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Impacts of human behaviour in agri-environmental policies: how adequate is *homo oeconomicus* in the design of market-based conservation instruments?

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Highlights

- Alternative behaviours are included in two ecological-economic models
- Exploring effects of alternative behaviours on performance of payment schemes
- Effects of alternative behaviours turn out to be moderate
- The results provide no argument for abandoning the model of *homo oeconomicus*

Abstract

Models of human-environment systems frequently employ the model of rational behaviour in which a rational, perfectly informed and self-interested *homo oeconomicus* maximises individual utility. This model has been criticised with regard to its adequacy in models of social-ecological systems, because other motives exist beyond profit maximisation that affect land-use decisions. The question arises what consequences do these other motives have on the design and performance of environmental policy instruments. For this, two existing generic models of agri-environmental schemes are expanded to consider alternative landowner behaviours: agents make mistakes in their search for the profit-maximising land-use decision, are inequity-averse and care about the profits of their neighbours, and are influenced by their neighbours' decisions. In the analyses even large deviations from the model of *homo oeconomicus* have generally only a small or moderate effect on the cost-effective design and the level of cost-effectiveness of the two agri-environmental schemes. With the models being rather simplistic, the results should not be used for specific policy advice but to point out and argue that the model of *homo oeconomicus* should not be abandoned prematurely, but its scope in environmental policy advice needs to be assessed more thoroughly both empirically and theoretically.

Key words

agent-based model, conservation payments, ecological-economic model, environmental policy, human behaviour.

1 Introduction

A large share of the world's biodiversity is located on private lands and is threatened by intensification of land use. To slow down or halt the loss of biodiversity on agricultural lands, many countries have established agri-environmental schemes that provide financial incentives to landowners who apply biodiversity-friendly measures or abandon biodiversity-harmful measures on their land (de Vries and Hanley 2016). The reason for the necessity of such incentive-based approaches is that the application of a conservation measure usually reduces agricultural profits, which is likely to reduce the attractiveness of conservation for the landowner. The financial incentive then is introduced to compensate the landowners for the profit loss and induce them to carry out the conservation measure. Assuming that landowners are rational profit maximisers, they will adopt a conservation measure if and only if the financial reward from participation in the scheme (e.g., a conservation payment) offsets the profit loss incurred by the conservation measure.

This assumption is based on the theory of rational choice, represented by the model of *homo oeconomicus* who assigns to each outcome of an action a utility, so that the utilities of all outcomes can be ordered, according to pre-defined preferences, without any contradictions, and that always the action with the highest utility is chosen (Becker 1976). Further, the canonical model of *homo oeconomicus* considers humans as entirely self-interested and perfectly informed.

The validity of this simplistic theory of human behaviour has been challenged from several angles (Arrow 1950, Anand 1993). Self-interest obviously contradicts, e.g., with the numerous observations of test subjects' behaviour in dictator and ultimatum games (Cherry et al. 2002, Henrich et al. 2005) which show that humans do not only care about their own well-being but also about that of others. Finally, Simon (1979) argues that real decision situations are often so complex that humans are not able to identify the action that maximises their utility, so they use decision heuristics and are often satisfied with an outcome or utility that exceeds a certain threshold ("satisficing behaviour").

Next to these, a number of other motives exist that affect the behaviour of humans in general and that of farmers in particular (Huber et al. 2018, Dessart et al. 2019). Thus, it has been argued that the disregard of these peculiarities and alternative motives of human behaviour renders the rational-choice theory and the model of *homo oeconomicus* unsuitable for the prediction of social-ecological systems and limits its use in model-based policy analysis (Van den Bergh et al. 2000, Schlüter et al. 2017).

Nevertheless, none of the above-cited references fully dismisses the model of *homo oeconomicus*. On the contrary, the substantial differences between the observed outcomes of dictator game experiments (in which selfishness is not punished), and the observed outcomes of ultimatum game experiments (in which selfishness can be punished by other players), as well as observations on real farmers (e.g., Bartkowski and Bartke 2018) strongly indicate that the maximisation of one's own utility (however this is defined) is a major determinant of human decision making. The question therefore is not whether the model of *homo oeconomicus* is suitable for the design of environmental policies or not, but the extent to which it is suitable.

Although a close agreement between theoretical prediction and real-world observation is not sufficient for proving the truth or adequacy of a theory or a model (Spiegler 2015), one may argue that even a false theory can be used successfully in practical applications. Classical mechanics, e.g., may be regarded as false, since it falsely assumes that there is no limit to the velocity of physical bodies. Nevertheless the consequences of there being a limit, given by the speed of light as described by Einstein's Theory of Relativity, can be ignored in many practical applications. As Einstein's theory shows, the scope of the theory of classical mechanics is, among others, determined by the physical body's velocity, v, relative to the speed of light, c; or more concretely: the larger the ratio v/c the worse are predictions that are based on classical mechanics rather than relativistic mechanics.

In an analogous manner, one may try to measure the scope of the model of *homo oeconomicus*. In contrast to classical mechanics, there will of course be no unique answer to the question of what that scope is – not even a unique way of asking that question. One possibility is to define variables that quantitatively describe the deviation of a behavioural model from the model of *homo oeconomicus* (henceforth termed *alternative behavioural model*) and change these variables to explore the consequences – as one would increase v/c to explore how this affects the behaviour of a physical system.

The present paper follows such an approach by exploring how the deviation from the model of *homo oeconomicus* affects the cost-effective design and the achieved level of cost-effectiveness of conservation payment schemes in which landowners are financially rewarded if they carry out biodiversity conservation measures (Engel et al. 2008). The employed experimental approach is ecological-economic modelling (Drechsler 2020). An ecological-economic model consists of two coupled modules: an ecological and an economic one. The economic module typically describes the response of landowners on the economic incentives and the implied spatio-temporal land-use dynamics, while the ecological module, e.g., describes the dynamics of species in the landscape to determine the species' viability.

The choice of the behavioural parameters for the present analysis is motivated by Dessart et al. (2019) who reviewed an extensive number of empirical papers of farmer behaviour, covering articles from economic, social, psychological and other journals and books. Below I briefly outline the authors' main findings as far as they are relevant in the present paper.

Dessart et al. (2019) distinguish three groups of behavioural factors in farmers: “dispositional”, “social” and “cognitive” factors. The “dispositional factors” comprise “personality”, “resistance to change”, “risk tolerance”, “moral” environmental concerns” and “farming objectives”. Moral and environmental concerns refer to “doing ‘the right thing’ ” for the environment and are positively related to the uptake of environmentally friendly farming practices. Farming objectives include economic but also other objectives which may be in conflict with each other. The authors state (p. 430) that the adoption of environmentally friendly farming practices is negatively correlated with economic objectives and positively related with conservation objectives.

The “social factors” comprise “descriptive and injunctive norms” so that farmers are influenced by their neighbours' behaviour and by what they think others expect from them, respectively; as well as “signalling motives”, such that environmentally friendly behaviour may improve social status.

Lastly, the “cognitive factors” comprise “knowledge” about environmentally friendly farming practices and the availability of agri-environmental schemes, “perceived control”, such that farmers are confident in their skills to undertake an action, “perceived costs and benefits” of environmentally friendly farming measures which – as the authors point out on p. 444 – may deviate from their correct values, and “perceived risks” related with environmentally friendly farming practices such as higher fluctuations in agricultural outputs.

Effects of risk tolerance on the adoption and performance of biodiversity conservation policies have already been addressed quite frequently (e.g., Derissen and Quaas (2013), Drechsler (2017), Facciola et al. (2018)), while concerns and preferences for the environment can to quite some extent be addressed simply by appropriately lowing the payment demanded by the farmers for carrying out a conservation measures (Drechsler et al. 2017). In the present analysis I will therefore address a “moral concern” that has not been mentioned by Dessart et al. (2019) but is very often relevant in human, including farmer, behaviour: altruism and equity concerns (e.g., Fehr and Schmidt (1999), Henrich et al., (2005), Van Herzele et al. (2013)).

The most important of the “social factors”, in the present context, appears to be the propensity to being influenced by the behaviour of other farmers. A prominent example of such a social interaction is that farmers adopt their neighbours’ actions (e.g., Bauch et al. (2016) and references in Dessart et al., (2019, pp. 433–435)).

Regarding the “cognitive factors”, while knowledge of farming practices and agri-environmental schemes as well as perceived control are difficult to model – and may be addressed by other research methods – perceived risks and perceived costs and benefits are well suitable for consideration in mathematical models. Since, as noted above, the issue of risk has already been addressed quite frequently, I will focus on the difficulty of farmers to correctly predict the costs of conservation measures. Next to the above-mentioned satisficing behaviour, a way of modelling this is to assume that a farmer is able to identify a profit-maximising land-use measure only with a certain probability.

The consequences of satisficing on the dynamics of a modeled social-ecological system have been explored by Gimona and Polhill (2011), Polhill et al. (2013) and Dressler et al. (2019). In Gimona and Polhill (2011) an increase of the aspiration level that defines the utility beyond which a satisficer accepts a choice, moderately decreased the effectiveness of a conservation payment scheme; in a very similar model, Polhill et al. (2013) observed an effect but were not able to disentangle it from other processes in the complex system dynamics; and Dressler et al. (2019) found in a resource management model that under satisfacing behaviour the resource is less strongly depleted than under profit-maximising behaviour.

While the cited papers provide some insights into the effects of satisficing behaviour on the dynamics of social-ecological systems and the performance of policy instruments, they do not provide a systematic understanding about the magnitudes of these effects. In addition, inequity aversion and social influences were not considered. The present analysis explores the effects of alternative behaviours more systematically by considering two published ecological-economic simulation models that originally consider *homines oeconomici* as agents. To allow for a systematic analyses the two models are relatively simple generic models; for the derivation of concrete policy recommendations for specific conservation problems which is not the aim of the study, specific models would be more appropriate (cf. Drechsler 2020). The two existing models are expanded, so the agents may fail to identify the most profitable action, be inequity-averse, or influenced by other agents. The model expansion is so that a continuous range of mixed agent behaviours can be considered, where *homo oeconomicus* represents a limiting case.

One can expect that the inclusion of the alternative behavioural models will change the outputs of the two original models, in particular the cost-effective design and the corresponding levels of cost-effectiveness of the modeled conservation payment schemes. Three questions are investigated. First, how large is the variance in the model outputs caused by the alternative behavioural models, compared with the variance caused by the other model parameters; second, how strongly do the alternative behavioural models change the model outputs; and third, which values of the other model parameters favour large impacts of the alternative behaviours.

2 Methods

2.1 Model description

To explore the consequences of alternative behaviours on the design and performance of market-based conservation instruments I consider two existing generic ecological-economic models which are outlined below (for details, see https://www.cambridge.org/de/academic/subjects/life-sciences/ecology-and-conservation/ecological-economic-modelling-biodiversity-conservation?format=PB, and Drechsler (2017)). In both models, land parcels i ($i \in \{1,\ldots,100\}$) are arranged on a 10 by 10 square grid, each owned by a landowner who can manage the land parcel either for (intensive) *agriculture* ($x_i = 0$) or for the *conservation* of a species (e.g., through extensive or other biodiversity-friendly agriculture) ($x_i = 1$). For simplicity, mixed uses of the land parcel are not considered. Both land use types may generate some profits. For simplicity, profit is scaled so that the profit on conserved land (extensive use) is zero and the profit on (intensively used) agricultural land is given by the difference to that of conservation. In economic terms, the profit on agricultural land (*agricultural profit*) is equal to the opportunity cost of conservation (henceforth termed *conservation cost*). This scaled agricultural profit is assumed to vary among land parcels and drawn randomly and independently for each land parcel from the uniform distribution with bounds $1 \pm \sigma$.

In the first model, to offset the conservation costs, a conservation agency offers a spatially homogeneous base payment (BP) to landowners who conserve their land parcel, plus an agglomeration bonus (AB) if the land parcel is adjacent to other conserved land parcels (Parkhurst et al. 2002). The latter is introduced to incentivise spatial agglomeration of conservation efforts in order to benefit dispersal-limited species.

In the simulation, landowners are assumed to be rational profit maximisers, where profit equals agricultural profit plus BP plus AB times number of conserved land parcels in the Moore neighbourhood *M* of the eight adjacent land parcels (where, as outlined, agricultural profit accrues only under (intensive) agricultural use and BP and AB are earned only if the land parcel is conserved). The simulation starts with all land parcels in agriculture. Since there are no conserved land parcels, those land parcels with conservation costs below the BP will conserve and the others stay in agricultural use. In the second time step of the simulation, the neighbours of these conserved land parcels will observe conserved land parcels in *their* neighbourhood, so as described above they will conserve if the sum of BP plus AB times the number of conserved land parcels in the neighbourhood exceeds the conservation cost. In the following time steps, an increasing number of landowners will conserve, until a stationary land-use pattern is obtained. The budget *B* required to induce this land-use pattern is obtained by summing the total payments for all conserved ($x_i = 1$) land parcels:

$$B = \sum_{i=1}^{100} x_i \left(BP + AB \sum_{j \in M_i} x_j \right), \tag{1}$$

where M_i is the (eight-cell) Moore neighbourhood around land parcel *i*. The total number of conserved land parcels and their spatial agglomeration depend on the levels of the base payment (BP) and the agglomeration bonus (AB). *Ceteris paribus*, an increasing AB leads to a higher level of spatial agglomeration. As shown by Drechsler et al. (2010) there is a trade-off between the amount and the spatial agglomeration of habitat, because spatial agglomeration *ceteris paribus* requires the conservation of more costly land parcels, so fewer land parcels can be conserved for a given conservation budget *B* (the ‘patch selection effect’ coined by Drechsler et al. (2010)).

The ecological favourability of the obtained landscape is assessed with a simple ecological simulation model, based on the metapopulation modelling approach by Hanski (1999). The model assumes that (intensive) agricultural land parcels are unsuitable for the species, while conserved land parcels can harbour a local population (e.g., Ojanen et al. 2013, Kentie 2015). A local population goes extinct at some rate *e*. Local populations on conserved land parcels colonise neighbouring empty land parcels at a rate *c* (Hanski 1999). The neighbourhood of a land parcel may be the eight adjacent land parcels (dispersal range $d = 1$), these land parcels plus the 16 adjacent land parcels ($d = 2$), or these land parcels plus the 24 adjacent land parcels ($d = 3$).

To analyse the model for a given combination of the five model parameters (σ, B, e, c, d), the economic module is simulated for 20 time steps, followed by 20 time steps simulation of the ecological module (in both modules stationary states are reached quickly after a few time steps). The favourability of the landscape for the species is measured by the temporal average (taken over the last ten time steps) of the proportion of land parcels occupied by the species, henceforth termed *ecological benefit*.

In the analyses below I am interested in the cost-effective design of the payment scheme which maximises the ecological benefit for given conservation budget B. In the present agglomeration payment scheme the decisive design parameter is the ratio of agglomeration bonus (AB) and base payment (BP) (the latter is, for given budget, uniquely determined by the level of the AB). As described above, a large ratio of AB and BP induces spatial agglomeration of conserved land parcels which benefits especially dispersal-limited species. On the other hand, as argued above, under spatial agglomeration fewer land parcels can be conserved for a given budget, so for species that are not dispersal-limited a low ratio of AB and BP which induces less agglomerated but more conserved land parcels for a given budget can be expected to be more cost-effective.

The core quantities of interest are thus the ratio of AB and BP that maximises scheme cost-effectiveness and the associated ecological benefit. To encompass the stochasticity in the model dynamics, the described simulations and evaluations are carried out 250 times and an average is taken.

The second test model considers the same model landscape as the first, to compare input- and output-based payments (IBP and OBP) with regard to their cost-effectiveness (Drechsler 2017). Under IBP the landowners receive a spatially homogeneous payment if they conserve their land (like the base payment BP in the first model), while under OBP they receive a payment if and only if a target species is present on their land (Derissen and Quaas 2013). The dynamics of the target species are described by the same ecological model as above, and the ecological benefit is also measured by the proportion of land parcels occupied by the species. In the IBP the conservation budget is given by the payment multiplied by the number of conserved land parcels, while in the OBP it is given by the payment multiplied by the number of land parcels occupied by the target species. The model analysis of Drechsler (2017) reveals that as long as the landowners are not too risk-averse, the OBP outperforms the IBP, i.e. delivers a higher proportion of occupied land parcels for given conservation budget.

To analyse the model for a given policy choice (OBP or IBP) and combination of the five model parameters (σ, B, e, c, d), I simulate the coupled ecological-economic dynamics for 100 times (each time step having the typical length of a conservation contract), and in the last 50 time steps record the proportion of land parcels occupied by the species and take a temporal average to calculate the ecological benefit. To encompass stochasticity in the model dynamics, the simulation is repeated 250 times and an average is taken. Next to the ecological benefits of the OBP and the IBP, I am interested in the efficiency advantage of the OBP over the IBP and subtract (for given conservation budget) the ecological benefit obtained in the IBP from that obtained in the OBP.

Both described models assume simple profit-maximising landowners who conserve their land parcel if the conservation payment exceeds the agricultural profit, and use the land for agriculture otherwise. As argued in the Introduction, this simple model ignores other factors that may influence landowner behaviour. Three major factors were identified in the Introduction: the landowners may fail to identify the profit-maximising land-use measure, they are altruistic and concerned about equity, and they are influenced by the behaviour of their neighbours. Below, four extensions of the simple profit-maximising model are resented that model four types of alternative behaviour.

1. Landowners make sub-optimal decisions – e.g., due to imperfect knowledge or limited cognitive abilities. With probability ε (henceforth termed *error rate*) each landowner erroneously chooses the "wrong" one of the two land-use measures (conservation or agriculture), i.e., the one with lowest profit. To determine the land use x_i on land parcel i (with $x_i = 1$ representing conservation and $x_i = 0$ representing agriculture), I draw a random number a from the uniform distribution with bounds of zero and one and calculate

$$x_i = \begin{cases} \arg\max\limits_{x_i \in \{0,1\}} \{\pi_i(x_i)\} & a > \varepsilon \\ 1 - \arg\max\limits_{x_i \in \{0,1\}} \{\pi_i(x_i)\} = \arg\min\limits_{x_i \in \{0,1\}} \{\pi_i(x_i)\} & a \le \varepsilon \end{cases} \qquad (2)$$

2. Landowners are averse to inequity in their profits relative to those of their neighbours, so the perceived favourability of the land-use choice of landowner i depends not only on the own profit π_i but also on the profits π_j of the eight neighbours in the Moore neighbouhood M_i (taken from the previous simulation time step to avoid circularities). To model such inequity-aversion I follow a popular model and assume that each landowner i maximises the following utility function (Fehr and Schmidt 1999):

$$U_i(\pi_i) = \pi_i - \frac{\alpha}{8}\sum_{j \in M_i} \max\{\pi_j - \pi_i, 0\} - \frac{\alpha}{16}\sum_{j \in M_i} \max\{\pi_i - \pi_j, 0\} \tag{3}$$

The first sum in eq. (3) considers that neighbouring landowners with higher profit $\pi_j > \pi_i$ reduce landowner i's utility at a rate α per neighbour ('envy'), while the second sum considers that landowners with lower profit $\pi_j < \pi_i$ reduce landowner i's utility at a rate $\alpha/2$ per neighbour ('compassion'). The parameter α is henceforth termed *inequity aversion*. To determine the land use x_i on land parcel i, I calculate

$$x_i = \underset{x_i \in \{0,1\}}{\arg\max}\{U_i(\pi_i(x_i))\} \tag{4}$$

3. Landowners are influenced by the actions of their (eight) neighbours. Two models of social influence are considered.

3a. Each landowner observes the number of conserved land parcels n in the Moore neighbourhood. With probability γ_1 (henceforth termed *social influence*) s/he bases the own land use on that number by conserving with probability $n/8$ and doing agriculture otherwise. Thus, if the landowner happens to be influenced by the neighbours her probability of conserving increases with the proportion of conserving landowners in the neighbourhood. Alternatively, with probability $1 - \gamma_1$ the landowner chooses the land-use measure that maximises her own profit. To determine the land use x_i on land parcel i, I draw two random numbers, a and b, from the uniform distribution with bounds of zero and one and calculate

$$x_i = \begin{cases} \underset{x_i \in \{0,1\}}{\arg\max}\{\pi_i(x_i)\} & a > \gamma \\ 1 & a \le \gamma, b \le n/8 \\ 0 & a \le \gamma, b > n/8 \end{cases} \tag{5}$$

3b. Each landowner identifies the highest profit (from the previous simulation time step) of the eight neighbours in the Moore neighbourhood M and chooses the associated land-use measure of that landowner with probability γ_2 (henceforth termed *social-economic influence*). Otherwise, with probability $1 - \gamma_2$, the landowner chooses the land-use measure that maximises her own profit. To determine the land use x_i on land parcel i, I draw a random number a from the uniform distribution with bounds of zero and one and calculate

$$x_i = \begin{cases} \underset{x_i \in \{0,1\}}{\arg\max} \{\pi_i(x_i)\} & a > \gamma \\ \underset{j \in M_i,\, x_j \in \{0,1\}}{\arg\max} \{\pi_j(x_j)\} & a \le \gamma \end{cases} \tag{6}$$

2.2 Model analysis

The two described models have altogether nine parameters, including the five *model parameters* (conservation budget *B*, spatial cost variation σ, local extinction rate *e*, colonisation rate *c* and species dispersal range *d*). The considered ranges for the values of these five parameters are given in Table 1. A value of $d = 1$ represents local dispersal, while with $d = 3$ an individual leaving a central land parcel can reach 48 out of the 100 land parcels. The rates *c* and *e* were chosen so that the proportion of occupied land parcels ranges between a few percent (population decline and high extinction risk) to about 50 percent (stable population and low extinction risk). While $\sigma = 0.1$ represents almost homogenous agricultural profits, with $\sigma = 0.5$ the profits within the model region vary by a factor of 3. The range of the budget *B* was chosen so that the proportion of conserved land parcels ranges between low to medium.

In addition there are the four *behavioural parameters* ε, α, γ_1 and γ_2. The setting $\varepsilon = \alpha = \gamma_1 = \gamma_2 = 0$ reproduces the model of *homo oeconomicus* while an increase in each of the behavioural parameters describes an increasing deviation from that model. The upper bounds of the parameters (Table 1) are based on the following considerations. An error rate $\varepsilon = 0.5$ represents the totally uninformed and random decision in which each of the two choices (conservation or agriculture) is equally likely. This may be regarded as an extreme and unrealistic representation of real landowner behaviour. Following Fehr and Schmidt (1999), the inequity aversion α has an upper bound of one. This value represents the case in which the average difference of the better-off neighbours (the 'envy' component) is weighted equally to ones own profit. The upper bound of the social and social-economic influences is chosen at $\gamma_1, \gamma_2 = 0.5$ which assumes that the predominant (γ_1) or most successful (γ_2) land-use measure in the neighbourhood is adopted with probability 0.5.

Three questions were raised in the Introduction: the contribution of the behavioural parameters (ε, α, γ_1, γ_2) to the total variance in the model outputs, the deviations in the model outputs caused by changes in these behavioural parameters, and the dependence of these deviations on the other five model parameters (*B*, σ, *e*, *c*, *d*). In all analyses, to keep complexity at an acceptable level, each behavioural parameter is treated independently and interactions between different behavioural parameters are not considered.

To address the first question, four *performance variables* $v_1, \ldots, v_4$, are considered that measure the cost-effective design and the corresponding level of cost-effectiveness of the two payment schemes. In the outline of the model of the agglomeration bonus it was explained that the essential scheme design parameter is the ratio of agglomeration bonus (AB) and base payment (BP). The two core quantities of interest are therefore

- v_1: the cost-effective ratio $(AB/BP)_{eff}$ of agglomeration bonus and base payment, i.e. the ratio that maximises in the first model the ecological benefit (proportion of land parcels occupied by the target species) for given budget B; and
- v_2: the asscociated ecological benefit (i.e., proportion of occupied land parcels).

The central question around the output-based payment scheme (OBP) is the question under which circumstances this is more cost-effective than input-based payments IBP. And in addition, we are interested in the performance of the OBP. The two core quantities of interest are therefore

- v_3: for given budget B, the difference between the ecological benefit (proportion of occupied land parcels) from the OBP and that from the IBP (i.e., the gain in cost-effectiveness when choosing an OBP instead of an IBP); and
- v_4: the associated ecological benefit of the OBP (i.e., the proportion of occupied land parcels).

The influence of the four behavioural parameters on these four performance variables are analysed in 16 separate analyses of variance (ANOVAs). Each ANOVA considers three treatment levels for the respective behavioural parameter (Table 1). The performance variables v_i ($i = 1, \ldots, 4$) are determined for 500 random combinations of the five model parameters, drawn from their ranges given in Table 1.

Table 1: Values of the five model parameters and the four behavioural parameters.

Model parameter	Values
Conservation budget B	$\in [20, 60]$
Spatial variation of conservation costs σ	$\in [0.1, 0.5]$
Species local extinction rate e	$\in [0.2, 0.4]$

Species colonisation rate c	$\in [0.3, 0.6]$
Species dispersal range d	$\in \{1, 2, 3\}$
Behavioural parameter	
Error rate ε	$\in \{0, 0.15, 0.3\}$
Inequity aversion α	$\in \{0, 0.5, 1\}$
Social influence γ_1	$\in \{0, 0.25, 0.5\}$
Social-economic influence γ_2	$\in \{0, 0.25, 0.5\}$

For the second research question, performance differences $\Delta_1, \ldots, \Delta_4$ are considered. Each Δ_i measures the *impact* of the considered behavioural parameter, i.e. the change in the performance variable v_i if the considered behavioural parameter is changed from zero to some value x:

$$\Delta_i(x) = v_i(behav.parm. = x) - v_i(behav.parm. = 0) \tag{7}$$

In the case of the performance variables v_2 and v_4, $\Delta(x)$ measures the change in the ecological benefit (for the chosen conservation budget) due to an increase in the behavioural parameter. Such a change in the ecological benefit is generally more relevant when the benefit is small and the species threatened by extinction. Therefore, next to the consideration of absolute changes in v_2 and v_4, I also consider *relative* changes, so that for instance a change from 50 percent occupied patches to 25 percent is valued equally to a decline from ten percent to five percent:

$$\begin{aligned}\Delta_2'(x) &= \frac{v_2(behav.parm. = x) - v_2(behav.parm. = 0)}{v_2(behav.parm. = 0)}\\ \Delta_4'(x) &= \frac{v_4(behav.parm. = x) - v_4(behav.parm. = 0)}{v_4(behav.parm. = 0)}\end{aligned} \tag{8}$$

Altogether, six Deltas are calculated for each behavioural parameter. Each of these 24 Deltas is determined for the 500 random combinations of the five model parameters drawn from their ranges (Table 1), and frequency distributions are determined.

Among others, the sets of parameter combinations that lead to large negative (positive) Deltas in their lower (upper) 5%-quantiles are determined. The third research question is whether these sets are special in terms of the model parameter values, such that a large Δ_1, e.g., might be observed especially with small conservation budgets. To address this question, I determine for each of the sets with particularly large negative or positive Deltas the means and standard deviations of the contained model parameter values. From the means and standard deviations I build for each of the five model parameters a "95%-confidence interval" with bounds given by the mean plus/minus two standard deviations and determine whether the mean of the full parameter range according to Table 1 is inside this "confidence interval" or not. If it is outside, this indicates that the focal model parameter has a significant impact on the considered Delta.

For instance, it might turn out that 25 out of the 500 random model parameter combinations lead to a large $\Delta_1 > 0.1$ and that the conservation budgets in these 25 parameter combinations have a mean of 20 and a standard deviation of 5, implying a "95% confidence interval" of the conservation budget with bounds 10 and 30. In contrast, the mean over all 500 sampled conservation budgets equals, with negligible sampling error, 40 (Table 1). This is above the upper bound of the "95%-confidence interval", so the conservation budgets in the set of the 25 parameter combinations that lead to $\Delta_1 > 0.1$ are significantly smaller than the mean conservation budget over all 500 parameter combinations – indicating that large $\Delta_1 > 0.1$ are favoured by small conservation budgets.

3 Results

3.1 Contributions of the behavioural parameters to model variance (ANOVA)

The contributions of the four behavioural parameters ε, α, γ_1 and γ_2 to the variance in the four performance variables v_1–v_4 are determined in 16 separate ANOVAs (Table 2). For each behavioural parameter the third column from the right shows the total variation (total sum of squares) in each of the four performance variables over the 500 random combinations of model and behavioural parameters, and the second column shows the variation in the performance variables caused by varying the three treatment levels, i.e. the levels of the considered behavioural parameter. The last column shows the ratio of the two variations and measures the relative contributions of the behavioural parameters to the total variation.

One can see that these relative contributions are generally in the low percentages – partly even smaller. The only exception are the impacts of the social and the social-economic influences (γ_1 and γ_2) on variables v_3 and v_4 (the advantage of the output-based payment OBP over the input-based payment IBP, and the ecological benefit (for chosen conservation budget) of the OBP). The social influence γ_1 has a substantial impact (Ratio ≈ 0.45) on the advantage of the OBP over the IBP, while both the social and the social-economic influence generate a moderate contribution to the variation

(Ratio ≈ 0.13) in the ecological benefit v_4 (for chosen conservation budget) of the OBP.

Result 3.1: The contributions of the behavioural parameters to the total variation in the performance variables is very small, except for those of the social and social-economic influences on the performance of the OBP (both in an absolute manner and relative to the IBP), which are moderate.

Table 2: ANOVA of the influences of the four behavioural parameters on the four performance variables. TotalSS represents the sum of the squared deviations from the grand mean over all 500 replicates, BetweenSS is the sum of the squared deviations of the three group means (corresponding to the three treatment levels) from the grand mean, and Ratio divides BetweenSS by TotalSS. Large values are bold-faced.

Performance variable v	Behavioural parameter	TotalSS	BetweenSS	Ratio
v_1: Cost-effective ratio of agglomeration bonus and base payment	Error ε	0.857	0.015	0.018
	Inequity aversion α	1.30	$1.28\cdot10^{-5}$	$9.9\cdot10^{-6}$
	Social-economic influence γ_2	1.67	0.061	0.037
	Social influence γ_1	1.03	0.001	0.001
v_2: Agglomeration bonus scheme's ecological benefit (for chosen conservation budget)	Error ε	10.1	0.069	0.007
	Inequity aversion α	9.83	$2.63\cdot10^{-6}$	$2.7\cdot10^{-7}$
	Social-economic influence γ_2	9.05	0.172	0.019
	Social influence γ_1	10.05	0.006	0.001
v_3: Performance difference between out-based and input-based payments	Error ε	1.23	0.006	0.005
	Inequity aversion α	0.963	$1.32\cdot10^{-4}$	$1.4\cdot10^{-4}$
	Social-economic influence γ_2	1.15	0.028	0.024
	Social influence γ_1	2.47	1.08	**0.438**
v_4: Out-based payments scheme's ecological benefit (for chosen conservation budget)	Error ε	7.74	0.002	$2.5\cdot10^{-4}$
	Inequity aversion α	8.68	$8.33\cdot10^{-5}$	$1\cdot10^{-5}$
	Social-economic influence γ_2	9.03	1.18	**0.130**
	Social influence γ_1	9.61	1.21	**0.126**

3.2 Distribution of the impacts of the behavioural parameters

Table 3 shows statistics of the absolute and relative impacts Δ_i and Δ_i' (eqs. (7) and (8)) of the four behavioural parameters on the performance variables v_1–v_4. The fourth column from the right shows the mean impact of each behavioural parameter over all 500 random combinations of the model and behavioural parameters. One can see that only in 7 out of the 24 pairings {impact variable × behavioural parameter} this mean deviates from zero by more than ±0.03 (italicised numbers in

Table 3), where a value of $\Delta_1 = 0.03$ means that the behavioural parameter on average increases the cost-effective ratio of agglomeration bonus and base payment by 0.03, a value of $\Delta_2 = 0.03$ means that it increases the ecological benefit (proportion of occupied land parcels) of the agglomeration bonus scheme by 0.03 (which equals three land parcels in the study region of 100 land parcels), a value of $\Delta_3 = 0.03$ means that it increases the difference between the ecological benefits achieved with the OBP and the IBP by 0.03, and a value of $\Delta_4 = 0.03$ means that it increases the ecological benefit of the OBP by 0.03; and $\Delta_2' = 0.03$ means that the behavioural parameter increases the ecological benefit of the agglomeration bonus scheme by three percent, and $\Delta_4' = 0.03$ means that it increases the ecological benefit of the output-based payment by three percent.

In particular, the error rate ε tends to increase the cost-effective ratio of agglomeration bonus (AB) and base payment (BP) (mean $\Delta_2' = 0.065 = 6.5$ occupied land parcels), and the social-economic influence (γ_2) tends to reduce the cost-effective ratio of AB and BP (mean $\Delta_2' = –0.097$) and considerably reduces the ecological benefit (for chosen conservation budget) of the OBP (mean $\Delta_4 = –0.067$ and mean $\Delta_4' = –0.191$). The social influence (γ_1) tends to reduce the advantage of the OBP over the IBP (mean $\Delta_3 = –0.063$) and considerably reduces the ecological benefit (for chosen conservation budget) of the OBP (mean $\Delta_4 = –0.068$ and mean $\Delta_4' = –0.193$).

The large negative mean impacts are associated with small 5%-quantiles of about –0.15 (bold-faced numbers), meaning that five percent of all 500 parameter combinations lead to large negative impacts of Δ_i and Δ_i' below –0.15. An exception are the relative impacts Δ_4' of the social and the social-economic influences on the ecological benefit of the OBP which have 5%-quantiles of about –0.45. The large positive mean impacts shown in Table 3 are associated with large 95%-quantiles of about 0.15 (bold-faced numbers), meaning that five percent of all 500 parameter combinations lead to large positive impacts above 0.15.

An interesting case is the relative impact of the error rate ε on the ecological benefit (Δ_4'). While the mean of this impact over all 500 parameter combinations is almost zero (0.001), both the 5%-quantile is quite large negative (–0.104) and the 95%-quantile is quite large positive (0.123). This indicates that the relative impact of the error rate on the ecological benefit of the OBP is quite variable and, depending on the considered parameter combination, can both be positive or negative.

Result 3.2: The results in Table 3 largely confirm those of the ANOVA (Table 2) that the behavioural parameters have generally only small or moderate influences on the performance variables, except *for the social and social-economic influences γ_1 and γ_2 which quite strongly affect the performance variables v_3 and v_4, i.e. the performance of the OBP (both in an absolute sense and relative to the input-based payment IBP).*

Table 3: Statistics of the six impact measures, Δ_1–Δ_4’ with respect to the four behavioural parameters: minimum, 5%-quantile, mean, 95%-quantile, and maximum, within the 500 random model parameter combinations. For the italic and bold styles and the superscripts, a–i, see text.

Variable	Behavioural parameter	Minimum	5%- quantile	Mean	95%- quantile	Maximum
Δ_1	ε	–0.08	–0.035	0.001	0.031	0.044
	α	–0.008	–0.002	$9.6 \cdot 10^{-5}$	0.003	0.008
	γ_1	–0.057	–0.03	–0.001	0.011	0.02
	γ_2	0	0.003	0.015	0.032	0.047
Δ_2	ε	–0.034	–0.004	0.017	0.034	0.04
	α	–0.003	–0.002	$-1.0 \cdot 10^{-4}$	0.001	0.004
	γ_1	–0.004	–0.002	0.004	0.013	0.017
	γ_2	–0.058	–0.048	–0.026	–0.006	0.011
Δ_2’	ε	–0.515	–0.023	*0.065*	**0.157**[a]	0.231
	α	–0.017	–0.008	$-4.9 \cdot 10^{-4}$	0.006	0.03
	γ_1	–0.01	–0.006	0.023	0.088	0.016
	γ_2	–0.181	**–0.157**[b]	*–0.097*	–0.028	0.136
Δ_3	ε	–0.03	–0.017	0.003	0.035	0.091
	α	–0.034	–0.017	$3.7 \cdot 10^{-4}$	0.015	0.057
	γ_1	–0.262	**–0.153**[c]	*–0.063*	–0.01	0.02
	γ_2	–0.105	–0.055	–0.005	0.023	0.055
Δ_4	ε	–0.066	–0.038	–0.002	0.033	0.046
	α	–0.035	–0.015	$3.2 \cdot 10^{-4}$	0.015	0.051
	γ_1	–0.276	**–0.167**[d]	*–0.068*	–0.013	0.015
	γ_2	–0.215	**–0.161**[e]	*–0.067*	–0.017	0.01
Δ_4’	ε	–0.199	**–0.104**[f]	0.001	**0.123**[g]	0.204
	α	–0.155	–0.045	0.001	0.045	0.232
	γ_1	–0.604	**–0.46**[h]	*–0.193*	–0.045	0.069
	γ_2	–0.613	**–0.445**[i]	*–0.191*	–0.065	0.051

3.3 Influence of the model parameters on the impacts of the behavioural parameters

As explained in the Methods, for the cases with 5%- and 95%-quantiles below –0.1 and above +0.1 (bold-faced and super-scripted by the letters in Table 3) I determine whether these are significantly associated with special values of the five model parameters. Observation a: the conservation budget

B is below average; b: the cost variation σ is above average; c: the dispersal range d is below average; d: the conservation budget is above and the dispersal range is below average; e: same as (d); f: the cost variation is below average; g: the conservation budget is below average, h: the conservation budget is above average and colonisation rate c and dispersal range are below average; and i: the dispersal range is below average.

Result 3.3: Some patterns can be detected in these findings: under small conservation budgets an increasing error rate appears to increase the ecological benefits (for chosen conservation budget) of both payment schemes while under large conservation budgets the social and social-economic influences tend to reduce the ecological benefits (for chosen conservation budget) of both schemes. And in the case of a small dispersal range, the social and social-economic influences appear to reduce the ecological benefit (for chosen conservation budget) of the output-based payment and its advantage over the input-based payment.

4 Discussion and Conclusion

The present paper takes up criticism of the theory of rational behaviour, i.e. the human model of *homo oeconomicus* in the modelling of social-ecological systems and policy making. Addressing the raised conceptual, philosophical or psychological concerns would be far beyond this paper which, instead, focuses on the practical question of how large mistakes one makes if the model of *homo oeconomicus* is employed within the model-based analysis of environmental policies such as agri-environmental schemes.

For this, two existing simple and generic ecological-economic models are considered: one for the analysis of the agglomeration bonus (Parkhurst et al. 2002) to conserve a mobile but dispersal-limited species, and the other one for the comparison of input- and output-based conservation payments for the conservation of the same type of species (Drechsler 2017, 2020).

Both models originally assume rational profit-maximising landowners. This human decision model is expanded to consider alternative behaviours by assuming that (i) the profit-maximising land-use measure is chosen only with probability ε (cf. eq. (2)); (ii) inequity-aversion, by reducing the landowner's individual utility according to the difference between the landowner's profit and the profits of the landowner's neighbours, multiplied with a coefficient α (cf. eqs. (3) and (4)); or (iii) social and social-economic influence, such that with probability γ_1 (γ_2) the landowner does not take the profit-maximising land-use measure but is influenced by the neighbours' current land-use choice and (iii.a) chooses the land-use that is predominantly applied in the neighbourhood ("social influence" γ_1; cf. eq. (5)) or (iii.b) adopts the measure of the neighbour associated with the highest profit ("social-economic influence" γ_2; cf. eq. (6)). The former model of social influence may be regarded as the spatial diffusion of a norm ("act in favour of the environment" or "be a successful farming entrepreneur", respectively) while the latter model describes exchange of information between, and learning from neighbouring landowners.

Rather broad ranges are considered for the behavioural parameters (cf. Table 1) to determine their influences on the cost-effective design and level of cost-effectiveness of the two conservation payment schemes. A global sensitivity analysis (Saltelli et al. 2008), followed by various statistical evaluations reveals that the influences of the behavioural parameters are generally rather small compared with the influences of the other model parameters (conservation budget, spatial heterogeneity in the conservation costs, species local extinction rate and colonisation rates and species dispersal range). Also, the results appear quite robust to the choice of the model parameter values within the considered ranges. For instance, the values of the species colonisation and extinction rates (c and e) did not significantly affect the influences of the behavioural parameters (section 3.3)

An exception are the social and the social-economic influences which considerably affect the performance of the output-based payment both in an absolute manner (number of land parcels occupied by the target species for given conservation budget) and relative to the input-based payment (difference in the numbers of occupied land parcels for given budget).

Could these results have been expected? In both models the spatial coordination of landowners plays an important role: in the first model the agglomeration bonus incentivises the spatial agglomeration of conservation efforts, while in the second model the spatio-temporal feedback between the influence of the land use pattern on the metapopulation dynamics and the landowners' responses to the spatial distribution of the metapopulation induces spatial agglomeration of conservation efforts (Drechsler 2020). Although such coordination can be expected to be disturbed by decision errors, the error rate ε has mostly only a rather small effect and even tends to increase the cost-effectiveness of the agglomeration bonus scheme.

Adopting land-use choices from neighbours is likely to aggregate like with like land use measures, i.e., conservation next to conservation and agriculture next to agriculture. Therefore one could have expected that such influences (γ_1 and γ_2) increase the cost-effectiveness of both considered conservation instruments. Interestingly, as discussed above, the effect of γ_1 and γ_2 on the output-based payment is the opposite, while the agglomeration bonus scheme is only slightly affected by γ_1 and γ_2.

It is not easy to predict the effect of inequity aversion (α). Choosing one's land use in order to minimise profit differences to "agricultural" neighbours will lead to agriculture if all landowners in the neighbourhood have similar conservation costs but could lead to conservation if the own costs strongly differ from those in the neighbourhood. The analogue holds for a landowner surrounded by conserving neighbours. And on the boundary of a cluster of conserving landowners it is even less clear whether inequity aversion will induce a landowner to conservation or to agriculture.

The observed results are likely to depend on the chosen parameter ranges in the global sensitivity analysis. As explained along Table 1, these cover quite a broad range of situations that can be expected in reality, but of course they represent a restriction of generality. In addition, while the analysis in section 3.3 indicates under which circumstances the influence of the behavioural parameters may be high and policy makers should put some attention to possible alternative behaviours in the landowners, the models are too simple to provide concrete policy advice in specific conservation problems. For such tasks more specific models are required that, e.g., consider several land-use types (with different agricultural profitability and suitability for the species), capture the population dynamical processes in agricultural landscapes more adequately (e.g., by explicitly considering the local population dynamics within the land parcels, which also addresses that species have different area requirements, and the dispersal behaviour of the individuals) and more realistic assumptions of land ownership (e.g., each landowner may own several land parcels – which may reduce the observed impacts of neighbourhood interactions). Such modelling studies may be interesting subjects of future research. The intention of the present analysis is instead to demonstrate that alternative landowner behaviours can have an impact on the performance of conservation payment schemes, but that this impact is not necessarily large. Or in other words, the model of h*omo oeconomicus* is neither right nor wrong but has – as most theories and models – a finite scope.

In the present two examples that scope appears to be quite large with respect to what can be reasonably assumed about alternative behaviours, but a general answer to the question of how large that scope is can only be given after more empirical and theoretical research. Future research may consider other types of conservation instruments, other environmental and economic settings such as spatially correlated agricultural profits, other types of landowner behaviour such as learning from past experience, landowner heterogeneity (e.g., with regard to the behavioural rules), other ecological models, etc.

The presently indicated favour for the model of *homo oeconomicus*, of course, does not deny the relevance of other behavioural factors behind landowner decision making outlined in the Introduction and discussed in detail by Dessart et al. (2019). Knowing these factors and motives are indeed relevant in the application of other measures of conservation policy, such as the education of landowners about the private and public costs and benefits of different land-use measures. However, as the present results indicate, when it comes to market-based instruments such as conservation payments, these other factors may be less relevant.

This conclusion quite well agrees with that of Bowles and Polanía-Reyes (2012) in a slightly different area. The authors investigate the importance of the interaction between economic incentives and social preferences that may lead to the crowding-in or crowding-out of pro-environmental behaviour through market-based instruments (Rode et al. 2015). Such interactions between economic incentives and other motives of human behaviour do not argue against the use of economic incentives *per se* but rather point to the importance of good communication between policy maker and landowners and the proper framing of the policy instrument (Bowles and Polanía-Reyes 2012).

For the formal design of market-based instruments, such as the choice of the cost-effective level of a conservation payment, these non-economic aspects are, however, probably less relevant. If the improvement of its communication and framing of policies is the motivation behind the European Union's recent interest in the behavioural factors behind landowners' decisions (Dessart et al. 2019) this is certainly a move into a good direction. On the other hand, one may question whether the failure of the EU agricultural policy to halt or even slow down the loss of biodiversity is due to improper communication and framing or a false assumption of rationality in the farmers, or whether it is rather due to an inappropriate allocation of agricultural budgets and the setting of false economic incentives (Pe'er et al. 2019) – to which the European farmers probably respond in quite a rational manner.

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