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Productive ecosystem services and collective management: Lessons from a realistic landscape model

Francois Bareille[a,b], Hugues Boussard[c], Claudine Thenail[d]

[a] DISTAL, University of Bologna, 40121 Bologna, Italy
[b] INRA, UMR1302 SMART-LERECO, Rennes France
[c] INRA UMR0980 BAGAP, 65 rue de Saint Brieuc, 35042 Rennes Cedex, France
[d] INRA, UMR 0980 BAGAP, CS 84215, 35042 Rennes Cedex, France

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ABSTRACT

Previous works based on the simulation of stylized landscapes with homogeneous farms have concluded that farmers would benefit from the coordinated landscape-scale management of ecosystem services. Here, we examine such benefits in a realistic landscape (Brittany, France), with diversely fragmented farm territories and locally validated field-based ecological functions (the abundance of a generalist pest-predatory insect). We test whether such properties modulate the previous results by simulating several management strategies of biological control with an agronomic-ecological-economic landscape model. We find that, if landscape-scale management improves the collective benefits, some farmers lose by collaborating. Due to the heterogeneity of farms, the stability of the collective action is rarely satisfied at the landscape scale: the probability that the collective management of productive ecosystem services occurs is 15% in our case.

1. Introduction

Occupying 37.5% of the world's lands, agriculture is the most land-intensive economic activity. On the one hand, there is increasing evidence that farmers affect the provision of diverse ecosystem services (ES). At the field scale, ecological functions involved in ES, such as natural pest control, depend on the diversity of farmers' choices of crops and cropping practices (*e.g.*, Seguni et al., 2011). Hypotheses and evidence have been presented regarding the relative influence of landscape structure (composition and configuration), field structure and field management on key ecological functions (Tscharntke et al., 2012). For instance, intensive farming practices in simplified landscapes negatively affect the biodiversity of pest predators (Chaplin-Kramer et al., 2011). Crop diversity positively affects carabids' activity, density and species richness (Woodcock et al., 2010). The specific spatial configurations of winter and spring crops also determine the availability and accessibility of complementary resources for carabids (Burel et al., 2013; Aviron et al., 2018). These results suggest that farmers affect natural pest control through the influence of land-use choices on populations of carabid beetles that are generalist pest-predatory insects.

On the other hand, these ES influence farmers' utility through the modification of agricultural productivity and profitability (Zhang et al., 2007). We refer to these services as productive ES, considering that they are inputs of agricultural technologies (Barbier, 2007). The literature considers that the management of productive ES is one solution, with precision agriculture (Monzon et al., 2018) or conservation practices (Jat et al., 2018), to increase the profitability of farming in the 21st century. Several works have assessed the value of productive ES at the field scale, *e.g.*, by considering yield gains or reductions in pesticide costs due to biological pest control (*e.g.*, Brainard et al., 2016). Several attempts have valued productive ES at the farm scale, *e.g.*, by assessing the impact of farm-favorable land use on average yield (Di Falco et al., 2010; Klemick, 2011). Other studies extend beyond the pure valuation of productive ES to examine farmers' management of productive ES. By relying on crop-allocation choice models at the farm scale, these works have demonstrated that farmers manage productive ES to benefit from them, either in terms of additional yields or input savings (Bareille and Letort, 2018; Orazem and Miranowski, 1994; Thomas, 2003) *i.e.*, productive ES are not pure externalities.

The knowledge about the impact of the landscape structure on the provision of productive ES has emphasized new issues regarding the collective agricultural management of productive ES (Zhang et al., 2007). One issue is estimating how and how much farmers' individual land-use choices generate externalities for other farmers who share the same landscape (due to the influence of these choices on mobile ES providers such as beneficial insects). Another related issue is estimating the potential benefits of the coordinated management of productive ES at the landscape scale. Examining such issues would help in the

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E-mail address: francois.bareille@unibo.it (F. Bareille).

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assessment of the impacts of different existing or novel policy instruments on the evolution of collective ES management and provision at the landscape scale.

To our knowledge, the first study that investigated the economic and ecological interdependencies between crop production and biodiversity (here, mobile ES providers) at the landscape scale was Cong et al. (2014, 2016). The main result of this study was that the coordinated management of pollination at the landscape scale (called "landscape-scale management" and noted hereafter as LSM) increases the profit of each farm compared to the uncoordinated management solution (called "farm-scale management" and noted hereafter as FSM). Epanchin-Niell and Wilen (2014) and Atallah et al. (2017) emphasized that LSM improves the individual profits in most cases when farmers regulate pest pressure in common. Cong et al. (2016) showed that the LSM solution is characterized by a landscape mosaic with a dispersed configuration of habitats. However, these works rely on simple raster-stylized representations of landscapes with homogeneous fields and homogeneous and continuous farms. Therefore, several aspects of agricultural heterogeneity have not been fully addressed. This remark also applies to the theoretical works that investigate this issue (*e.g.*, Costello et al., 2017; Zavalloni et al., 2019). In fact, the spatial structure of farm territories is very heterogeneous, at least in many European landscapes: fields differ, *e.g.*, in size, shape, and soil quality. The fragmentation of farm territories, *i.e.*, both the parceling and the scattering of fields of each farm in space, is also highly heterogeneous (Latruffe and Piet, 2014). Agricultural landscape mosaics largely comprise these interwoven farm territories, which induces complex spatial interdependencies between ecological processes and agricultural management. These features should be considered when examining farmers' behavior in realistic situations (Martel et al., 2017; Sutherland et al., 2012). As suggested in the sensitivity analysis of Atallah et al. (2017), who indicated that the benefits of collective management depend on the heterogeneity of the product quality, more realistic modeling settings are suspected to change the conclusions of the literature on the benefits of collective management for productive ES.

The aim of our study is to examine the benefits of collective ES management in a realistic landscape with heterogeneous farms. For this purpose, we simulate different biological control management strategies through an agronomic-ecologic-economic landscape model on a realistic landscape site of north-western France. The model that we develop relies heavily on the model of Martel et al. (2017) that allows to evaluate the impact of land-use allocations on populations of carabid beetles, those being considered as providers of biological control. The modeled ecological function relies on recent results in landscape ecology that highlighted the role of interfaces within agricultural landscape mosaics on the life cycle of carabids (Martel et al., 2017). We consider several degrees of biological control management: (i) no management at all (ii) a naïve-FSM strategy where farmers do not communicate with one another; (iii) a rational FSM strategy where farmers communicate with one another regarding their crop-allocation intentions; and (iv) the LSM strategy. Therefore, three main hypotheses are tested. Our first hypothesis is that the total landscape-scale profit gradually increases from the no-management scenario to the LSM scenario due to the gradually increasing degree of management of carabid beetle populations. Second, we hypothesize that not all farms benefit from LSM due to their heterogeneity. Finally, Martel et al. (2017) found that both the share of the area and the relative crop patterns of the farms in the landscape influenced their contribution to carabid abundance. By applying the same perspective, we hypothesize that the relative structural characteristics of the farm territories *vis-à-vis* the landscape site influence the gains in all scenarios.

This paper is structured as follows. We first describe our model and empirical strategy (Section 2). We then present the results of 100 simulation replicates; we analyze the distribution of the total and individual profits in the different scenarios and investigate the farm and landscape characteristics as potential drivers (Section 3). Finally, we discuss our results and methodological choices (Section 4) before to conclude (Section 5).

2. Materials and method

2.1. Genesis of the landscape model

Our empirical approach consists of modeling different levels of collective management to optimize profits based on productive ES within a continuous landscape site. For this purpose, we adopt the models and data of Martel et al. (2017), who used the APILand landscape modeling framework (Boussard et al., 2010).[1]

APILand is a JAVA® library that includes the following features: (i) a meta-model of landscape representation in terms of thematics, space and time that facilitates the combination of farm territories within a non-agricultural matrix (*e.g.*, roads, buildings and woodlots); (ii) a set of simulation tools for managing the virtual experience plans; (iii) a spatio-temporal dynamic crop-allocation module (CAPFarm) that explicitly considers farm system constraints and territories;[2] and (iv) a landscape metrics analyzer (Chloe) that uses sliding windows to ecologically characterize agricultural landscapes.

The aim of Martel et al. (2017) was to understand the impact of farm and landscape spatial organization on carabid beetle populations to design territorial management solutions. Their model, called Agriconnect, determines carabid beetle abundance according to landscape configuration (due to the size and dispersion of the plots) and composition (of the crops and other fixed elements) in a circle with a 500-m radius, which is considered relevant to account for functional populations of carabid beetles (*e.g.*, to account for the movement capacities of beetles). Agriconnect was implemented on two realistic landscape sites: one with few woody elements and one with many woody elements (woodlots and hedgerows). Martel et al. (2017) considered two realistic farm systems, named 'swine' and 'cattle', with specific crop-allocation rules that were calibrated based on farmers' interviews. Agriconnect also contains two statistically validated ecological models for two distinct carabid beetle species groups: the species associated with woody habitats (the 'woody' model) and the species associated with maize crops (the 'maize' model).

To focus on our issue, we adapt and further develop the Agriconnect model. We use the sole landscape site with few woody elements and extend the area from a 500-m radius circle to a 1-km radius circle (see part 2.2.). We use only the 'swine' farm system (see part 2.3.). We generalize the 'maize' carabid model to the entire cropped area (see part 2.4.). We add an economic module that defines crop-specific profitability that positively depends on the carabid beetles' abundance (see part 2.5.). These adaptations lead us to a new virtual experiment (see part 2.6.) that considers four scenarios with distinct objective functions regarding the management of carabid beetles (see part 2.7.).

2.2. The landscape site and the farm territories

The landscape site is a spatially continuous 1-km radius circle where crops are allocated, carabid beetles' abundance is computed and profit-based objective functions are maximized. The landscape site is a subzone of a larger area containing all the farm territories, which is necessary for running consistent crop allocations at the farm level (see Fig. 1).

The landscape comprises a non-agricultural part and an agricultural part. The non-agricultural part consists of fixed landscape elements (hereafter referred to as fixed elements and noted **L**), including (i) artificial elements, such as roads and buildings, (ii) natural elements, such as water bodies, and (iii) semi-natural elements, such as woodlots,

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[1] APILand: Application Programming Interface for Landscape modeling.

[2] CAPFarm: Crop Allocation Problem at the farm level.

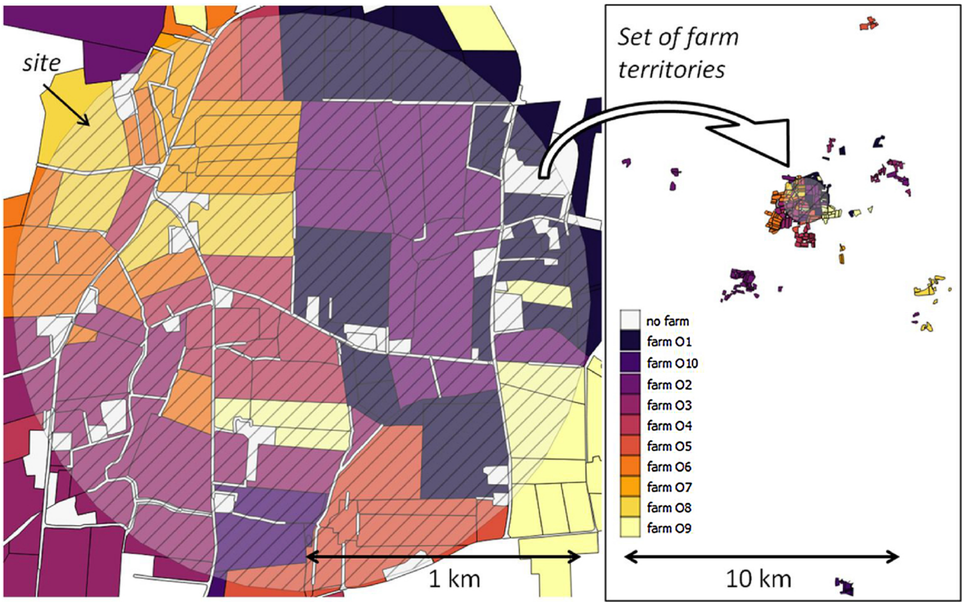

Fig. 1. The landscape site included in the entire set of farm territories.

herbaceous field margins and hedgerows. These elements cannot be modified by farmers and are thus considered to be exogenous in the simulation process. The farmsteads are also fixed and are part of $\mathbf{L}$. All the crop covers of the agricultural part are endogenous in the simulation process, except permanent grasslands, which are considered to be fixed and exogenous.

Ten farm territories contribute to the agricultural part of the landscape site. The territory of each farm j comprises one farmstead and a vector $\mathbf{I}_j$ of fields; the farms together contribute to the landscape mosaic of $\mathbf{I}$ fields. Farms can neither exchange their fields nor modify the shape and size of their fields. $\mathbf{I}_j^s$ represents the subset of fields that are at least partly contained in the landscape site and that belong to farm j.

The landscape site is modeled as a raster data set with 31,214 pixels. Each pixel p is sized 100 m^2 and belongs to a single field or to a single fixed landscape element. Accordingly, each field i in $\mathbf{I}_j^s$ consists of a specific vector of pixels $\mathbf{P}_i$. Farms are thus heterogeneous due to their farm territories constituted of heterogeneous fields in terms of size, shape and localization.

The selected landscape site represents an area of 314.16 ha, with 272.33 ha of crop fields and the rest consisting of fixed elements, including 9.67 ha of woody elements. There are 120 fields totally or partially included in the landscape site. The table in Appendix 1 displays the descriptive statistics of the fixed characteristics of the farm territories. The interfaces between fields that belong to the same farm are called "fixed within-farms interfaces" hereafter, and the interfaces between two distinct farms are called "fixed between-farms interfaces". Farms stretch in diverse proportions beyond the landscape site: the individual farm-area share in the site ranges from 53.86% to 22.11%. In total, there are 21.22 km of fixed interfaces in the landscape site, and 59% are within-farms interfaces. This illustrates how considerably the farm territories are fragmented and interwoven in the landscape site.

2.3. The crop allocation sub-model

The crop cover of the fields is the single endogenous variable in our model. The crop allocation model is run under the CAPFarm solver (Boussard et al., 2018). We consider that each farm j allocates the K crops that it produces among its $\mathbf{I}_j$ fields according to a set of farm-level agronomic constraints adapted from the Agriconnect realistic 'swine' farm system (Appendix 2). The CAPFarm solver randomly generates a crop allocation that verifies this set of spatial and temporal constraints because one field is covered by a single crop k each year. The cover of pixel p by k is denoted as $\gamma^s_{p,k}$, which produces a landscape mosaic covered by the matrix $\boldsymbol{\gamma}^s$ of crop pixels (embedded into the matrix $\mathbf{L}^s$ of fixed elements within the landscape site). The cover function is applied to the fields throughout the farm territories; each field i is covered by $\boldsymbol{\gamma}^s_{i,k}$ and $\boldsymbol{\gamma}_{i,k}$ inside and outside the landscape site, respectively, and the entire farm territory is covered by $\boldsymbol{\gamma}_j$.

The 'swine' farm system considers five crops with six types of constraints (see Appendix 2).[3] The only change from Agriconnect is that we do not impose a minimum area for cash-crop and on-farm pig-food productions as in Martel et al. (2017) as our purpose is precisely to select the optimal landscape based on profit maximization. We also constrain farms to maintain permanent grasslands. We generate a historical background of crop allocation to ensure that the dynamics of crop allocation respect temporal constraints.

2.4. The ecological sub-model

We need an ecological model that applies to the whole landscape site to specify productive ES on the entire site and account for the links between ecological features and farms' spatial layouts. We are not aware of any field-validated ecological model with all of these specifications, which is why we mobilize the ecological model of Martel et al. (2017) with two stylization choices.[4] First, the model of carabid beetles' abundance is used as a surrogate of the model of pest regulation by the carabid beetles (see Section 2.5.). Second, we consider that the 'maize' carabid beetles' abundance model used by Martel et al. (2017) also applies to other crops and grasslands. Therefore, we can specify a carabid beetle density for the entire utilized agricultural area (UAA) of the landscape site. In this way, farmers can create favorable adjacencies of crops for carabid beetles involved in pest regulation through their land-

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[3] Note that winter crops include wheat, rapeseed and barley.

[4] This model was statistically estimated to measure the abundance of some carabid species in maize fields based on the surrounding landscape metrics, notably the length of interfaces between winter cereals and maize crops. Aviron et al. (2018) assumed that the positive effects of these metrics on the measure of the density of carabid beetles is explained by the availability and accessibility of complementary resources for these carabid species during the year when winter cereals and maize are adjacent crops (Burel et al., 2013), as carabid beetles migrate from winter cereals to maize following their growing periods.

use choices. The function is computed on each pixel of the landscape site as

$$c_p(\boldsymbol{\gamma}, \mathbf{L}) = e^{(4.98+(6.78^{E-04}E_{WIC-MA500,p})-(7.05^{E-06}C_{W500,p}))} \tag{1}$$

where c_p is the carabid beetles' abundance on pixel p. The landscape metric $E_{WIC-MA500,p}$ is the length of the interfaces between winter crops (WIC) and maize (MA) in a 500-m radius circle around p.[5] The metric $C_{W500,p}$ is the Hanski connectivity of woody elements in a 500-m radius circle around p. Eq. (1) expresses that there is a positive relation between the length of interfaces between maize and winter crops (WIC_MA) in a 500-m radius circle and the carabid beetles' abundance. It also expresses a negative relation between the connectivity of woody elements and the carabid beetles' abundance (Martel et al., 2017). The carabid beetles' abundance depends on farms' crop allocations $\boldsymbol{\gamma}$ through $E_{WIC-MA500,p}$. The impact of $C_{W500,p}$ on carabid beetles is exogenous to farmers' choices and is fixed. We compute the used landscape metrics with the Chloe software (Boussard and Baudry, 2018).

Our 500-m buffer analysis centered on each pixel p is influenced by some 'site edge effects'. There are missing values outside the landscape site, but the extent of farm territories around the landscape site provide additional information, which leads to varying degrees of spatial uncertainty regarding the carabid beetles' abundance. Appendix 3 shows the uncertainty of the ecological model due to the site edge effect (9% on average and 44% at the most).

2.5. The economic sub-model

We assume that farmers' profits depend on productive ES such that gross margins $\pi_{k,p}$ specifically differ among pixels depending on the carabid beetles' abundance. Profit Π_j for farm j is the sum of the gross margins across all the pixels managed by j in the landscape site. We denote the profit for farm j as

$$\Pi_j = \sum_{i \in \mathbf{I}_j^s} \sum_{p \in \mathbf{P}_i} \pi_{k,p}(c_p(\boldsymbol{\gamma}, \mathbf{L}))$$
$$s.\ t.\ \mathbf{A}\boldsymbol{\gamma}_j \leq \mathbf{B} \tag{2}$$

where is the set of constraints used to generate the different possible crop allocations, which applies at the farm level across the entire farm territory (Appendix 2). Here, we consider that the gross margins $\pi_{k,p}$ for crop k in pixel p depend only on carabid beetles' abundance $c_p(\boldsymbol{\gamma}, \mathbf{L})$; all other elements that are suspected to influence the gross margins are exogenous and assumed to be equal across farms. As noted in Section 2.4, carabid beetles' abundance depends on farmers' crop-allocation decisions $\boldsymbol{\gamma}_j$. We assume that the degrees of biological control are proportional to the number of carabid beetles and that the gross margins $\pi_{k,p}$ positively depend on $c_p(\boldsymbol{\gamma}, \mathbf{L})$, such as

$$\pi_{k,p} = \left(\alpha_k + \beta_k \frac{c_p}{\bar{c}}\right)\bar{\pi}_k \tag{3}$$

where $\bar{c}$ is the average carabid beetles' abundance computed by the Chloe software for 500 randomly generated landscapes by CAPFarm ($\bar{c}$ is equal to 56 carabid beetles per m^2). The gross margin $\pi_{k,p}$ is a function of (i) α_k, the share of the gross margin independent from carabid beetles, (ii) β_k, the share of the gross margin depending on the ES provided by the carabid beetles such that we have $\alpha_k + \beta_k = 1$, (iii) $\bar{\pi}_k$, a parameter that represents the normalized profitability for output k and (iv) c_p. This notation is the translation of the production function used by Cong et al. (2014, 2016) to gross margins. In their case, $\alpha_k$represented the crop yield that was independent from the pollination, and β_k represented the crop yield that depended on pollination. Here, β_k represents both the gains from additional yields and a reduction in the costs linked to the reduction in pesticide utilization. In contrast to Cong et al. (2014, 2016), who tested different sets of parameters (α_k, β_k), we specifically calibrate the parameters $\boldsymbol{\beta}$ by following Bareille and Dupraz (2017) and Bareille and Letort (2018), who estimated these parameters in northern France for the five considered outputs. These studies estimated the additional yields and input savings due to on-farm biodiversity indicators, which allows for a determination of the elasticities of the gross margin to these indicators (corresponding to $\boldsymbol{\beta}$). These studies conclude that the highest effect of biodiversity indicators was on pesticide savings, which they interpreted as an increase of the level of biological pest control (Bareille and Letort, 2018). We assume here that the benefits in (3) are totally due to carabid beetles. The defined parameters are available in Appendix 4.

2.6. Resolution of simulations

We solve our model as follows. First, we generate a random series of 100 crop allocations for three years for each farm, which constitutes the historical background of farmers' crop allocations and defines the initial conditions. Second, for a given historical background, we simulate thirty crop allocations that respect the constraints of a single year per farm, which leads to 30ˆ10 possible crop allocations for the entire set of 10 farm territories. We restrain the number of possible crop allocations for three reasons: (i) the computation of profit for each pixel for one possible landscape (one loop) takes approximately five seconds (see Fig. 2); (ii) the number of possible landscapes increases exponentially with the number of possible crop allocations per farm, which increases the required number of loops; and (iii) it is not possible to explore the whole range of solutions. More crop allocations would increase profits as farms have more flexibility but would require more computation time.[6] In addition, we consider that selecting 30 crop allocations is sufficient to explore the range of alternative solutions that a farmer may formulate in real conditions. Third, we perform the simulation loop described in Fig. 2, which (i) generates the possible landscapes given the different farmers' crop allocations, (ii) computes the carabid beetles' abundance on each pixel for each possible landscape, (iii) computes farmers' individual profits on each pixel for the considered landscape and (iv) selects the optimal farm crop allocations that maximize individual or collective profit functions according to the four scenarios (see Section 2.7). Note that this process optimizes profit in an *a posteriori* way since we cannot *a priori* solve the optimization problem when we introduce ES into the gross margin functions. Given the slow *a posteriori* procedure, we repeat this resolution procedure only 100 times (called replicates hereafter), which according to the law of large numbers, leads to a maximum error risk of 10% for our results.

2.7. Four management scenarios

The purpose of the four scenarios is to consider successive ES management possibilities, namely, no-management (scenario 1), naive farm-scale management (scenario 2, noted naive-FSM hereafter), Nash farm-scale management (scenario 3, noted Nash-FSM hereafter) and landscape-scale management (scenario 4, noted LSM hereafter).

Scenario 1 represents the constrained profit maximization with carabid beetles modeled as externalities. Accordingly, farmers ignore that carabid beetles influence the profitability of different crops. We consider that farmers maximize the following expected profit function:

$$\max_{\boldsymbol{\gamma}_j} E(\Pi_j) = \sum_{i \in \mathbf{I}_j^s} \sum_{p \in \mathbf{P}_i} \bar{\pi}_{k,p}$$
$$s.\ t.\ \mathbf{A}\boldsymbol{\gamma}_j \leq \mathbf{B} \tag{4}$$

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[5] The interfaces between winter crops and maize crops are hereafter referred to as "interfaces WIC_MA".

[6] Thirty crop allocations per farm correspond to the number of crop allocations that provides the highest marginal information per unit of time when considering five to forty crop allocations.

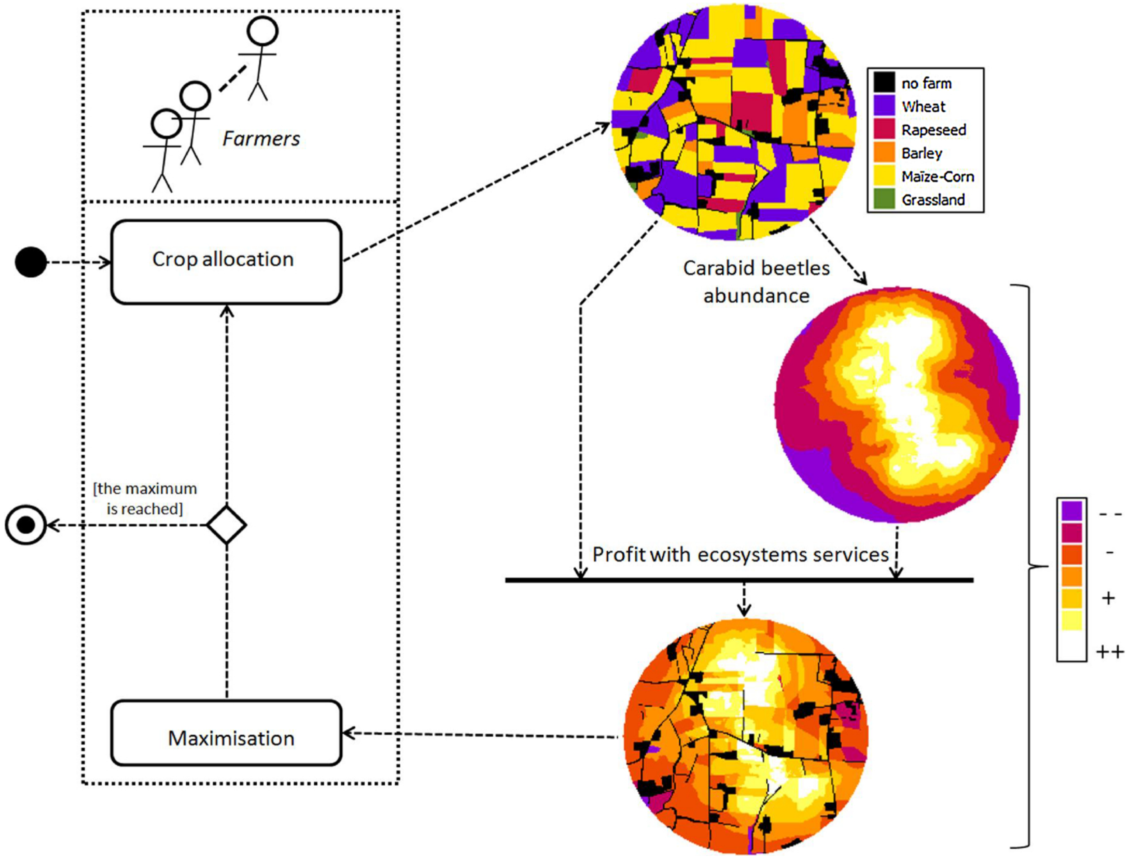

Fig. 2. Resolution process of a simulation loop represented in a UML activity diagram (UML: unified modeling language).

The expected profit for farm j depends only on the direct benefits $\bar{\pi}_k$. Without any constraints , the results of (4) lead to the monoculture of the most profitable crop. The resolution of (4) for the ten farms leads to the optimal landscape $\boldsymbol{\gamma}^{1*}$. The real profits generated from (4) are computed with relation (2); the difference between the real and expected profits represent the externalities generated by the carabid beetles. Concerning the resolution process (*c.f.* Fig. 2), the farmers' crop-allocation decision is directly determined due to the maximization of the profit without the integration of the effects of the ES.

Scenario 2 (naïve-FSM) represents constrained profit maximization with farmers recognizing that carabid beetles influence crop profitability. Farmers thus choose their crop allocation to create favorable adjacencies of crops for carabid species to increase their profits.[7] In this scenario, we consider that farmers do not communicate with one another and therefore formulate false expectations regarding other farmers' choices. In particular, our model assumes that one farmer considers the resulting crop allocation from Scenario 1 as given and that the carabid beetles' abundance depends only on her own choices. In this context, farmers maximize the following expected profit function:

$$\max_{\gamma_j} E(\Pi_j) = \sum_{i\in \mathbf{I}_j^S} \sum_{p\in \mathbf{P}_i} \pi_{k,p}(c_p(\gamma_{i,k}|\boldsymbol{\gamma}^{2*}_{-i,j}, \boldsymbol{\gamma}^{1*}_{-j}, \mathbf{L}))$$
$$s.\ t.\ \mathbf{A}\boldsymbol{\gamma}_j \leq \mathbf{B} \tag{5}$$

where $\boldsymbol{\gamma}^{2*}_{-i,j}$ is Farmer j's crop-allocation choices for her fields other than i, and $\boldsymbol{\gamma}^{1*}_{-j}$ represents the optimal crop allocation of the other farmers in Scenario 1. The profit of Farmer j depends on the direct benefits due to her crop-allocation choices and on the indirect benefits generated by the crop-allocation choices through the evolution of the carabid beetles' abundance (Bareille and Letort, 2018). The crop-allocation decisions $\gamma^{2*}_{i,k}$ depend on farmers' anticipated effects on carabid beetles' abundance. Here, Farmer j considers that the cover of the other farmers' fields is fixed at $\boldsymbol{\gamma}^{1*}_{-j}$ and knows that her other crop plots are $\boldsymbol{\gamma}^{2*}_{-i,j}$. However, as each farmer makes a similar assumption, the real level of $\boldsymbol{\gamma}_{-j}$ is not $\boldsymbol{\gamma}^{1*}_{-j}$ but $\boldsymbol{\gamma}^{2*}_{-j}$. That is, each farmer considers that the other farmers do not also optimize the carabid beetles' abundance and therefore face externalities in this respect. The resolution of (5) for the ten farms leads to the optimal landscape $\boldsymbol{\gamma}^{2*}$, where obviously, the real profits (2) differ from the expected profits. In terms of the resolution process (*c.f.* Fig. 2), the crop-allocation decision for each farm is realized by computing the carabid beetles' abundance based on the anticipated crop allocation of the nine other farms.

Scenario 3 (Nash-FSM) is similar to Scenario 2 but consists of changing the form of a farmer's expectations regarding the other farmers' behavior. We consider that the farmers communicate their ideal crop-allocation plan with one another, *i.e.*, that they have rational expectations regarding the other farmers' choices. This scenario is similar to the FSM strategy of Cong et al. (2014) and leads to another optimal landscape that corresponds to the Nash equilibrium. In this context, the farmers maximize the following expected profit function:

$$\max_{\gamma_j} E(\Pi_j) = \sum_{i\in \mathbf{I}_j^S} \sum_{p\in \mathbf{P}_i} \pi_{k,p}(c_p(\gamma_{i,k}|\boldsymbol{\gamma}^{3*}_{-i,j}, \boldsymbol{\gamma}^{3*}_{-j}, \mathbf{L}))$$
$$s.\ t.\ \mathbf{A}\boldsymbol{\gamma}_j \leq \mathbf{B} \tag{6}$$

where $\boldsymbol{\gamma}^{3*}_{-i,j}$ is Farmer j's crop allocation for her fields other than i, and $\boldsymbol{\gamma}^{3*}_{-j}$ represents the optimal crop allocation of the other farmers. The farmers internalize the effects of the other farmers' decisions regarding the carabid beetles' abundance but maximize their profits individually. In terms of the resolution process (*c.f.* Fig. 2), we solve this equilibrium by successively running the crop-allocation decision models until the cover of each field remains fixed between two periods. Cong et al.

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[7] We assume that farmers know about the beneficial effects of carabid beetles on biological control, which is partly supported by Smith and Sullivan (2014).

(2014) used a similar optimization procedure to imitate rational anticipations.

Scenario 4 (LSM) is similar to the LSM strategy in Cong et al. (2014) and consists of simulating the grand coalition described in the cooperative game theory. Here, all the farmers manage their crop allocations collectively to maximize the sum of the individual profits. That is, while the first three scenarios maximize the private optimums, scenario 4 maximizes the social optimum. By definition, one farmer in the grand coalition does not need to anticipate the other farmers' choices because the farmers in the grand coalition make their choices collectively. Scenario 4 leads to a fourth optimal landscape. In this scenario, the farmers maximize the total profit Π under the choices of $\boldsymbol{\gamma}$ as

$$\max_{\boldsymbol{\gamma}} \Pi = \sum_{j=1}^{10} \Pi_j = \sum_{j=1}^{10} \sum_{i \in I_j} \sum_{p \in \mathbf{P}_i} \pi_{k,p}(c_p(\gamma_{i,k} | \boldsymbol{\gamma}_{-i}^{4*}, \mathbf{L}))$$
$$s.\ t.\ \mathbf{A}\boldsymbol{\gamma}_j \leq \mathbf{B}\ \forall\ j \in [1, 10] \tag{7}$$

Although the total profit Π corresponds to the sum of the profits of the ten farms, each farmer is still subject to farm-scale constraints. Each farmer perfectly knows the crop allocations performed for all other fields $\boldsymbol{\gamma}_{-i}^{4*}$. In terms of the resolution process (*c.f.* Fig. 2), the optimal landscape is obtained by directly considering the ten farms as one single farm; there is no need to present anticipated landscapes. We make the assumption that no other coalition formation than LSM is possible.

3. Results

3.1. Analysis of total profits: is LSM the best strategy at the landscape scale?

Fig. 3 presents the distribution of total profits (the sum of the individual profits) among the four scenarios for the 100 replicates. Table 1 presents the relative total profits for the different scenarios.

Total profit increases among the four scenarios (Fig. 3). LSM increases total profit by 16.7% on average compared to the absence of management (Table 1). The p-value of the Student test comparing the total profits in the naive-FSM and Nash-FSM is 0.14, which indicates that the communication in the Nash-FSM does not significantly improve overall profits. However, there is a significant difference between LSM and the other scenarios. In particular, we find results that are similar to the results of Cong et al. (2014): on average, LSM increases total profit by 4.2% compared to the Nash-FSM, and the impact ranges from +0% to +17% on all 100 replicates. The introduction of heterogeneous farms does not change the previous results. Accordingly, farmers benefit from a better allocation of the habitat across the landscape when they act collectively.

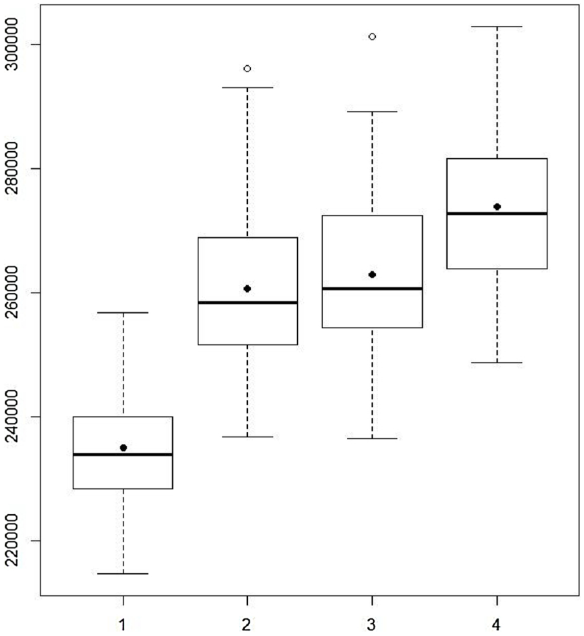

Fig. 3. Box-plot representation (medians - quartiles) of the distribution of total profits (in €) at the landscape scale for the four scenarios (N = 100). *The black points represent the means. Legend: 1: "no-management", 2: "naïve-FSM", 3: "Nash-FSM" and 4"LSM".*

Table 1
Relative total profits for the four scenarios (N = 100).

	mean	median	min	max
Profit Naive-FSM/Profit no-management	1.109	1.099	1.026	1.227
Profit Nash-FSM/Profit no-management	1.120	1.115	1.025	1.232
Profit LSM/Profit no-management	1.167	1.170	1.063	1.348
Profit Nash-FSM/Profit Naive-FSM	1.009	1.000	0.945	1.099
Profit LSM/Profit Naive-FSM	1.052	1.051	1.000	1.125
Profit LSM/Profit Nash-FSM	1.042	1.038	1.000	1.170

Fig. 4 presents the average spatial distribution of the carabid beetles' abundance and the gross margins for the four scenarios across the 100 replicates. We observe a progressive increase in the carabid beetles' abundance across the four scenarios. The carabid beetles are less abundant close to the boundaries due to site-edge effects (see Appendix 3). Fig. 4 also emphasizes that LSM is the best management strategy at the landscape scale. However, if the gross margins increase for the majority of the landscape, the spatial distribution of benefits varies across the landscape. Some parts receive more benefits from coordination than others, which justifies an analysis of the spatial dimension of the collaborative approaches (see Section 3.3.).

3.2. Analysis of the individual profits: is LSM the best strategy at the farm scale?

We now analyze the distribution of the LSM gains at the farm scale. Fig. 5 presents the relative profits for the LSM case compared to the no-management and the Nash-FSM cases. We find that, on average, farmers have higher individual profits for LSM, and all farmers win by acting collectively. However, we find considerable differences in the individual profits across the ten farms. For instance, farm O10 presents an average gain of +0.9% with LSM compared to the Nash-FSM, while farm O7 presents an average gain of +10.2%. The introduction of heterogeneous players leads to a greater difference in the results compared to the findings of Cong et al. (2014).[8]

Furthermore, we find that compared to the Nash-FSM, LSM leads to gains for all farms in only 15% of the replicates. According to the framework of cooperative game theory, this result indicates that the stability of the grand coalition is unverified in 85% of the replicates; thus, *ceteris paribus*, LSM is stable in only 15% of the replicates (in the absence of side-payments between farms). This is a major finding as previous studies have suggested that farmers' individual profits always increase with coordination (*e.g.*, Cong et al., 2014). Specifically, we compute that the total profits in the cases where all farms win due to LSM are significantly higher by 3.2% than in the cases where at least one farm loses. We also find across farms different degrees of probability to benefit from LSM. For instance, Farmer O2 gains by acting cooperatively in 93% of the replicates, while Farmer O10 gains in only 56% of the replicates. These differences are due to farm territories' heterogeneity and farms initial conditions that determine the possible farms' crop-allocations patterns.

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[8] The relative gain from the Nash-FSM to LSM between the farm winning the most and the farm winning the least was limited to 4 in Cong et al. (2014), whereas gains are 11 times higher for farm O7 relative to farm O10 here.

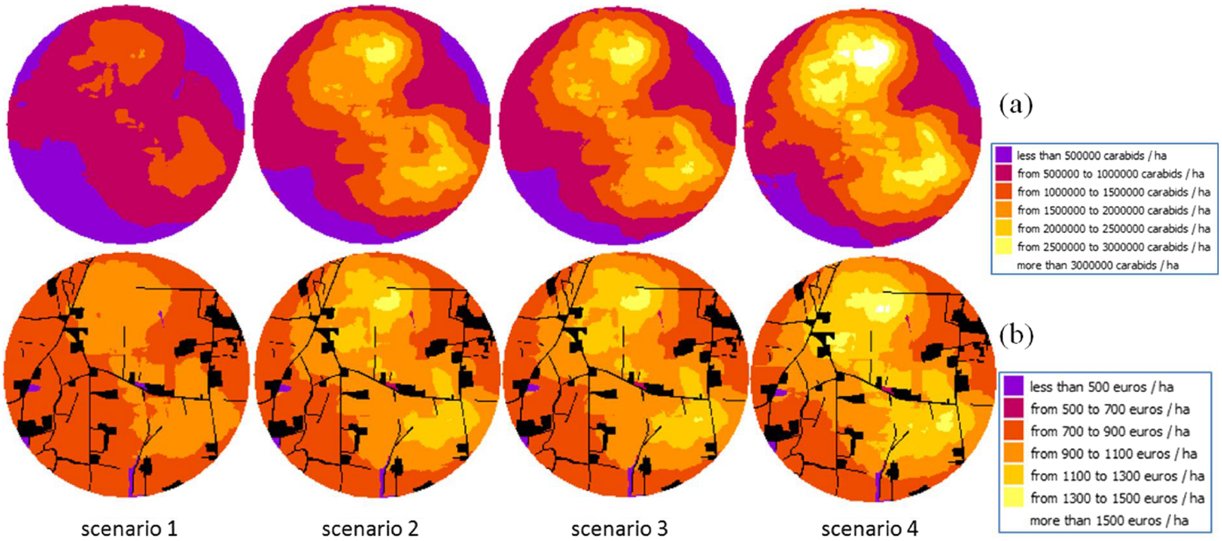

Fig. 4. Average distribution of (a) carabid beetles' abundance and (b) the gross margins across the modeled landscape.

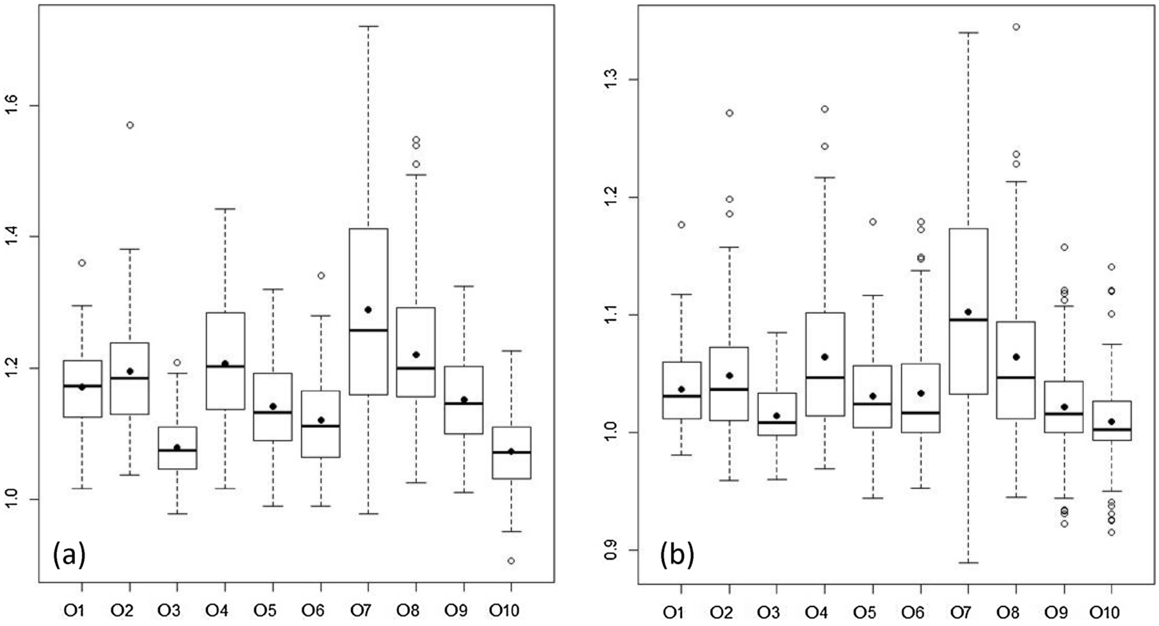

Fig. 5. Box-plot representation (medians - quartiles) of the distribution of farms' profits with LSM compared to (a) no-management and (b) Nash-FSM. *The abscissa axis indicates the 10 farms. The ordinate axis indicates the profit relative gains. The black points represent the means.*

We find similar results when comparing the individual profits of the no-management and LSM scenarios (Fig. 5). Although total profits increase by 16.7% with LSM, some farms are better off outside the coalition. Once again, this result is explained by the initial conditions and the heterogeneity of the farms.

3.3. Analysis of the drivers of collective gains

We now examine the relationships between the profits of the four scenarios and the structural characteristics of the farms to provide insights into the spatial aspects of the interdependencies between the ecological and economic processes.

Tables 2 and 3 present the ordinary-least square regressions of total profit for the four scenarios (Table 2) and the difference in total profits between two successive scenarios (Table 3) as a function of the characteristics of the dynamic crop mosaics at the landscape scale.[9] The advantage of analyzing the difference in total profits between two successive scenarios is removing the historical background effects and thus specifying the gains arising from the different strategies independently of the initial conditions (Table 3).

The regressions on the four scenarios show that the two types of WIC_MA interfaces increase total profits. The between-farms WIC_MA interfaces seem to marginally increase total profits more in the three scenarios with effective management than in the no-management scenario (Table 2). This difference is consistent with the effects of the two types of interfaces on biological control; the between-farms WIC_MA interfaces explain 7% more carabid beetle abundance than the within-

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[9] We selected the descriptors of crop diversity (computed as the Shannon index for the five crops) and the total length of the within-farms and between-farms WIC_MA interfaces at the landscape scale.

Table 2
Landscape scale drivers of total profits.

	No-management			Naive-FSM			Nash-FSM			LSM		
	estim.	std		estim.	std		estim.	std		estim.	std	
Constant	171,067	15,368	***	156,584	17,078	***	170,391	17,826	***	121,559	24,512	***
Crop diversity	−14,219	22,934		−83,567	23,501	***	−97,197	24,936	***	−64,393	34,266	°
Within-farms WIC_MA interfaces	7,533	416	***	12,221	644	***	11,704	638	***	13,710	845	***
Between- farms WIC_MA interfaces	6,881	483	***	12,619	701	***	12,643	610	***	14,141	1,052	***
Fixed effect	No			No			No			No		
N	100			100			100			100		
R^2	0.836			0.878			0.886			0.803		

Legend: °, *** mean a significance level of 10% and 0.1%, respectively; "WIC_MA interfaces" designates the dynamic interfaces between winter crops and maize crops expressed in km; "Fixed effect" designates the fixed effects due to the historical background of simulation.

Table 3
Landscape scale drivers of the differences in profits.

	Naive-FSM – No-management			Nash-FSM – Naive-FSM			LSM – Nash-FSM			Carabid beetle abundance		
	estim.	std		estim.	std		estim.	std		estim.	std	
Crop diversity	−35,302	25,384		−83,318	22,550	***	−25,772	23,360		1,256E3	707,997	°
Within-farms interfaces WIC_MA	8,005	688	***	6,708	837	***	7,813	965	***	521,550	16,768	***
Between-farms interfaces WIC_MA	10,493	860	***	11,520	542	***	11,843	517	***	559,047	18,418	***
Fixed effect	Yes			Yes			Yes			Yes		
N	100			100			100			400		
R^2	0.955			0,834			0,169			0.819		

Legend: °, *** mean a significance level of 10% and 0.1%, respectively; "WIC_MA interfaces" designates the dynamic interfaces between winter crops and maize crops expressed in km; "Fixed effect" designates the fixed effects due to the historical background of simulation.

farms WIC_MA interfaces. At the average point, we find that an increase of 1% of the between-farms WIC_MA interfaces increases average carabid beetle abundance by 0.85%.

The between-farms WIC_MA interfaces also play a greater role than the within-farms WIC_MA interfaces in the profit gaps from one scenario to another (Table 3). In particular, the between-farms WIC_MA interfaces explain 71.2% more of the gains of the Nash-FSM than the within-farms WIC_MA interfaces. Similarly, the between-farms WIC_MA interfaces explain 51.4% more of the gains achieved by LSM than the within-farms WIC_MA interfaces. By contrast, even if the between-farms WIC_MA interfaces still result in greater interest for naive-FSM compared to within-farms interfaces, this advantage is limited to 31%. Therefore, at the landscape scale, the advantage of the between-farms WIC_MA interfaces over the within-farms WIC_MA interfaces increases across scenarios, which emphasizes the key role of the coordinated choices.

Tables 4 and 5 present the regressions on individual profits in the four scenarios (Table 4) and the difference in individual profits in consecutive scenarios (Table 5) as a function of farm-scale descriptors. In addition to dynamic structural descriptors of the farm territories (*i.e.*, the Shannon diversity of crops and the length of WIC_MA interfaces), we consider the descriptors of the fixed structure of the farm territories (*i.e.*, the descriptors of the farm size and length of the between-fields fixed interfaces).

Without controlling for the fixed effects due to the fixed structures of farm territories and the historical background of simulation (Table 4), we find that the within-farms WIC_MA interfaces play a greater role than the between-farms WIC_MA interfaces. This differs from the landscape-scale analysis presented earlier. However, when we control for the fixed effects by considering the variations among scenarios, the role of the between-farms WIC_MA interfaces prevails again (Table 5). In fact, we find that the within-farms WIC_MA interfaces play a smaller role than the between-farms WIC_MA interfaces in the gap from the naive-FSM to the Nash-FSM gain (+47% of the explanation) and in the gap from the Nash-FSM to the LSM gain (+77% of the explanation), while both types of interfaces play a similar role in the gap from no-management to the naive-FSM gain. This result suggests that the communication in the Nash-FSM and the coordinated management in LSM lead to additional individual gains mainly due to the reorganization of the between-farms WIC_MA interfaces across the landscape. Overall, the results suggest that the farmers' choices of the within-farms WIC_MA interfaces are already relatively optimal in the naive-FSM case. These results are consistent with the results for the total profits.

Regarding the effects of the fixed structures of the farm territories (Table 4), we find that when the share of the landscape that a farmer manages is larger, she benefits more from collective management. This result is intuitive: the benefit for larger farms from coordinated management is greater. However, we find that the farm-UAA share in the landscape site has no impact, except in the LSM scenario: when the farm is included to a greater extent in the site, the farmer benefits more from coordinated management. It follows from the common sense that farmers whose lands are less included in the landscape site have fewer incentives to cooperate than other farmers with larger stretches of land in the site. Similarly, we find that the farms with more within-site fixed interfaces allow for more benefits from collective management, *i.e.*, that the farmers who own the largest shares of the interfaces within the landscape site benefit the most from coordination. Then, we find that the length of within-farms fixed interfaces increases individual profits as the degree of collective management increases, whereas the length of between-farms fixed interfaces decreases individual profits. This suggests that farmers whose land displays more between-farms fixed interfaces have more incentives to turn from the private optimum towards the social optimum as the degree of coordination increases.

Finally, we find mixed results regarding the effects of crop diversity on profits. If we find that on-farm crop diversity increases farmers' individual profits in the four scenarios (Tables 4 and 5), then we find that at best, crop diversity at the landscape scale has no effect and at worst, has negative effects on total profits (Tables 2 and 3). These opposite results may represent an aggregation effect regarding the greater heterogeneity of the Shannon index at the farm scale or the non-linearity of the functions that constitute the Shannon index.

Table 4
Farm-scale drivers of individual profits.

	No-management			Naive-FSM			Nash-FSM			LSM		
	estim.	std		estim.	std		estim.	std		estim.	std	
Constant	−3,433	278	***	−3,334	434	***	−3,460	436	***	−3,629	441	***
Farm-UAA share in the site	−1	47		26	64		55	63		322	64	***
Site-UAA share by farm	1,702	129	***	2,775	188	***	2,747	186	***	2,727	191	***
Within-site fixed interfaces	216	25	***	345	35	***	362	35	***	379	35	***
Within-farms fixed interfaces	416	33	***	506	53	***	506	53	***	512	54	***
Between-farms fixed interfaces	−505	46	***	−674	64	***	−716	64	***	−1,029	66	***
Crop diversity	127,486	5,707	***	87,904	8077	***	90,042	8,066	***	92,536	8,036	***
Within-farms WIC_MA interfaces	2,761	191	***	4,070	317	***	4,190	321	***	4,820	315	***
Between-farms WIC_MA interfaces	1,522	126	***	1,840	164	***	1,911	155	***	1,983	160	***
Fixed effects	No			No			No			No		
N	1,000			1,000			1,000			1,000		
R^2	0.984			0.976			0.977			0.977		

Legend: *** means a significance level of 0.1%; "UAA" means Utilized Agricultural Area; "site" means "landscape site"; "WIC_MA interfaces" designates the dynamic interfaces between winter crops and maize crops in km; "fixed interfaces" designates the interfaces between fields irrespective of crops in km; "fixed effect" designates the fixed effects due to the historical background of simulation and the fixed structures of farm territories.

Table 5
Farm-scale drivers of the difference in individual profits.

	Naïve-FSM – no-management			Nash-FSM –Naïve-FSM			LSM – Nash-FSM		
	estim.	std		estim.	std		estim.	std	
Crop diversity	−55,295	9,295	***	−72609	7,902	***	−75,224	8,740	***
Within-farms WIC_MA interfaces	2,182	195	***	1,909	248	***	1,309	296	***
Between-farms WIC_MA interfaces	2,020	156	***	2,808	143	***	2,316	151	***
Fixed effects	Yes			Yes			Yes		
N	1,000			1,000			1,000		
R^2	0.216			0.079			0.169		

Legend: *** means a significance level of 0.1%; "WIC_MA interfaces" designates the dynamic interfaces between winter crops and maize crops; "fixed effect" designates the fixed effects due to the historical background of simulation and the fixed structures of farm territories.

4. Discussion

Our modeling exercise on a realistic landscape is aimed at extending the knowledge about the main relationships among collective ES management, heterogeneous farm territories and the distribution of gains.

4.1. Heterogeneous farms and the emergence of coordination

The fact that our work considers heterogeneous farms is a major contribution to the previous studies of Cong et al. (2014), Epanchin-Niell and Wilen (2014) and Atallah et al. (2017). If we find average gains in LSM that are similar to the average gains found by Cong et al. (2014), then we find that LSM improves all farmers' profits in only 15% of the cases. By comparison, previous works that consider homogenous farms have concluded that coordination has a beneficial role in productive ES in all cases (*e.g.*, Cong et al., 2014) or in most cases (*e.g.*, Atallah et al., 2017). The heterogeneity of the agent implies that, *ceteris paribus*, the probability that LSM occurs is 15% in our case, which casts doubt on the effective achievement of LSM in real landscapes. This result confirms that not only the heterogeneity of farms but also the initial conditions of the landscape and farm territories are key elements when analyzing coordination processes (Atallah et al., 2017; Costello et al., 2017). However, we are the first to empirically verify this result from the perspective of productive ES management through land-use choices.

The success of LSM may however be influenced by other factors than farms' heterogeneity and landscapes' actual complexity. First, LSM may arise only if no alternative coalition structure improves the profit of at least one player (this is the principle of stability). Cong et al. (2014) noted that this condition may not be respected regarding the collective management of pollinators: farms still face incentives to deviate from LSM and to act as free-riders. The consideration of heterogeneous farms increases these incentives (Costello et al., 2017). Second, farms may design collective contracts such that the "winners" compensate the "losers" (Cong et al., 2014). The probability of the occurrence of LSM can be improved by incorporating side payments in the farms of the coalition (Wätzold and Drechsler, 2014). The payments, at a minimum, can be based on the compensation for losses that occur as the farms move from the Nash-FSM to LSM, but alternative strategies can use payments based on either the marginal contribution of the farms to the grand coalition or on the Shapley value (McGinty et al., 2012; Zavalloni et al., 2016). Third, the consideration of heterogeneous farms makes the issue of inequity in cooperation even more important. Theoretical studies have explained that an aversion to inequity may lead to a negative relation between heterogeneous coordination gains and coordination success (Fehr and Schmidt, 1999). This is a major issue, as unequal gains increase with the heterogeneity of the farms (*e.g.*, the relative difference between the farmer who earns the most and the farmer who earns the least from coordination is 2.75 times higher in our study than in Cong et al.'s (2014) study). However, laboratory experiments seem to indicate that such worries may be unfounded in the case of the coordinated management of a public input (Gueye et al., 2018).

4.2. Structure of farm territories at the origin of heterogeneous gains

Our results show that the fragmentation of farm territories generates complex spatial ecological-economic interdependencies that influence the gains in all scenarios. Two main issues are discussed.

First, as the majority of farm territories stretches beyond the landscape site (only three farms have more than 40% of their farm territory located within the landscape site), the interest for coordinated management concerns a relatively small part of these farms. Therefore, the landscape site may not be an appropriate scale for a profitable management of carabid-related ES. Nevertheless, our results show that when more farm territories are spatially included in the landscape, the concerned farmers are more interested in managing productive ES and in managing it in a coordinated manner. Finally, these findings do not lead to the rejection of the principle of a landscape site but show ways to enhance the relevance of a landscape site for the management of carabid-related ES by (i) testing and revealing the most appropriate size for a landscape site and (ii) differentiating farmers' incentives according to the degree of the spatial inclusion of their land in the landscape site.

The second aspect relates to the role of the within-farms and between-farms interfaces to foster the profitable management of carabid-related ES. Even with homogeneous one-block farms, Cong et al. (2016) demonstrated that farmers' land-use allocation in an LSM frame differs regardless of whether their farms have a few or numerous neighbors (whether the one-block farm is close to the site center or to the site edge), *i.e.*, the interfaces between farms matter in the LSM of productive ES. Our results express such spatial issues in the context of heterogeneous and fragmented farm territories. We show that LSM leads to (i) additional gains at the farm and landscape scales due to the length of the between-farms maize/winter crop interfaces and (ii) additional gains at the farm scale due to the length of the within-farms fixed interfaces (referring to the field fixed boundaries). These results suggest that (i) farm territory fragmentation can be envisaged not only as a constraint that decreases profits (*e.g.*, Latruffe and Piet, 2014) and (ii) in collective ES management, farmers' land-use allocations should not be considered without also contemplating land consolidation options.

4.3. Methodological issues

This work required us to make several trade-offs to consider realistic landscapes and ecological functions while ensuring the means to test our hypotheses (Cong et al., 2016; Sun et al., 2016). The ecological function used here is more complex than the ecological functions usually used in studies of the coordinated management of productive ES where species density depends on the distance to a specific area (Cong et al., 2014; Epanchin-Niell and Wilen, 2014; Atallah et al., 2017). This higher complexity is increased not only by the representation of realistic landscapes and farm territories (heterogeneous fields, non-agricultural areas and interconnected farms – see Fig. 1) but also by considering a larger number of decision variables (5 crops on several fields) than what is usually considered. Our choice to focus on realism over method manageability prevents us from exploring the entire diversity of landscape solutions. We thus generate a subset of possible landscapes that is made possible by the generation of 30 possible crop-allocation patterns for the ten farms, given the random landscape histories and the farm-level agronomic constraints (Martel et al., 2017). Additionally, we analyze the results that emerge from 100 replicates of this procedure. This series of choices are well suited to an action-research framework, since farmers from a real territory may actually communicate regarding coordinated management. This study also illustrates the interest of considering the realism of complex landscapes and heterogeneous farms for both the theoretical and empirical studies on collective landscape management.

However, our method also has several limitations. First, the analysis on sub-possibilities implies that we do not examine all the possible landscapes. In particular, we only find a local optimum in the LSM scenario, which constitutes the validity domain of our results. Thus, our result showing that coordinated management improves individual profits in 15% of the cases is probably misestimated if considering all possible landscapes. Nevertheless, the large difference between our results and the results of previous studies feeds the hypothesis that the heterogeneity of farm territories significantly matters for collective ES management. Second, to manage several sources of uncertainty, we made several choices that have their own limitations. There were already uncertainties about carabid beetles' abundance on maize fields, as noted in Martel et al. (2017). We added to the uncertainty by applying the abundance function to all crops and considering that the gains from ecosystem functioning determined in Bareille and Letort (2018) were linked only to carabid beetles. Since we apply the abundance model to a 1-km radius circle, uncertainties originate also from the site-edge effects of the landscape site (see Appendix 3), which is a common feature of this type of model. Third, we considered the optimization for a single year although farming is characterized by dynamic and temporal choices (as illustrated by our constraints). Given the importance of the initial conditions to the emergence of coordinated management solutions, long-term coordinated management may be different from our results. Considering that long-term management provides more flexibility to manage rotations, LSM is more likely to emerge since farmers optimize their profits according to the sum of the discounted benefits that arise in the long run from cooperation. Alternatively, if farmers make their choices on a repeated year-stage basis, long-term coordinated management is unlikely to arise over two or more agricultural campaigns (Embrey et al., 2017). These critical assumptions require further validation and work.

These methodological choices are consistent with our objectives of considering a higher degree of realism and heterogeneity than what is usually considered. We studied the profitability of collective ES management for a particular type of farming system (swine production) with a particular landscape type in the Brittany region and a single ES. Therefore, our results should be interpreted as illustrative examples of this particular setting. Nevertheless, our method based on the APILand modeling framework can be adapted to different landscapes and different agricultural and ecological conditions.

5. Conclusion

Previous works based on the simulation of stylized landscapes and homogeneous farms have concluded that the coordinated landscape-scale management of ecosystem services are a promising strategy to increase farmers' profits. Here, we examine such benefits in a realistic landscape (Brittany, France) with heterogeneous farm territories (in terms of spatial layout) by using an adaptable agronomic-ecological-economic modeling method inspired by Martel et al. (2017). We run four different management strategies of biological control that range from no-management to collective landscape-scale management and two situations of individual management. We find that if LSM improves the collective benefits, the heterogeneity of the farms implies that the stability of the collective action is rarely satisfied. In our modeling exercise, the probability that the collective management of productive ES occurs is 15%. The heterogeneity of the gains depends on the structure of the farms, notably on the number of interfaces between their plots.

Our study is an example of model coupling field, farm and landscape scales that allow studying the link among land-use choices, ES and coordination, with a specific focus on the role of farms' heterogeneity. Many challenges remain in understanding the emergence of a collective management of ES in real landscapes (including, *e.g.*, the role of endogenous group formation of the overall landscape structure or of coordination costs), but our modeling framework provides solid foundations for possible extensions. Developing such supports for landscape managers to represent the complex spatial economic-ecological interdependencies in their local situations may help them to combine farm-scale land consolidation and management with the LSM of ES providers and derive rules for collaborative solutions.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolecon.2019.106482.

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