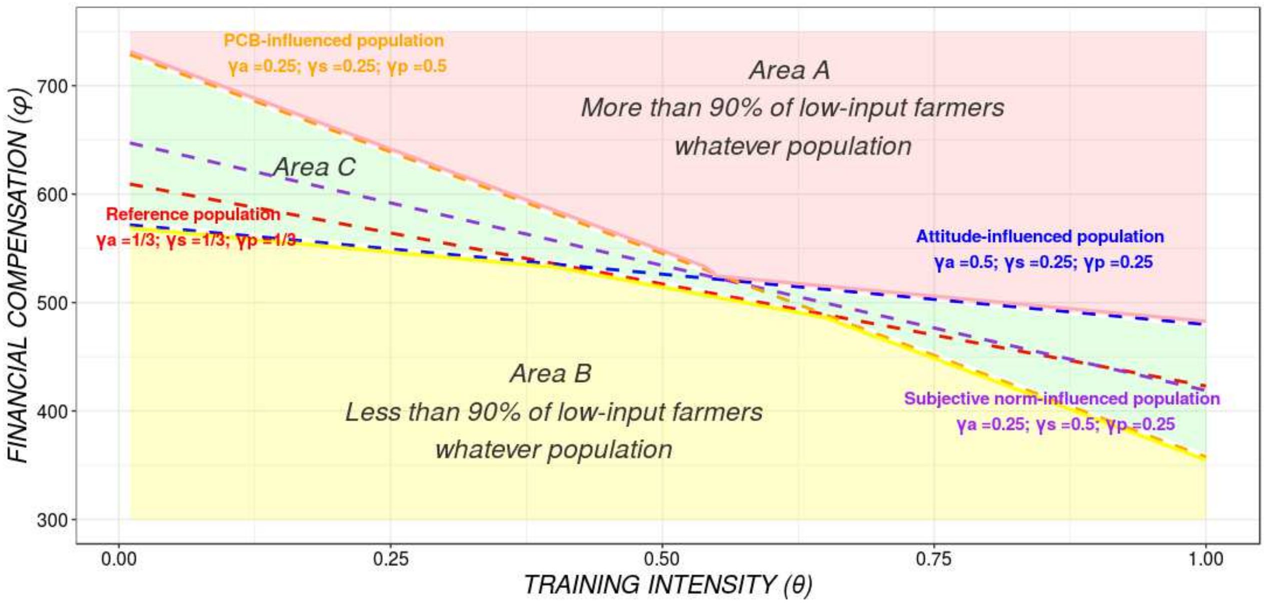

Figure 9: Isoline participation of 90% on average based on training and financial compensation for four populations: attitude influence, reference (equal weight), subjective norm influence and PBC

influence. In zone A, regardless of the behavioural characteristics of the population, 90% of the farmers will choose low-input farming. In zone B, regardless of the behavioural characteristics of the population, less than 90% of the farmers will choose low-input farming.

Thus, taking into account information about the farmer populations and their behavioural characteristics in the definition of policies can lead to measures with the minimal levels of financial compensation and/or training intensity needed to trigger farmers' adoption of the low-input practice. Without information on the behavioural characteristics of the population, policy-makers may choose a mix of policy measures in a zone crossing all areas to reach at least a certain target in terms of the share of low-input farmers.

4.3. Mix of policy measures: Not the most efficient policies but also not the least

As we have shown, different combinations of measures may lead to the same results. However, all combinations are not equivalent, especially in terms of costs. To analyse the efficiency of policies, we analyse the combinations of measures with a fixed cost. We use the attitude-influenced and PBC-influenced populations because they do not have the same sensitivity to the two measures.

Considering a fixed cost per farmer of 2500€, we tested the three following protection programmes: an entirely financial programme, denoted F, with no training and a financial compensation of 500€/year; an entirely training programme, denoted T, with one training session per year and no financial compensation; and a balanced training-financial programme, denoted E, with half of the training sessions planned in the entirely training programme and a compensation of 250€/year. These different mixes of policy measures do not lead to the same final shares of low-input farmers (Figure 10). The comparison of the different policy mixes for a given population allows us to find the most efficient mix. For the attitude-influenced population, the most efficient mix, at fixed cost, corresponds to the entirely financial programme without training (point F_A in Figure 10), while for the PBC-influenced population, it is the entirely training programme (point T_{PBC} in Figure 10). These different policies are the most efficient for the one type of population, while they are the least efficient for the other.

Policies with average levels of each of the two measures lead to relatively similar shares of low-input farmers among the different populations. Thus, without knowledge about a population, the choice of a mix of policy measures seems to reduce the variations in the effectiveness of the protection programme at a fixed cost per farmer. A mix of policy measures, even if it is never the most efficient, guarantees that it will not be the least efficient policy.

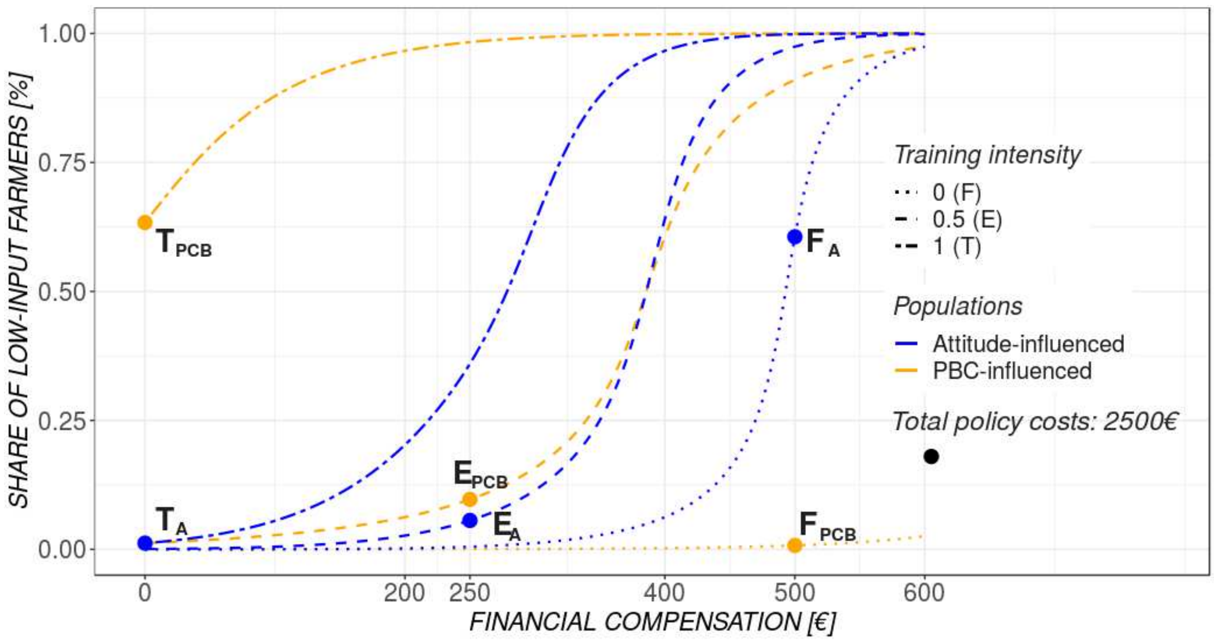

Figure 10: Share of low-input farmers depending on financial compensation. Curves in orange and points X_{PBC}, Y_{PBC} and Z_{PBC} belong to the PBC-influenced population ($\gamma_a = 0.25; \gamma_s = 0.25; \gamma_p = 0.5$). Curves in blue and points X_A, Y_A, and Z_A belong to the attitude-influenced population ($\gamma_a = 0.5; \gamma_s = 0.25; \gamma_p = 0.25$). Points in the short dashed lines represent the same total cost of a protection programme (2500€). Dashed lines, dotted lines and dashed lines are, respectively, from programmes with 1, 0.5 and 0 training intensities.

5. DISCUSSION AND CONCLUSIONS

The purpose of our study was to explore how the behavioural characteristics of farmer populations in drinking water catchments impact the efficiency and effectiveness of programmes designed to protect water quality. Our results showed that the involvement of farmers in protection programmes depends closely on the interactions between their behavioural characteristics and the governance system. Farmers' behavioural characteristics must be taken into account to design efficient and effective policies. Mixes of policy measures with financial compensation and training are more costly but may be a better option in situations where knowledge of farmers' behavioural characteristics is not available.

5.1. Contributions and policy implications

Despite the wealth of existing theories derived from experimental and empirical research in various fields (psychology, behavioural economics, sociology, etc.) and the recognised importance of human behaviour in SES models, many formal models are often still based on the oversimplifying assumptions of the rational actor (Schlüter et al. 2017). However, farmers' decisions to adopt more sustainable practices can be affected by multiple behavioural factors (Dessart et al. 2019). Models used for real-world policy support should include agents who behave more like humans. An incorrect representation of actors' decision-making processes can lead to the design of inadequate policies. Many examples can be cited where the agents' behaviour is not well understood and not taken into account, leading to problems of policy effectiveness, or even unintended results, particularly in fields where, in addition to economic motivations, social or environmental motivations matter (Bénabou and Tirole 2006, Brown et al. 2021). Our analysis therefore aimed to contribute to the operationalisation of a theory in social psychology, the theory of planned behaviour, in an SES model. The results highlight the links between the governance system and the agents' decision-making processes and thus the importance of considering the behavioural processes of agents in the design of policies. More specifically, our analysis contributes to enhancing the understanding of the influence of the relative importance of TPB factors on behavioural intention.

The analysis contributes to the literature on the drivers of adoption of agri-environmental measures by showing the important link between farmers' behavioural characteristics and the effectiveness and efficiency of water quality protection programmes. Improving the effectiveness and efficiency of such programmes would benefit from information on farmers' characteristics influencing their participation. Moreover, we highlighted that the success of water protection programmes is influenced by dispositional and social factors in interaction (e.g., the influence of attitude and subjective norm on intention). This is in line with the results of Januchowski-Hartley et al. (2012) and Yeboah et al. (2015), who conclude that it may be helpful to communicate with farmers not only about their personal benefits of participation in agri-environmental programmes but also about the associated social and environmental benefits.

Previous studies focusing on EU agri-environmental schemes (component of the EU Common Agricultural Policy (CAP)) have shown that a lower level of governance, that is, at the local level rather than at the centralised EU level, helps to better adapt measures (e.g., the level of subsidies) to the characteristics of farmers (Kuhfuss et al. 2012, Bareille and Zavalloni 2020). In water catchment areas, Amblard (2019) concluded that strengthening the autonomy of local actors in adapting measures and compensations to the local context could improve the effectiveness of water quality management programmes. Our results highlight the importance of tailoring agri-environmental policies to the characteristics of farmers. Despite the decentralisation of the EU agri-environmental scheme, which leaves room for decisions at the Member State and local levels, the possibility of adapting the measures to the characteristics of farmers remains limited (Kuhfuss et al. 2012, Saïd et al. 2017, Amblard 2019). The decentralisation of agri-environmental programmes is still the subject of much debate both in the EU context with the post-2020 CAP negotiations (MAA 2020) and in other settings (Wright et al. 2016, Vorley 2002, Bareille and Zavalloni 2020).

5.2. Limitations and perspectives

Although the TPB has already been implemented in different fields, the implementation of this theory in ABMs still has limitations. In fact, the TPB is based on conceptual psychological notions. The modeller has to decide how to implement these concepts and how to link them together (Muelder and Filatova 2018). Our study constitutes a first step in the integration of TPB in an SES-ABM. Several perspectives and improvements are under consideration. First, we consider only the behaviour of change towards low-input farming, which implies little change in farm structure and organisation. This means that the model is less appropriate for representing the water catchment areas where the evolutions considered involve substantial changes in farming systems, e.g., the conversion to organic farming. A perspective of the current work would be to modify the PBC – which in our model is a combination of knowledge, past experience and qualification – to include some of the barriers associated with such major changes. For example, a financial constraint due to the need for structural change in organic farming could be considered in the PBC (e.g., Verwaart and Valeeva 2011). Second, we assumed that the learning process only includes a change in knowledge, but it can also change attitude beliefs, e.g., a change the share of eco-friendly and economicus farmers, or a change in networks, e.g., the creation of new networks supported by training groups. Third, we stylized the hydrological and biophysical systems and neglected the possible feedbacks between the actors and the ecological system. A better perspective would be to integrate feedback between the ecological system and actors through the influence of farmers' perception of the state of the ecological system. Finally, one remaining challenge would be to perform empirical studies to calibrate our model with real-world data on farmers' characteristics and decision-making processes. While we assumed that all farms are the same (in terms of size, gross margin, and environmental impacts) in the catchment area, this may be a good approximation of reality in some areas but not in others. The characteristics of agriculture (e.g., size, location, type of farming systems) could be defined using data from the French agricultural census (e.g., Xu et al. 2018). Furthermore, the issue concerning the integration of real data in the decisional model, also described by Scalco et al. (2018), is a recurring question, partly because the factors involved in intention are latent factors. Some statistical methods allow us to identify and estimate the behavioural characteristics of farmers through questionnaires, such as structural equation models (SEM) (e.g., Kaufmann et al. 2009; Schwartz and Ernst, 2008), or by using fuzzy logic or regression coefficients (e.g., Casillas, Martínez-López, and Martínez 2004).

5.3. Concluding remarks

The ability of our model to capture the real-world patterns of the evolution of farming practices in a catchment area indicates that our findings may yield important insights for water governance. We highlighted that efficient water quality management requires an adaptation to the local behavioural characteristics of the targeted farmers to enhance their involvement. Moreover, improved knowledge about farmers' behavioural characteristics can reduce the costs of protection programmes. Nevertheless, this investment in knowledge also has a cost that should be taken into account in the global cost of the programme. There is therefore a trade-off between reducing the programme costs and investing in research on farmers' characteristics. Finally, if knowledge on behavioural characteristics is not available, mixes of policy measures are more costly but may be a better option. Understanding the impact of the characteristics of farmers on water policy outcomes is essential for designing public policies faced with increasing water security challenges. In view of the growing significance of pollution on the sustainability of water resources, we believe that our model and our results may represent a valuable contribution to the growing literature on the interactions between resource management and society.

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Appendix 1: ODD+D protocol

After the ODD+D protocol for describing human decisions in agent-based models (Müller et al. 2013)

List of abbreviations:
TPB: theory of planned behaviour

		Guiding questions	Own ODD+D Model description
Overview	I.i Purpose	I.i.a What is the purpose of the study?	To explore how farmers, who are connected in a network, that have either a financial or an environmental orientation, choose whether or not to join a protection programme (and thus to practice low-input farming, the farming practice promoting by protection program). Furthermore, the study evaluates the consequences of their decision in terms of drinking water quality that are influenced, on the one hand, by different behavioural specifications and, on the other hand, by different characteristics of a protection programme.
		I.ii.b For whom is the model designed?	For scientists of different disciplinary backgrounds, particularly those interested in natural resource governance.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	One ecological entity: A groundwater with a certain concentration of nitrate. Two types of social entities: Farmers and governance. Dozens of agents represent farmers whose farming practices have the unintended consequence of releasing pollutants into the groundwater. They decide to enter or not to enter into the protection programme (which is whether or not to practice low-input farming promoted by the protection programme). Governance is represented by an agent, and its function is to encourage farmers to become involved in the proposed protection programme, which aims to ensure that farmers practice low-input agriculture.
		I.ii.b By what attributes (i.e., state variables and parameters) are these entities characterised?	Ecological entity: The groundwater has a certain quantity of water (Q). There is a natural flow that feeds (E) the groundwater and a quantity that exits (D) in the groundwater aquifer. The concentration of pollutants in water ($C(t)$), in mg/l, is used as a proxy to measure water quality, i.e., the quantity of pollutant ($N(t)$) relative to the quantity of water in the groundwater (Q). Farmers (one agent representing one farmer (i)) are characterised by: a location, a farming practice ($B_i(t)$), which can be low-input (l) or high-input (h) (low-input farming practice is more favourable to water quality than the high-input practice but less economically profitable), a residual pollutant affecting the groundwater ($R_i(t)$) of the agent i depending on her practice, a social network (S_i), a behavioural type (*economicus* or *eco-friendly*), a behavioural threshold to change (Ω_i), a financial preference (w_i), an intention factors preferences $(\gamma_a\ \gamma_s\ \gamma_p)$, a set of knowledge and past experiences about farming practices p. Governance is characterised by these variables: an amount of compensation (φ), an intensity of training practice (θ).

		I.ii.c What are the exogenous factors/drivers of the model?	There are none.
		I.ii.d If applicable, how is space included in the model?	N/A
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	One time step equals to one year, and the simulations were run at two time horizons: 10 years, corresponding to the policy time scale, and 500 years, to evaluate ecological equilibrium. Rectangular grid 10*10 represented a water catchment area.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	<u>Step 1</u>: Governance - Update of the protection program <u>Step 2</u>: Farmers – Choose to enter into or choose not to enter into the protection programme and therefore switch or not switch their farming practice <u>Step 3</u>: Ecological system - Update of watershed (concentration of pollutants)
Design Concepts	**II.i Theoretical and Empirical Background**	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel**(s) (apart from the decision model)?** What is the link to complexity and the purpose of the model?	The ecological submodel is a linear reservoir model whose storage law and discharge law vary linearly as a function of the water level. "The linear reservoir model, in its simplest form, appears well adapted to quite variable situations ranging from small, highly urbanised watersheds to watersheds of several hundred hectares." (Ministère de la transition écologique et solidaire 2020). The governance submodel is a choice of a protection programme that can include the following measures: financial compensation, individual training and technical support. The choice is about the level of the measure (the amount of the compensation and the intensity of the training). *Financial compensation:* They are based on agri-environmental scheme that are EU Common Agricultural Policy's instruments. Farmers voluntarily commit to adopt low-input farming practices in return for a financial compensation. This compensation aims at covering the costs and income losses resulting from the change, as well as transaction costs. It influences the economic profits associated with a farming practice, hence the economic component of the attitude. The compensation is provided annually for five years. *Training*: Technical support and awareness raising are individual support measures provided to farmers in support of their decision to change or not change their practices (e.g., technical advice, meetings, technical tests, experiments). According to Paineau et al. (1998) and Lastra-Bravo et al. (2015), training and information for farmers are key elements that promote a greater respect for the environment. In the model, this measure affects the perceived control by increasing farmers' knowledge of a farming practice. Knowledge persists over time.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	We adapt the theory of planned behaviour (TPB) (Ajzen 1991). In this framework, the intention towards a behaviour, considered as a trustworthy predictor as to whether or not the behaviour will be performed, is influenced by three global variables: judgement about the desirability of the behaviour and its consequences (attitude towards behaviour), considerations of the influence and opinions of others on that behaviour (subjective norm), and beliefs about the individual's ability to succeed in the behaviour (perceived behavioural control).

		II.i.c Why is a/are certain decision model(s) chosen?	One of the most frequently used approaches to understanding farmers' decision-making with regard to agri-environmental policies is the theory of reasoned action developed by Ajzen and Fishbein (Ajzen and Fishbein 1980; Toma and Mathijs 2007; Falconer 2000), which was later extended into the TPB model (Ajzen 1991).
		II.i.d If the model or a submodel (e.g., the decision model) is based on empirical data, where does the data come from?	<u>Data about farming practices:</u> Gross margin (organic farming)→ (Réseau DEPHY 2014) Gross margin (conventional farming)→ (Chambre d'Agriculture de la Mayenne 2017) Treatment frequency indices (TFI) organic farming → (Jézéquel et al. 2007) TFI with seed treatment→ (Agreste 2016) <u>Data about the ecological system:</u> Quantity of water in the watershed → (Chambre d'Agriculture de L'allier 2015) Quantity of extracted water → (Amblard and Reynal 2015)
		II.i.e At which level of aggregation were the data available?	<u>Data about farming practices:</u> Gross margin (organic farming)→ average/ha from regional data (Midi-Pyrénées) for organic wheat Gross margin (conventional farming) → average/ha from regional data (Mayenne) for conventional wheat TFI organic farming → average/ha from national data for organic wheat TFI with seed treatment average/ha from regional data (Auvergne) for conventional wheat <u>Data for ecological system:</u> Quantity of water in the watershed → data available from the department Allier Quantity of extracted water → data for the drinking water catchment area of Allier
	II.ii Individual Decision-Making	**II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision-making included?**	Farmers decide if there are involved in the protection programme and accordingly apply low-input farming practice. Governance chooses the characteristics of the protection program: minimum duration, amount of compensation, training intensity.
		II.ii.b What is the basic rationality behind an agents' decision-making in the model? Do agents pursue an explicit objective or do they have other success criteria?	Farmers act if their intention exceeds a threshold. This intention is a function of their beliefs about the behaviour in terms of attitude, subjective norm and perceived behavioural control.

		II.ii.c How do agents make their decisions?	If the farmer is not in the protection programme (and thus does not practice low-input farming), they compare their intention to be involved in the programme *($I_i(t)$)* and their behavioural threshold *(Ω_i)*. If the behavioural threshold is exceeded, they enter into the programme and change to low-input farming. 1. Calculation of intentions *($I_i(t)$)*, which is a linear function of the following factors *(γ_a γ_s γ_p)* weighted by their contributions in the intention: - attitude *(a_i)*: the weighted sum of a comparison between the profit component and the environmental component - subjective norm *($s_i(t)$)*: the percentage of low-input farmers in the networks - perceived behavioural control *(p)*: knowledge and past experiences 2. Compare intentions with behavioural threshold *(Ω_i)* Attributes of farmers concerning the decision-making process are: the weight of the importance of attitude in intention, the weight of the importance of perceived behavioural control in intention and the weight of the importance of the subjective norm in intention, the weight of the importance of the financial component of the attitude, the weight of the importance of the environmental component of the attitude, and the behavioural threshold (indicates when the intention become a behaviour).
		II.ii.d Do the agents adapt their behaviour to changing the endogenous and exogenous state variables? And if yes, how?	Yes, attitude is modified by the compensation from the protection programme and perceived behavioural control is modified by the training intensity of the protection programme.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Yes, a social norm represented by the percentage of low-input farmers in an agent's network constitutes the subjective norm.
		II.ii.f Do spatial aspects play a role in the decision process?	No
		II.ii.g Do temporal aspects play a role in the decision process?	Yes, - the farmers communicate their farming practice of the previous year to others
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	No
		II.iii.b Is collective learning implemented in the model?	

	II.iv Individual Sensing	II.iv.a What **endogenous** and **exogenous** state variables are individuals assumed to sense and consider in their decisions? **Is the sensing process erroneous?**	Individuals sense the characteristics of the protection programme, and profits of the different farming practices. The sensing process is not erroneous.
		II.iv.b What state variables of which other individuals can an individual perceive? **Is the sensing process erroneous?**	Farmers know the farming practices of others. The sensing process is not erroneous.
		II.iv.c What is the spatial scale of sensing?	Networks
		II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?	Farmers are assumed to know these variables.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No
	II.v Individual Prediction	**II.v.a Which data uses the agent to predict future conditions?**	Data from the protection programme (changes to the expected profit of the farming practices and the expected control).
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	Farmers' attitude is the judgement about the desirability of their behaviour and consequences. This attitude is divided in a financial component and an environmental component. The financial component of the attitude uses the expected income from the farming practice, and the environmental component uses the output effect of the farming practice on the watershed.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	No, they are not erroneous. For the financial component, they calculate the difference normalised between the expected income of actual farming practice and the other farming practice. For the environmental component, it's equal to 1, as we assume that the actors consider that the adoption of low-input practice has a real impact on the water quality and that it is completely desirable.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Direct interactions through communications of their farming practices
		II.vi.b On what do the interactions depend?	Social network (based on links with famers, which are in one of the 8 farm patches around the farmer, that are randomly renewed with other farmers - based on the Small World model of Wilensky (2015), which is an adaptation of a model proposed by Watts and Strogatz (1998))
		II.vi.c If the interactions involve communication, how are such communications represented?	Communication about farming practices
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	N/A

	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	Individuals are affected by the practices of farmers in their network.
		II.vii.b How are collectives represented?	N/A
	II.viii Heterogeneity	**II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?**	There are two types of farmers, *eco-friendly* and *economicus.* Differences are in their decision-making processes, and in the weights of the finance component in the calculations of their attitude (a_i).
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	They are heterogeneous in their decision-making. They don't have the same weights of the importance of the financial component of the attitude. *Eco-friendly* farmers place more emphasis on the environment than on the profit in the calculations of their attitude. *Economicus* farmers, on the other hand, place more emphasis on the profit.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modelled by assuming they are random or partly random?	Stochasticity is in part in initialisation only. Location, type, social network and the behavioural threshold are assigned randomly to farmers. The random distribution of the behavioural threshold follows the normal law. The social network is random.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analysing it, and how and when are they collected?	Number of farmers entering in protection programme. Evolution of factors attitude, subjective norm and perceived behavioural control in function of farmers' types and farming practices. Evolution of intention in function of farmers' types and farming practices. Costs of the protection programme. Concentration in nitrates.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	Number of farmers involved in the protection programme and concentration of nitrates depend on the behavioural characteristics and measures of the protection programme.
Details	**II.i Implementation Details**	**III.i.a How has the model been implemented?**	Netlogo (Wilensky 1999) version 6.0.3
		III.i.b Is the model accessible, and if so, where?	
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e., at time t=0 of a simulation run?	80 farmers, 50% economicus type, 50% eco-friendly type, all in high-input farming
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	
		III.ii.c Are the initial values chosen arbitrarily or based on data?	The initial values for the watershed have been estimate based on data (groundwater body, withdrawn) from the catchment area of the Allier (Amblard and Reynal 2015; Chambre d'Agriculture de L'allier 2015) Data for farmers are assumed.

	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	No
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	For the following processes see below: Calculation of intention Decision Update concentration
		III.iv.b What are the model parameters, their dimensions and reference values?	
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	

Appendix 2: Values of agent-farmer's parameters

Parameters

	Grid size	10*10
Name	**Agent parameters**	**Value**
n	Number of farmers	80
$B_i(0)$	Farming practice of farmer i at t = 0	high
w_i	Weight of the financial aspect in attitude for economicus farmers	0.9 [w.u.]
	Weight of the financial aspect in attitude for eco-friendly farmers	0.5 [w.u.]
Ω_i	Behavioural threshold of farmer i	N(0.5; 0.125)
S_i	Social network	
p_0	Initial aggregation of past experiences, knowledge and qualification	0

Name	**Farming practices**	**Value**
π_l π_h	*Gross margin*	low: 600 high: 900 [€/ha/an]
$R(k^t_i)$	*Residual pollutant affecting the groundwater*	low: *0* high: *3* [w.u.]

Appendix 3: Ecological system submodel

The water resource system is represented as a groundwater aquifer with a quantity of water (*Q*). There is a natural flow that feeds the groundwater aquifer and a quantity that exits from the groundwater aquifer, consisting of a natural flow and the quantity of water abstracted. We consider that the quantities of water feeding and leaving (natural flow and abstracted water) the groundwater system are equal and constant over time (*E*). The concentration of pollutants in the water ($C(t)$), in mg/L, is used as a proxy to measure the water quality. It is the ratio between the quantity of pollutant ($N(t)$) and the quantity of water in the ground water:

$$C(t) = N(t)/Q \qquad (A3.1)$$

Depending on the soil and climate conditions, the characteristics and use of inputs, farming practices can contribute to water pollution (link 1 in Figure 1), measured by the residual pollutant affecting the groundwater ($R_i(t)$ *of farmer* i). We assume that agricultural activities are the only source of groundwater pollution and that only high-input farming practices lead to residual groundwater pollution. Thus, the pollutant quantity ($N(t)$) is:

$$N(t+1) = N(t)*(1-E/Q) + \sum_i R_i(t) \qquad (A3.2)$$

At t = 0, all farmers practice high-input farming. We assume that the high-input farming practice of the whole population has led to an initial pollutant concentration of 60 mg/L in the reservoir.

Name	**Ecological system parameters**	**Value**
Q	Groundwater quantity	200 [million m^3]
E	Withdrawn	4 [million m^3]
C(0)	Initial pollutant concentration	60 [mg/L]

Appendix 4 – Construction of the social network

The construction of the social network is based on the Small World model of Wilensky (2015), which is an adaptation of a model proposed by Watts and Strogatz (1998). The network develops based on a neighbouring network and on a probability to rewire a link with another random farmer. It begins with a network where each farmer is connected to their neighbours located on nearby patches (x_i +/- 1; y_i +/- 1). Half of the connections are rewired, i.e., half of the connections are deleted and replaced by new connections with random farmers. Two coefficients characterising the network are calculated: the clustering coefficient and the average path length. The clustering coefficient of the network is the average of the clustering coefficients of all farmers. The clustering coefficient of a farmer is the ratio of existing links connecting a farmer's neighbours to each other to the maximum possible number of such links. The average path length is the average shortest path between all pairs of farmers. Networks with short average path lengths and high clustering coefficients are considered small world networks. In our model, the clustering coefficient is approximatively equal to 0,111, and the average path length is 2,571. For each simulation, the network is different because it depends on the random location of farmers in the grid and on the randomly rewired links.

Appendix 5 – Calculation of training costs

We calculated the training costs used in the model based on data from a planning document concerning a water quality protection programme implemented in drinking water catchments in the Allier Department in France and the website of the firm in charge of the farmers' training.

The document indicates that the planned training sessions, carried out by the VIVEA organisation, are 15 days per farmer for the 5-year programme (SMEA 2013). The aim of this training is to improve the agronomic knowledge of individual farmers and encourage them to adopt more water-quality-friendly practices.

In 2019, VIVEA carried out 1,920,000 hours of training for 94,000 beneficiaries (VIVEA 2019). The recorded cost of these training sessions was €47.14 million, i.e., an hourly rate of €24.6/h and an average rate per beneficiary of €501.5. If we consider that a training day is 7 hours, the training would cost €2583 per farmer.

According to these calculations, we assumed in the model that a 5-year training costs 2500€/farmer.

Appendix 6 - Reference scenario

Farmer population variables

Name	*Farmer population variables*	**Reference scenario**	**Scale**
γ_a	Weight of attitude in intention [w.u.]	1/3	[0.1]
γ_s	Weight of subjective norm in intention [w.u.]	1/3	[0.1]
γ_p	Weight of perceived behavioural control in intention [w.u.]	1/3	[0.1]
	Initial share of low-input farmers [%]	0	[0.100]
	Share of eco-friendly farmers [%]	50	[0.100]

Governance system variables

Name	*Governance system variables*	**Reference scenario**	**Scale**
φ	Financial compensation of the AES [€/year]	300	[0.600]
θ	Training intensity [w.u.]	0.5	[0.1]