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RESEARCH ARTICLE

Farmers' land-use decision-making: A dynamical modelling approach that integrates qualitative knowledge about social norms into a quantitative model

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Abstract

1. The concept of the *homo oeconomicus* is often used to model human behaviour in economic contexts. However, other factors like tradition or the preference to comply with social norms can play a role in decision-making processes.
2. To emphasize the need for incorporating non-pecuniary values in economic models, we use data for participation in several agri-environment schemes (AES) in Europe and show that dynamical patterns can not be simulated by models using the *homo oeconomicus* concept.
3. The presented data show gradually increasing participation levels in AES even if payment levels are constant. Furthermore, low participation levels are sometimes observed despite appropriate incentive schemes.
4. We propose and investigate a dynamic mathematical model to implement social norms in farmers' land-use decision-making in the face of AES. This socio-economic model can help to explain the variety of observed behavioural patterns. It can generate multistable dynamics regarding the level of AES participation in the long-term. We further assume that informative campaigns can modify farmers' perception of norms. Campaigns can have a stabilizing effect if strong enough.
5. The attempt of this work is to gain a better understanding of how the integration of social human behaviour in economic models affects simulation patterns.

KEYWORDS
agri-environment schemes, campaigns, multistability, utility function

1 | INTRODUCTION

Biodiversity loss is an increasingly pressing problem and a variety of measures are implemented worldwide to mitigate, stop or revert it. The task is particularly challenging in agricultural landscapes where several ecosystem services vital for human welfare are competing (IPBES, 2019; Waldron et al., 2017). On the one hand, agriculture has seen enormous increases in productivity, for example, due to external inputs of fertilizers, pesticides and irrigation water, thus improving food security for billions of people (Tilman et al., 2011). On the other hand, agriculture now covers nearly 40% of the Earth's ice-free land surface, often replacing forests, savannas and natural grassland (Foley et al., 2005). The global food system accounts for approximately 21%–37% of annual anthropogenic greenhouse gas emissions (Mbow et al., 2019). Agriculture significantly releases nitrogen and phosphorus to land and water ecosystems, and contributes to contamination with pesticides (Foley et al., 2005; Steffen et al., 2015). Human agricultural activities, thus, profoundly impact agroecosystems and beyond, in fact they may feed back to humanity due to impacts on biodiversity, soil erosion, water quality, pollination and other ecosystem services. Hence, effective conservation in agricultural landscapes is both affecting the life of many people and comes along with possible unknown consequences and side-effects.

Agri-environment schemes (AES) constitute a conservation measure designed to account for the conflicting interests of agriculture: farmers are compensated for costs and forgone farming revenue if they fulfil a requirement of a scheme with conservation purpose (Bateman et al., 2013; Baylis et al., 2008; Kuhfuss et al., 2016). However, even after decades of the Common Agricultural Policy in the EU, many environmental problems still exist (Henderson et al., 2013; Reimer et al., 2012; Thomas et al., 2019), and many species continue to decline; see, for instance, insect declines in Germany (Hallmann et al., 2017) or the 'Farmland Bird Index' in the United Kingdom (Ramírez, 2018). One potential explanation for the failure of AES might be the oversimplification of the agricultural system, leading to false conclusions and ineffective conservation. Human decision-making, for instance, is often reduced to the assumption that people make rational choices to maximize profits. However, the behavioural economics literature indicates that profits are an important but not the only driver of decision making in economic contexts (Reimer et al., 2012; Sattler & Nagel, 2010; Wynne-Jones, 2013). Non-pecuniary factors like the relationship with other farmers and their opinion on environmentally friendly practices, called *social norms*, were found to play a role for participation in an AES as well (Beedell & Rehman, 1999; Defrancesco et al., 2008; Le Coent et al., 2018; Thomas et al., 2019). Social norms are behavioural rules supported by a combination of empirical and normative expectations (Thøgersen, 2014). Many examples like littering, smoking or fashion can be found in everyday life (Bicchieri & Mercier, 2014; Bikhchandani et al., 1992; Sunstein, 1996). However, social norms also appear in economic contexts (Nyborg et al., 2006). A well-known example comes from a case study on winter tires in Oslo where only 20% of the vehicles used non-studded winter tires before the introduction of a tax on the use of studded tires and subsidies for new non-studded tires. After the announced goal of 80% non-studded winter tires was reached, the taxes and subsidies were removed. As a consequence, the use of non-studded tires dropped to 68% but remained constant on that level rather than returning to the initial value (Nyborg et al., 2006). The observed behaviour is not rational and, thus, cannot be explained by the neoclassical economics concept. Another driver needs to be responsible. Social norms were also found in the context of agriculture (Dessart et al., 2019; Kuhfuss et al., 2016; Thomas et al., 2019; Willock, Deary, Edwards-Jones, et al., 1999) but this knowledge is barely used in quantitative models (Drechsler, 2021). This is a lost opportunity since quantitative models can help to identify complex interactions systematically towards a holistic understanding and, thus, to more effective conservation measures (Aspinall & Staiano, 2017; GLP, 2005).

To show that oversimplification can lead to ineffective policies for biological conservation and to strengthen the necessity of a new concept in modelling human behaviour, we aim at making a contribution in this direction by presenting a model that accounts for social norms and captures the following typical dynamical patterns in empirical data of AES participation in Europe: first, time delays in behavioural changes of farmers after the start of an AES. Direct responses by farmers after the start of an AES are only likely if changes in the farming practice are small (McCracken et al., 2015; Sutherland & Darnhofer, 2012), a fact that is not captured under the assumption of rational decision-making. Second, low participation levels despite appropriate compensation payments. Le Coent et al. (2018) report that it is observed in practice that some farmers are extremely reluctant to switch to new farming practices even when a payment level is above additional costs and income foregone. We show that these dynamic patterns can be reproduced with a model that includes social norms in farmers' decision-making (Sutherland & Darnhofer, 2012).

The effect of social norms in this example is understood as the tendency of a farmer to rather participate in an AES when farmers in the social network[1] do so (Kuhfuss et al., 2016). Vice versa, a farmer participates less when few peers do. This effect is also known as *descriptive norms*, which describe the perception of which behaviour is typically performed by others (Cialdini, 2003). Furthermore, we assume that farmers can change their perception and attitude due to information that promotes the AES, for example, via newsletters, lobbies, professional magazines (Defrancesco et al., 2008; Henderson, Reis, et al., 2016; Kuhfuss et al., 2016; Mathijs, 2003; Rogers, 2003; Schultz et al., 2007; Willock, Deary, Edwards-Jones, et al., 1999; Willock, Deary, McGregor, et al., 1999). This assumption is based on the *availability heuristic*, which states that people tend to overestimate the frequency of events they have encountered recently or frequently (Ajzen, 1996; Tversky & Kahneman, 1973).

The social behaviour is represented in the model by a utility function (Henderson et al., 2013; Henderson, Bauch, et al., 2016). Utility in economics is understood as ranking different situations regarding their desirability. Thus, if a person prefers option one over option two, the utility assigned to option one is higher (Nicholson & Snyder, 2012). This concept is used in this paper to reflect that a farmer perceives a utility in complying with social norms. The behaviour of farmers provided with different information[2] is incorporated in our model by a shift of the social utility function. We use this to explain why farmers react differently to schemes with equal compensation level.

The model developed in this work is not meant as a proof for the presence of social norms; many studies already did that (Dessart et al., 2019; Kuhfuss et al., 2016; Thomas et al., 2019; Willock, Deary, Edwards-Jones, et al., 1999). We rather show that models incorporating social norms are more suited to simulate the variety of dynamical patterns of AES uptake. By that, our results indicate that the classical economics concept commonly used for modelling human behaviour fails and needs to be replaced or augmented by other factors decision-makers face in their lives. The model developed in this paper should be a step into this direction by gaining a better understanding of why farmers might not participate in AES and which implications that can have for the design of future conservation schemes.

2 | MATERIALS AND METHODS

2.1 | Agri-environment scheme participation in Europe

Two datasets of AES participation in Europe are used to motivate the model presented in this paper. First, we use data from registered organic farms[3] in the EU in the period from 1997 to 2018 (indicator OIH 03 in European Commision, 2020). Since the data are divided into countries, it allows us to compare dynamical patterns of the development of organic farming in the 28 member states. The data need to be treated with caution, however. EU reforms regarding cross-compliance (2003) and greening measures (2013) changed the conditions during the time period (Thomas et al., 2019). That might have influenced behavioural patterns. It is also not feasible to assume the same amount of compensation for all farmers for two reasons: first, organic farmers have various options to receive subsidies, for example, for animal welfare, support for areas with natural constraints and aid for marketing and promotion of organic products. Second, differences between countries arise since payments are split into support by the EU Common Agricultural Policy and national co-financing (European Commission, 2019).

We distinguish three categories of temporal developments in AES participation, namely sudden increases, gradual increases and no clear increases. The classification criteria are set as follows. If the number of participants in a country doubles within 3 years after the start or a reform of the scheme (which we treat as a start of a new scheme) and stays almost constant otherwise, we consider it a *sudden increase*. If no such marked time period of drastic increase exists but participation numbers grow over time, we consider it a *gradual increase*. All other countries, for which the data show no or a decreasing trend or only few data points exist, are considered to show *no clear increases* in participation numbers.

The second dataset is from the Program for Agriculture and Rural Development (PROFIL) in Lower Saxony and Bremen, Germany. The program promoted, inter alia, extensive grasslands in the funding period 2007–2014 (Reiter et al., 2016). The data used in this paper consist of the area (ha) farmers applied for the AES for, corrected by withdrawn areas. PROFIL replaced previous programs for agriculture and rural development in Lower Saxony and Bremen after EU reforms. Thus, as a simplifying assumption, 2007 can be seen as the start of the scheme. Extensive grasslands were promoted twofold under PROFIL. On the one hand, an action-oriented payment B1 compensated farmers when they fulfilled requirements regarding watering, fertilizer usage and the date of first mowing. On the other hand, a result-based payment B2 compensated farmers if they annually proved the presence of four indicator species (Reiter et al., 2016). The payments were, with an amount of 110 €/ha, the same for both schemes.

Note that the two datasets are different in what is measured: the first one present organic operators, whereas the second one present area of land under the AES. For simplicity, we assume that operators participating in an AES and the area they apply for are positively correlated, being aware that farm size and characteristics are highly variable.

2.2 | Model

We consider a grid of $n \times n$ patches to model a landscape of agricultural fields. Each patch represents a field of 1 ha size and is owned by one farmer. All land-use decisions are assumed to be independent of each other. In the model, the land-use decision for a field is based on either solely economic factors or based on a combination of economic factors and social pressure due to descriptive norms. Similar to Allaire et al. (2009), we use the local network of adjacent fields to determine what a farmer perceives as the typically performed behaviour. An overview of the model is given in Figure 1.

2.2.1 | Economic assumptions

We follow Barraquand and Martinet (2011) to describe the pecuniary factors that influence the land-use decision (Figure 1, optimization box). For simplicity, we consider only whether a farmer participates in the AES (extensive grassland) or not (intensive cropland). Note that this assumption does not display the decision farmers face in reality and should be modified for more applied studies. A farmer chooses the more profitable land use. The profit for cropland depends on various factors like the temporally varying crop selling price p_C $[€/t]$ (Deaton & Laroque, 1992) and the spatially heterogeneous soil quality Q. Thus, the expected net present value varies over time and in space. The annual gross return is given by the function

$$\pi_C(p_C, Q, f) = p_C\, Y(Q, f) - \omega f - \nu, \tag{1}$$

where $Y(Q, f)$ $[t/ha]$ is the crop yield given by the Mitscherlich-Baule yield function (see Supporting Information). It depends on the beta-distributed soil quality $Q \sim \beta(1.15, 2.05)$ and the agricultural intensity f for fertilizer and pesticide use, which is assumed to be optimized.[4] Parameter ω $[€/ha]$ describes the input cost and ν $[€/ha]$ fixed costs of cropland. Extensive grassland is assumed not to be affected by soil qualities or temporally varying factors. The annual gross return is, thus, given by the constant term

$$\pi_G = p_G + s_G + u_s, \tag{2}$$

where p_G is the grassland revenue $[€/ha]$. The subsidies for extensive grassland are denoted by s_G $[€/ha]$. We expanded Barraquand and Martinet (2011) by the *social utility* function u_s for non-pecuniary effects described below (Figure 1, descriptive norm box). It describes the strength of the preference for one land use as a result of social pressure from neighbours. Note that u_s can be either positive or negative and, thus, favour either cropland or grassland use, respectively. The

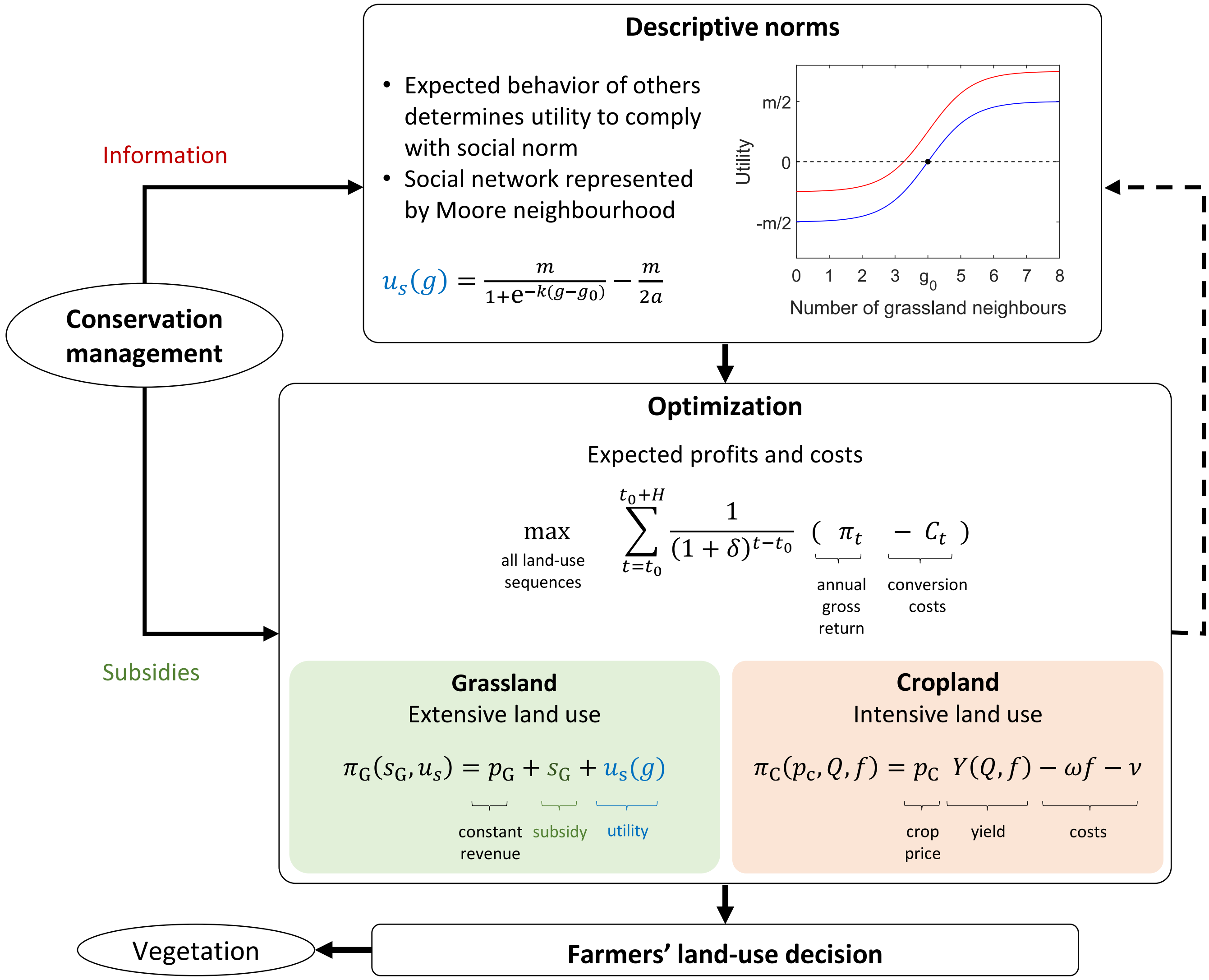

FIGURE 1 Conceptual framework for the land-use decision process of farmers.

land-use decision consists of an optimization problem to maximize expected profits for a given time horizon H when starting at time t_0 and assuming that u_s remains constant in the future:

$$\max \sum_{t=t_0}^{t_0+H} \frac{1}{(1+\delta)^{t-t_0}} \times (\pi_t - C_t). \tag{3}$$

δ is the discount rate and π_t is the expected gross return in year t according to (1) and (2). Parameter C_t serves to include the assumption that a change from one land use to another is accompanied by additional conversion costs. H is chosen such that $\pi_C(p_{C,t_0+H}, Q, f) \approx \pi_C(\bar{p}, Q, f^*)$, where $\bar{p}$ is the mean crop selling price. This is true for H sufficiently large since the expected crop selling price converges towards $\bar{p}$. Then the expected profits for grassland and cropland can be regarded as constant for all $t \geq t_0 + H$, which results in a terminal condition for backward optimization.

After the land-use decision in 1 year, the forward-time spatially explicit simulations make u_s vary, and the farmer adapts the strategy. For all details and parameter values of the model, we refer to the Supporting Information.

2.2.2 | Descriptive norms

The effect of descriptive norms is incorporated in the model as follows: the behaviour of the social network, represented by the Moore neighbourhood,[5] determines a farmer's preference for their land use. However, this does not mean that farmers are influenced only by neighbours in reality, but it serves as a representation of a unique dynamical social network of each farmer. Let g be the number of Moore neighbours with grassland use, $g = 0, 1, \ldots, 8$. Then, following Henderson, Bauch, et al. (2016), social utility can be implemented by a sigmoidal function of g:

$$u_s(g) = \frac{m}{1 + e^{-k\,(g-g_0)}} - \frac{m}{2a}, \tag{4}$$

where $m \geq 0$ controls the maximum value for social pressure. In the following, m will be denoted as the *sociality coefficient*. Parameter k gives the slope at g_0, the midpoint of the curve. Figure 2 shows a graph of u_s (lower, solid blue curve). If $m = 0$ (Figure 2, dashed line), we will call our model the *classical economic model*, which coincides with Barraquand

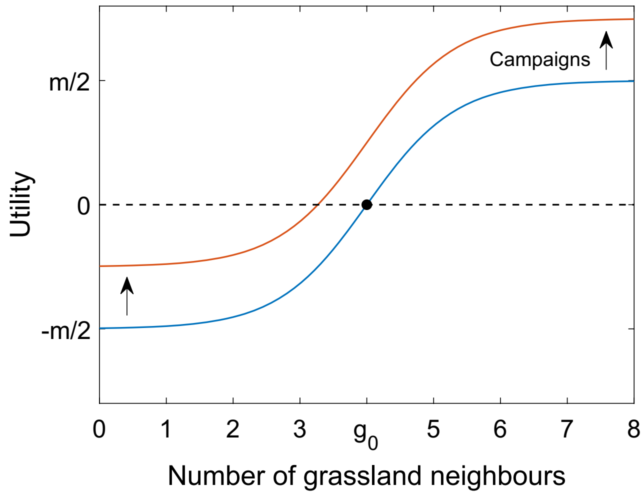

FIGURE 2 Social utility function (4) for descriptive norms. Utility is calculated as a function of grasslands in the neighbourhood ($a = 1$, solid blue curve). The introduction of informative campaigns shifts the curve upwards ($a = 2$, solid red curve). Here, $g_0 = 4$ and $k = 1.5$.

and Martinet (2011). It represents the case without social norms where decisions are exclusively based on profit maximization. If $m > 0$, we will call our model the *socio-economic model*. A farmer is then, in addition to pecuniary factors, influenced by the land use performed in the neighbourhood.

Parameter $a > 0$ defines the effect of informational campaigns on the promotion of the scheme. $a = 1$ represents the baseline case without additional information. Then, farmers have on average no preference for one or the other land use. Informational campaigns that should encourage farmers to participate in the AES are realized by a shift of u_s upwards, $a > 1$ (see Figure 2, upper, solid red curve). That is, with campaigns, the utility for grassland is higher than without campaigns ($a = 1$) for all values of g. Therefore, the model with shifted utility function will hereafter be referred to as the *socio-economic model with campaigns*.

Note that the utility function is not validated with data or mechanistically driven. However, a sigmoid function is commonly assumed (Lade et al., 2013; Tavoni et al., 2012) and complements game-theoretical research on quantifying non-pecuniary values.

2.2.3 | Numerical simulations

Numerical model simulations are performed for the classical economic model ($m = 0$) as well as for the socio-economic model in the baseline case ($m > 0$, $a = 1$) and the socio-economic model with campaigns ($m > 0$, $a > 1$). For the model comparison with the PROFIL data of the applications for B1 and B2 schemes, an initial grassland share of 0.1% is chosen and randomly distributed over the grid. A grid size of 250×250 is calibrated such that the classical economic model predicts the correct grassland proportion for B1 applications. Due to the simplified situation in the model, it is not possible to scale the grid to an appropriate proportion of agricultural land in Lower Saxony and Bremen. For the simulations in Section 3.2, the landscape size is reduced for computational reasons to a grid of 50×50 patches. The proportion of participants in the AES is given by the share of extensive grassland in the overall land use. Long-term behaviour of the system is analysed testing initial grassland proportions in steps of 10% points. For each initial grassland proportion, 50 stochastic replicates are produced to compute the 'mean grassland share at $t = 100$' to average out random effects. In each replicate, the initial grassland share is distributed randomly in the landscape.

3 | RESULTS

3.1 | Social norms influence agri-environment scheme participation patterns

The datasets of AES participation we used to motivate the socio-economic model have two key properties regarding their dynamical patterns: first, a gradually increasing participation level after the start of (constant) compensation payments and, second, a long-term level of participation that does not necessarily match the participation level that leads to maximal profits. The first property is prominent in the numbers of organic farms in the EU (Figure 3). Out of 28 member states, 16 member states show a gradual increase in participation numbers (red graphs), whereas only three member states show a sudden increase (black graphs). The dynamics of nine member states show different patterns with no clear increase (grey graphs).

We now show that simulations of the socio-economic model presented in Section 2.2 can reflect the gradual increase in participation much better than classical economics theory. To that end, we consider the data for the grassland schemes in Lower Saxony and Bremen, Germany. The applications for the B1 and B2 schemes show a gradually increasing trend over time (Figure 4, red solid lines), similar to the participation in organic farming in the majority of EU member states, even though the level of subsidization has remained constant over the whole funding period. Figure 4 also shows numerical simulations of the classical economic (dashed lines) and the socio-economic model (dashed-dotted lines), under the simplifying assumption that farmers can only decide for or against the schemes. The classical economic model predicts that all farmers for which participating is more profitable do so immediately with the start of the AES. Changes in the participation level after 2007 are only due to variations in the crop selling price. This result is due to the rationality assumption and therefore robust to different parameter choices. The situation in 2008 is the same as in 2013 (except for stochasticity). Therefore, the increasing trend of the data cannot be simulated with the classical economic model unless the crop price was increasing linearly. By contrast, the socio-economic model predicts a gradually increasing trend of applications for both B1 and B2 as observed in the data. With the start of the AES, only a small proportion of farmers applies to change land use to grassland. This is due to the sigmoidal utility functions with negative values for low participation proportions,

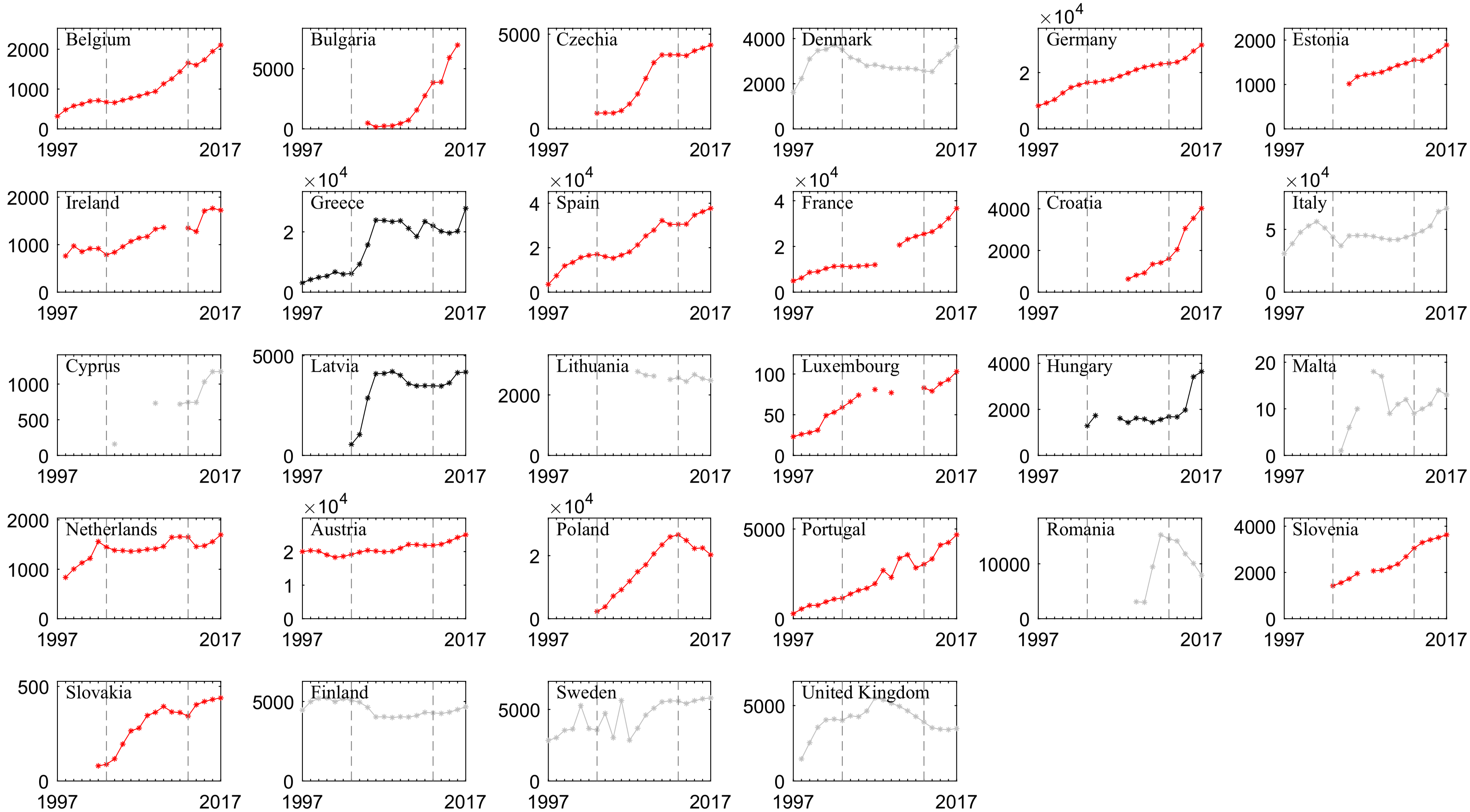

FIGURE 3 Number of organic operators in the EU, divided into member states (indicator OIH 03 in European Commission, 2020). Reforms regarding cross-compliance (2003) and greening measures (2013) are indicated with dashed lines (Thomas et al., 2019). Data for the member states are coloured according to their dynamical pattern: sudden (black) or gradual (red) increases after the start or reform of the scheme or dynamics that do not fall into either of these categories (grey). See Section 2.1 for classification criteria.

which initially inhibit the participation of the other farmers. With more and more farmers participating, the social pressure increases and the utility functions for B1 and B2 become positive. This stipulates continually increasing applications over time. Note that the gradual increase in the data could be also explained by monetary factors, for example, due to a gradual decrease in the crop selling price. However, since the simulation results are robust to various price scenarios, we conclude that non-pecuniary factors driving the dynamics are more likely.

Another property of the PROFIL data in Lower Saxony and Bremen is that many more farmers applied for the action-oriented scheme B1 than for the result-based scheme B2 (compare Figure 4a,b)—even though the compensation payments were, with an amount of 110 €/ha, the same for both schemes. The classical economic model fails to capture this property. It predicts the same participation level for both the B1 and B2 schemes (Figure 4, black dashed lines). If all farmers based their land-use decision only on maximizing profits, we would expect an equal distribution of B1 and B2 schemes due to identical compensation payments. By contrast, the socio-economic model allows to differentiate only by changing one parameter in the utility function and thereby matches both datasets well (Figure 4, black dashed-dotted lines). Since the action-oriented scheme B1 is promoted in a way in which the farmer knows pretty well what to do and what to expect, it is put in a good light ($a = 2$). In contrast, the result-based scheme is promoted with focus on the risk of not receiving the payment ($a = 1$). Therefore, the socio-economic model and all parameters are similar for B1 and B2 except for how the schemes are promoted. This choice of parameters requires some further comments: the two schemes (B1 and B2) are in fact different. The action-oriented program B1 has a lower risk for the farmer not to receive the payment. Hence, farmers might be more sceptical of B2, consider it less likely to have indicator species on their fields or be less confident in having the expertise in which farming practices help to create good habitats for these species. This risk perception is not incorporated into the model and will definitely play a role for the decision-making. Thus, it is not only the framing which is different for the two schemes. What we want to address is, however, that the narrative of the two schemes may not account for all (dis-)advantages. A possible advantage of B2 over B1 is that farmers have less restrictions in the farming practices and can bring in their own expertise. Furthermore, the ecological benefits of B2 are directly visible, which assures the effectiveness of the scheme. Finally, the economic outcome of the farming practice itself is more expectable when not being confined to certain actions and can be optimized with learning. In contrast, the ecological impact of B1 is doubtful and restrictions impede flexible reactions to deal with unforeseen circumstances (e.g. weather). For this reason, we suggest that the B1 and B2 schemes are presented by government agencies or perceived by farmers differently, namely in such a way that justifies the choice of the socio-economic model with campaigns for B1 and without campaigns for B2.

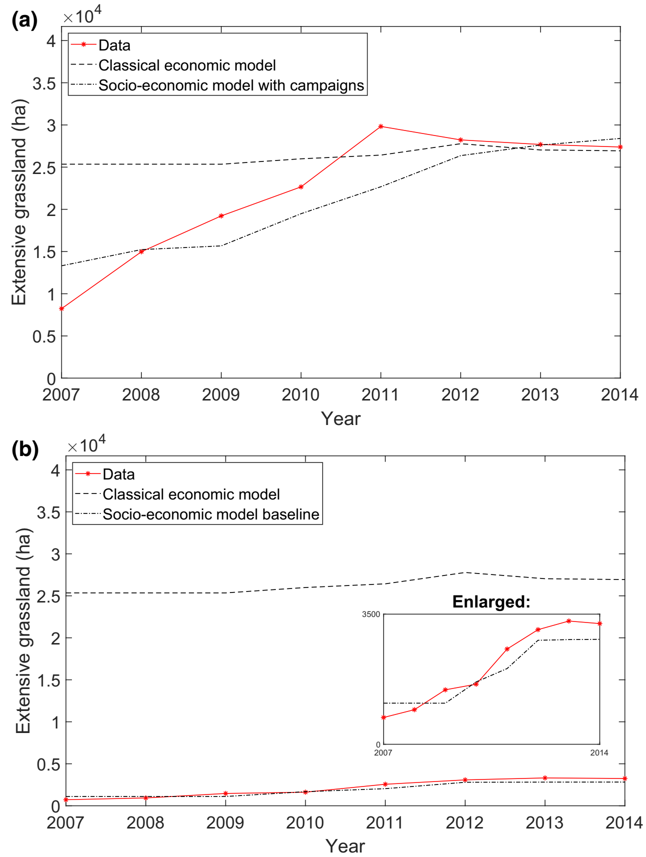

FIGURE 4 Areas for which farmers applied for B1 and B2 payments in Lower Saxony and Bremen (Germany) compared with predictions by the classical economic (dashed) and the socio-economic model (dashed-dotted). A subsidy level $s_G = 110$ is used according to the data. Parameter values $m = 300$, $k = 1.5$, $g_0 = 4$ are chosen for the socio-economic model. Additional campaigns $a = 2$ in (a). Data from Reiter et al. (2016).

3.2 | Implications for modelling social norms

We now provide a theoretical model analysis to derive general rules for dynamic participation patterns in the presence of social norms. We are interested in both the temporal development of participation immediately after the start of an AES (i.e. the transient dynamics) and the participation level in the long term (i.e. the stationary behaviour).

3.2.1 | Transient dynamics

The participation level after the start of an AES crucially depends on the model parameters (Figure 5). The classical economic model (red solid line) predicts an instantaneous jump in the grassland share right in the first year of the AES and no further trend over time. Fluctuations are due to crop price variability (grey solid line). The subsidy level of $s_G = 110$ €/ha results in an average grassland share of around 40%. The existence of social norms in the model ($m > 0$) changes the dynamical behaviour. The socio-economic model in the

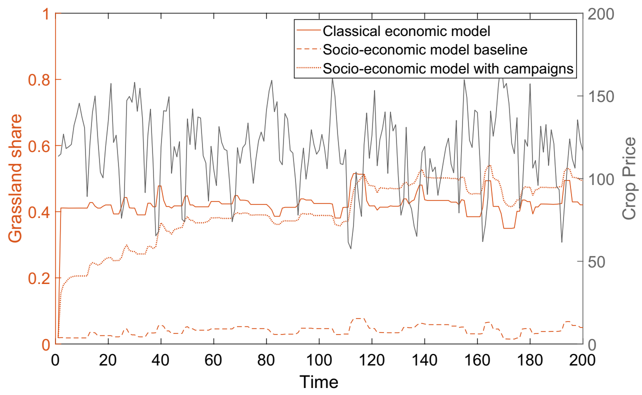

FIGURE 5 Grassland share in the landscape under different model assumptions (red, left *y*-axis) and crop price over time (grey, right *y*-axis). Initial grassland share: 1%, economic parameter: $s_G = 110$, parameters for utility function: $m = 300$, $k = 1.5$, $g_0 = 4$, $a = 1.5$.

baseline (dashed line in Figure 5) predicts a grassland share that is much lower (at around 5%) and barely increasing. Since the initial grassland share is low, the utility function is negative and inhibits AES participation. Cropland is dominant in the surrounding of every patch and, thus, farmers do not choose extensive grassland even if it was more profitable. Note that the situation can change if the initial grassland share is larger; this will be discussed in Section 3.2.2.

The socio-economic model with campaigns (dotted line in Figure 5) shows a gradual increase of the grassland share over the first 100 time steps up to 40%. Due to the preference for grassland, less participating farmers in the neighbourhood are required to push farmers to adopt the grassland scheme. After the drop in the crop price at around $t = 110$, the average grassland share increases to a level of around 50% and exceeds the participation level in the classical economic model. Interestingly, the grassland share does not decline when the crop price increases again. Thus, the long-term dynamics in the classical economic model and the socio-economic model with campaigns are similar, even when campaigns slightly elevate participation levels. Only the transient phase is different.

The average level of participation is a result of an interplay between different factors: the varying crop price and the level of subsidies determine the pecuniary factors which can vary over time. The initial land use is spatially heterogeneous and determines the effect of social pressure. Note that the land use also strongly depends on the heterogeneous soil qualities of the fields, which is not discussed in this paper but addressed in Vortkamp et al. (2020).

3.2.2 | Long-term participation

In the following, we investigate the impact of the utility function on the long-term AES participation, indicated by the mean grassland share at $t = 100$. Figure 6 shows this as a function of the sociality coefficient and for different initial grassland shares. When social norms play a minor role in the decision (i.e. small sociality coefficient m), a long-term grassland share of around 50% can be identified for all

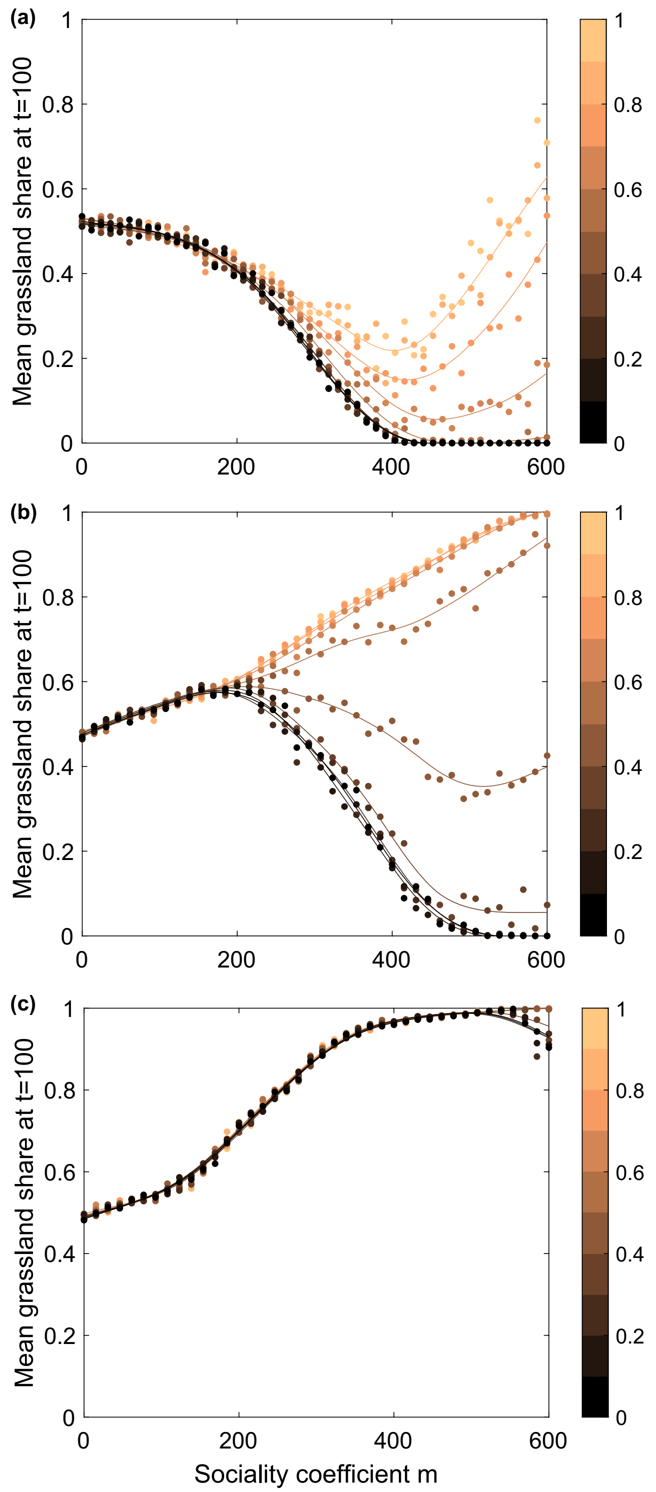

FIGURE 6 Mean long-term grassland share in the landscape as a function of the sociality coefficient $m \in [0, 600]$. Without campaigns: $a = 1$ (a) and with campaigns: $a = 1.5$ (b), $a = 2$ (c). Initial grassland share grouped in 0.1 steps indicated by the colour bar. 50 replicates for each initial condition. Lines connect outcomes for the same initial conditions. Other parameter values $k = 1.5$, $g_0 = 4$, $t_{end} = 100$, $s_G = 120$.

initial conditions. That is, the system has a unique stable equilibrium where all initial conditions lead to. This holds not only for the baseline socio-economic model (Figure 6a) but also for different intensities of campaigns (Figure 6b,c). Thus, campaigns only take effect when social norms affect the land-use decision strongly enough.

Now, we consider the impact of stronger social norms and first focus on the baseline case of the socio-economic model ($a = 1$). For increasing sociality coefficients, the mean long-term grassland share steadily decreases, as long as approximately $m < 400$. For even larger sociality coefficients, the long-term behaviour depends on the initial conditions. The majority of initial conditions continue the declining trend and result in a long-term grassland share of 0% for $m > 400$ (dark curves in Figure 6a). By contrast, a few initial conditions with large initial grassland shares reverse the declining trend and exhibit an increase for $m > 400$ (light curves in Figure 6a). That is, social norms have a non-monotonous effect if the initial grassland share is large. We note two key results for the baseline socio-economic model. First, the tendency of decreasing long-term grassland shares in response to stronger social norms reflects that farmers often refuse to participate in AES even if it was more profitable. Thus, farmers adopt AES less than expected under the assumption of rational decision-making, as it was seen in the B2 application data. Second, for large sociality coefficients, the system reveals multistability. That is, the initial participation level is crucial for long-term AES participation. When a critical proportion of participating farmers is exceeded, the system approaches a different stable state with another long-term grassland share. However, in the baseline case, quite large initial grassland proportions are required to prevent the system from being locked in a zero long-term grassland share for $m > 400$.

In the remainder, we additionally consider the impact of campaigns. First, we focus on the socio-economic model with a smaller effect of campaigns ($a = 1.5$). Figure 6b reveals an increase in the long-term grassland share in response to increasing sociality coefficients, for all initial conditions provided that $m < 200$. This contrasts the declining trend for the baseline socio-economic model in the same parameter range, even though the subsidy level remained the same. For approximately $m > 200$, the long-term outcome again depends on the initial grassland share. The multistability is more pronounced and occurs over a wider parameter range than in the baseline case. There seem to be two dominating branches of curves, one leading to zero grassland use for small initial grassland shares and one leading to complete grassland use for large initial grassland shares. This indicates a fragile system that tips to either very low or very high grassland use. The simulations suggest that, if social norms are present, campaigns can push the system to higher grassland shares, except for high sociality coefficients ($m > 500$) in combination with low initial grassland shares (≤30%). Second, a stronger effect of campaigns ($a = 2$) effectively eliminates multistability from the system (Figure 6c). For a given value of m, all initial conditions approach the same long-term grassland share, except for $550 < m < 600$. The long-term grassland share steadily increases from about 50% to almost 100% in response to an increasing sociality coefficient. That is, for high values of m the preference for grassland is so strong that even if the initial grassland share is almost zero, many farmers are pushed by the norm to participate in the grassland scheme. This may not be realistic in the context of AES and parameters potentially need to be adapted to interpret the result more precisely. However, it can help to understand the effects of campaigns on dynamic patterns.

We note two key effects of informational campaigns. First, as they increase the preference for grassland use, they achieve higher participation levels in the AES. This holds true for all initial grassland shares if social pressure is weak (small values of m) or if the effect of campaigns is strong (large value of a). Second, while social norms have the tendency to lock in small initial grassland shares in reinforcing feedback loops, campaigns have the potential to counteract this feedback structure and steer the grassland use in the reversed direction.

4 | DISCUSSION

Coupled human-environment systems like agricultural landscapes are complex. Different parts of the system can be described by different disciplines. The value of multidisciplinary work is to bring different disciplines together and mediate between actors. In this paper, we developed a socio-economic model for farmers' decision-making when AES are available and thereby combine approaches from classical and behavioural economics. A sigmoidal utility function with no preference for one land use is developed to reflect that farmers' land-use decisions are influenced both by economic and social factors. The model complements game-theoretical research on quantifying non-pecuniary values (Bikhchandani et al., 1992; Le Coent et al., 2018) and can explain why AES participation levels are often lower than predicted by classical economic models (Burton et al., 2008; Lobley & Potter, 1998; Mathijs, 2003; Nyborg et al., 2006). The model is designed so that a farmer is hindered from AES participation when he or she perceives that only few farmers in the neighbourhood do so even if compensation payments were large enough to stipulate participation from a purely economic point of view.

The socio-economic model with campaigns captures the situation when farmers are provided with information that promotes the scheme and can be sufficient to trigger a higher proportion of farmers to participate in the AES. This confirms empirical studies, which have demonstrated that how a policy is framed and promoted can significantly alter the perception and reaction of the target group of this policy (Bikhchandani et al., 1992; Nyborg et al., 2006; Sutherland & Darnhofer, 2012; Thomas et al., 2019). Our modelling approach is able to reproduce different dynamical patterns of two grassland schemes in Lower Saxony and Bremen (Germany) that compensate farmers equally. This was not possible given only rational assumptions. We are aware that farmers rather participate in action-oriented schemes (Sutherland & Darnhofer, 2012), which may be considered less risky to receive payments. However, a biased description that confronts farmers with the risks of a result-based scheme rather than the opportunity to bring in their own expertise and flexibility in the farming practice can increase the gap of participation levels between the two. Framing in campaigns is highly debated, though (Loewenstein et al., 2015). Arguments against framing range from the possibility of misguidance of social norms (Cialdini, 2003) to manipulation of the target group (Kuhfuss et al., 2016). Furthermore, one should have in mind that the effect of framing is highly

TABLE 1 Examples of steadily increasing AES participation patterns.

Study	Type of AES	Location	Funding period
Lobley and Potter (1998)	Environmentally sensitive area	England, UK	1987–1996
Johann Heinrich von Thünen-Institut (2008a)	Extensive grassland	Bremen, Germany	2000–2006
Johann Heinrich von Thünen-Institut (2008b)	Extensive grassland	Lower Saxony, Germany	2000–2006
Ministerio de Agricultura, Ramaderia, Pesca I Alimentació (2016)	Forest scheme	Catalonia, Spain	2007–2013
Johann Heinrich von Thünen-Institut (2016)	Extensive grassland	North Rhine-Westphalia, Germany	2000–2004
Reiter et al. (2016)	Extensive grassland	Lower Saxony, Germany	2007–2014
Ministere de l'Agriculture, de l'Agroalimentaire et de la Foret (2017)	Forest scheme	France	2007–2013
Zenger and Schöber (2018)	Extensive grassland	Bavaria, Germany	2007–2017

context-dependent, which is why it is hard to optimize environmental campaigns (Mosler & Martens, 2008; Thomas et al., 2019).

However, both versions of the socio-economic model (baseline and with campaigns) could produce gradually increasing participation patterns as in the data. This is not an exceptional property of the German and the European datasets considered in this paper. We have found similar gradual increases in AES participation all over Europe, a collection of which is listed in Table 1. Direct responses after the start of an AES as predicted by classical economic theory are only likely if changes in the farming practice are small (McCracken et al., 2015; Rogers, 1958; Schramek & Schnaut, 2004; Sutherland & Darnhofer, 2012). Finally, our analysis of the long-term behaviour shows that social norms, if strong enough, can push a monostable system to a region of multistability. How is that possible? Villanueva et al. (2015) performed a choice experiment and categorized farmers in potential participants (in AES), non-participants and farmers willing to participate but having different requirements. In light of our model simulations, we can argue that the behaviour of the last group finally depends on positive feedback by the behaviour of others. Thus, the proportion of the last group may determine how pronounced the branches in Figure 6 are. Empirical explanations for multistability are diverse. One explanation is that AES gives time to acquire new skills and better knowledge of the risk, leading to long-term behavioural changes. Transitions towards conservation-oriented attitudes through scheme participation are also possible (Wilson & Hart, 2001). Moreover, social norms can supercharge non-pecuniary but selfish motivations (warm-glow feeling) and, thus, increase the likelihood that farmers maintain pro-environmental practices (Kuhfuss et al., 2016). If the decision-making process does have multiple stable states, it shows that not only the decision towards an AES is represented insufficiently by classical economic models but also the long-term effects are not captured well. The so-called 'end-of-contract problem' is not addressed in this study but a possibility for further research (Kuhfuss et al., 2016).

The question of determinants for economic decisions in an agricultural context remains controversial in the literature (Bikhchandani et al., 1992; Henderson, Reis, et al., 2016; Lobley & Potter, 1998; Pavlis et al., 2016; Willock, Deary, McGregor, et al., 1999) and one can argue that different or additional mechanisms than social norms may be responsible for the observed dynamical patterns. This is true and hence the question would need further exploration to be answered conclusively. However, we translated the findings of empirical studies about social norms into a quantitative model to break with the paradigm that classical economic models are adequate to simulate human behaviour in economic contexts. This first attempt makes simplified assumptions about the social network of farmers represented by the nearest neighbours. Further studies that investigate the effect of strong and weak players in the system as well as differently structured farmer communities with early and late adopters would be desirable (e.g. Rogers, 2003). However, the limited success of many AES has shown that the assumption that farmers' decision is just profit-based is too short-sighted and new concepts are needed (Henderson, Bauch, et al., 2016; Thomas et al., 2019). This becomes obvious by comparing the participation patterns of the action-based scheme B1 and the result-based scheme B2. The former scheme is much more attractive to farmers but its impact on conservation is doubtful (Sabatier et al., 2012). The latter, on the contrary, is rarely adopted by farmers, even if it contributed more to the goal of biodiversity maintenance. It is crucial to understand the motives leading to or against participation in an AES for successful conservation.

Overall, our simulations show the importance of feedback in the social subsystem of a complex human–environment system and suggest that conservation will probably not be successful if simply more money is allocated to compensate farmers (Wilson & Hart, 2001). Preferably, AES are designed such that farmers are involved with their knowledge and skills to use the social norm for conservation (Thomas et al., 2019; Wilson & Hart, 2001; Wynne-Jones, 2013). A precautionary, integrated approach can use synergies between societal goals and nature conservation (Harris et al., 2003).

AUTHOR CONTRIBUTIONS

Irina Vortkamp and Frank M. Hilker: conceptualization and model development; Irina Vortkamp: data analysis; Irina Vortkamp: writing the manuscript; Frank M. Hilker: critical review of the drafts; Irina Vortkamp and Frank M. Hilker: final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

All data used are cited in the document and drawn from academic publications or grey literature.

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ENDNOTES

[1] The social network will be represented as the neighbourhood in the model. Hence, neighbourhood could be understood not only geographically, but also as social network in this context.

[2] Informing farmers in a specific way can be seen as a form of nudging, which is an aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives (Thaler & Sunstein, 2008).

[3] Organic farming is not an AES in the strict sense but administered as one.

[4] f is optimal when it solves the equation $\frac{\partial \pi_C}{\partial f} = 0$. For details, we refer to the Supporting Information.

[5] Eight cells that surround the selected cell.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section.

Table S1. Parameter values for the economic model.

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