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Agri-environmental policies for biodiversity when the spatial pattern of the reserve matters

Laure Bamière, Maia David and Bruno Vermont*

June 13, 2012

Abstract

The aim of this paper is to compare different environmental policies for cost-effective habitat conservation on agricultural lands, when the desired spatial pattern of reserves is a random mosaic. We use a spatially explicit mathematical programming model which studies the farmers' behavior as profit maximizers under technical and administrative constraints. Facing different policy measures, each farmer chooses the land-use on each field, which determines the landscape at the regional level. A spatial pattern index (Ripley L function) is then associated to the obtained landscape, indicating on the degree of dispersion of the reserve. We compare a subsidy per hectare of reserve with an auction scheme and an agglomeration malus. We find that the auction is superior to the uniform subsidy for cost-efficiency. The agglomeration malus does better than the auction for the spatial pattern but is more costly.

Keywords: agri-environmental policies, biodiversity, spatial pattern, mathematical programming, auction schemes, agglomeration bonus/malus.

JEL Classification: H23, Q57, Q12, Q28

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1 Introduction

In many regions, agricultural lands host a significant share of biodiversity including common and emblematic species. Over the last fifty years however, farmed landscapes have experienced dramatic changes, mainly due to the intensification of farming techniques and increases in the size of agricultural fields. As a result, natural habitats have been transformed and fragmented, leading to many species' decline (Söderström and Part 2000, Chamberlain et al. 2000). Common farmland birds in Europe, for instance, have declined by 25% since the 1980's (Gregory et al. 2005).

In farmlands, dominated by private ownership, providing sufficient incentives to landowners to preserve biodiversity is essential. Agri-environmental policies have progressively been introduced for example in Europe (eg. *Natura 2000*) and in the United States (eg. the *Conservation Reserve Program*) to preserve habitats. In designing these policies, the economic issue lies in the trade-off between environmental effectiveness and economic costs (opportunity costs¹, compensation payments to farmers, transaction costs). The environmental result depends on the size of the protected area but also on the spatial configuration of this area. An habitat reserve² of a given size does not have the same ecologic impact when reserve sites are fragmented, agglomerated or distributed as a random mosaic. The best spatial pattern depends on the considered specie: the grizzly bear would prefer an agglomerated reserve for instance whereas a black-footed ferret survives better on dispersed reserves (see Parkhurst and Shogren 2007; see also Soule and Simberloff 1986 for insights on the famous SLOSS debate: Single Large or Several Small reserves).

The aim of this paper is to compare different policy instruments for cost-effective habitat conservation on agricultural lands, when the desired spatial pattern of the reserve is a random mosaic. This spatial pattern is adapted to certain threatened bird species that breed on agricultural lands, such as the Little Bustard (*Tetrax Tetrax*), an Annex 1 specie of the European Union Birds Directive (79/409/EEC). Note that most contributions on the spatial configuration of the reserve are concerned with avoiding fragmentation, which

¹The opportunity costs of habitat conservation can be defined as the forgone profits due to setting aside lands instead of implementing a more profitable land-use.

²We define here the "reserve" as all sites characterized by environment-friendly land-uses and management options. In our case, the reserve can thus include some agricultural land-uses (eg. grassland).

is harmful to many species. However, on agricultural lands, where land-uses are generally spatially aggregated due to aggregated land qualities, natural habitats are often aggregated. Therefore, examining the adapted policies to protect species that evolve on agricultural lands and need a dispersed reserve is a new and useful topic.

Many studies have been devoted to optimal reserve design, mainly in the field of conservation biology (see Williams et al. 2005, for a general review; see Wossink et al. 1999, and van Wenum et al. 2004, for a more specific analysis on agricultural lands). These contributions have focused on the question of *where* the reserve should be located to adequately (and cost-efficiently³) protect the biodiversity. However, they do not address the question of *how* to reach this optimal reserve. They implicitly assume that the social planner has perfect knowledge on landowners' characteristics and selects reserve sites minimizing opportunity costs. Unfortunately, governmental agencies have imperfect information on private costs and cannot implement the first-best reserve location in a direct way (Lewis et al. 2009).

Designing incentive-based conservation policies, aiming at a cost-efficient reserve under information asymmetries, is thus a further step. Many economic articles have examined this issue using mechanism design theory but without taking into account the spatial characteristics of the conserved area (see Ferraro 2008 for a survey). Recent contributions have introduced the spatial aspects. Lewis and Plantinga (2007), Lewis et al. (2009) and Lewis et al. (2011) study incentive-based policies to reduce habitat fragmentation. These authors use an econometric model to estimate the farmers' decisions (land-use conversion probabilities based on past observations) but do not model the farmers' behavior. Wätzold and Drechsler (2005), Drechsler et al. (2007), Hartig and Drechsler (2009) and Drechsler et al. (2010) ingeniously combine an economic and ecological model to assess various conservation policies. However, they consider exogenous costs for land conservation and do not detail the process explaining these costs (which depend on the landowners' optimal decisions given agricultural prices and yields as well as technical and institutional constraints). Smith and Shogren (2002), Parkhurst et al. (2002), Parkhurst and Shogren (2007, 2008) and Reeson et al (2011) use experimental economics to see whether rational individuals can achieve the desired spatial pattern of reserve but do not look into the mechanism that

³An extension of the basic literature to the field of economics has consisted in incorporating land costs (Polasky et al. 2008; Naidoo et al. 2006; Hamaide and Sheerin 2011).

drives the farmers' decisions.

We use an economic mathematical programming model (OUTOPIE) which simulates the farmer's behavior as a profit maximizer under technical and administrative constraints. This leads to land-use choices at the field level and eventually generates a landscape at the regional level. A spatial pattern index (Ripley L function) is then associated to the obtained landscape, indicating on the degree of dispersion of the reserve. See Bamière et al. (2011) for a detailed description of the OUTOPIE model.

Mathematical programming farm-level models have largely been used to assess the efficiency of agri-environmental policies (Wossink et al. 1999; Falconer and Hodge 2001; van Wenum et al. 2004; Havlik et al. 2005; Mouysset et al. 2011). Our model differs in that it takes into account, in addition to the farm-level, both the field and landscape levels, linked to a spatial pattern indicator. As explained above, taking into account these three spatial levels is essential when analyzing biodiversity conservation: the field is the elementary unit of the spatial pattern, the farm is the landowner's decision level, and the resulting landscape level determines the ecological result.

Our model is applied to a Natura 2000 site in France (*Plaine de Niort*), which aims at protecting the Little Bustard. This bird relies exclusively on insects found in temporary grasslands, and preferentially breeds in an arable landscape constituted of a mosaic of alfalfa, grasslands and annual crop fields (Wolff et al. 2001). Its conservation therefore implies a random mosaic of extensively managed grasslands and annual crops. While contiguity and connectivity have been studied, to the best of our knowledge Bamière et al. (2011) was the first attempts to account for a random mosaic distribution of the reserve.

While Bamière et al. use the OUTOPIE model to investigate the suitable allocation of reserve patches and whether a subsidy per hectare of reserve reaches it, we introduce other policy instruments. We compare three instruments - a subsidy per hectare of reserve, an auction scheme and an agglomeration malus - to reach a given percentage of land enrolled in the reserve. The comparison is based on two main criteria: the spatial criterion (reserve patches must form a random mosaic) and the cost criterion (including opportunity costs, public costs and administrative costs).

The auction scheme works as a procurement auction where farmers indicate the minimum payment they wish to receive to convert one parcel of their

land to reserve⁴. The public regulator selects the lowest amount and pays it to the winning farmer against his commitment to convert one parcel to reserve. By favoring competition among farmers, this instrument improves cost-efficiency even when the regulator does not detain detailed information on the individual opportunity costs. Empirical studies have demonstrated that cost reductions through conservation auctions can be substantial (Stoneham et al. 2003; Schilizzi and Latacz-Lohmann 2007). This instrument has increasingly attracted the attention of economists (Latacz-Lohmann and Van der Hamsvoort 1997, 1998; Latacz-Lohman and Schilizzi 2005; Said and Thoyer 2007; Glebe 2008). This literature however, based on decision theory, usually simplifies bidders' behavior by assuming an exogenous threshold above which bids are not accepted. One of our contributions is the use of auction theory based on game theory, allowing more realism and precision in modeling the bidders' behavior (McAfee and McMillan 1987; Klemperer 1999).

The agglomeration malus is an instrument which accounts for the spatial issue. It consists in a subsidy per hectare of reserve completed with a malus (i.e. a reduction of the payment) when the additional reserve site is adjacent to another reserve site. This malus is relevant in cases, such as ours, where the desired pattern of the reserve is dispersed. Some authors have examined a similar instrument, an agglomeration bonus (which is relevant when the desired pattern is agglomerated), using experimental economics (Parkhurst et al. 2002; Parkhurst and Shogren 2007, 2008) and bio-economic modeling (Drechsler et al. 2010).

The rest of the article is structured as follows. First, we present our modeling approach and our method in comparing policy instruments. Then, we introduce an auction scheme and compare it to the subsidy per hectare. Next, we study the agglomeration malus and compare it with the two other instruments. Conclusions and scope for further research are given in the last section.

2 The mathematical programming model

OUTOPIE is a mixed integer linear programming model which accounts for three spatial levels: the field, the farm and the region. Fields are charac-

⁴A procurement auction is a type of auction where there are multiple sellers and one central buyer, here the public agency (Fudenberg and Tirole 1991).

terized by their soil type, irrigation equipment and the farm to which they belong. This determines the agricultural activities and cropping techniques that can be chosen on each field, as well as the resulting yield and gross margin. The farmer makes the decisions concerning land allocation, taking into account policy constraints (e.g. milk quotas and obligatory set-aside) and technical constraints (e.g. feed requirements). Spatial relationships between fields, constituting the landscape, are accounted for at the regional level.

The model includes the major crops in the considered area (wheat, winter barley, sunflower, rapeseed, maize, and sorghum), permanent and temporary grasslands, including alfalfa, and set-aside lands. The reserve is defined here as all lands covered with alfalfa and temporary or permanent grassland, managed in an environment-friendly way⁵.

The model maximizes the sum of farms' gross margins including incomes and costs due to the participation in an agri-environmental program, subject to field, farm and landscape level constraints. This is represented in program (1), where $X_{f,i,r}$ is the level of farm activities for farm f , on field i , enrolled (or not) in reserve type r (i.e. in one of the environment-friendly managed grassland); Π_f is the farm's gross margin from agricultural activities; cp_r is the compensation payment for an enrolment in reserve type r ; vtc_r is a variable transaction cost per hectare of reserve; ftc is a fixed private transaction cost for program participation and RP_f is a binary variable equal to 1 if the farm participates in the agri-environmental program.

$$\begin{aligned} \max \sum_f [\Pi_f(X_{f,i,r}) + (\sum_{r,i} (cp_r - vtc_r) X_{f,i,r} - ftc) RP_f] \quad (1) \\ s.t. Field(X_{f,i,r}), Farm(X_{f,i,r}), Landscape(X_{f,i,r}) \end{aligned}$$

This model is applied to a Natura 2000 site located in *Plaine de Niort*, in *Poitou-Charente*, France. This area was traditionally dedicated to mixed farming but has recently undergone a rapid specialization in crop production, threatening some populations of birds such as the Little Bustard (*Tetrax Tetrax*). The whole Natura 2000 site is about 20 000 hectares (ha) but we have chosen to concentrate on a restricted stylized area of 2 700 ha divided in 900 fields of 3 ha each (see Figure 1). There are three main groups of soils

⁵We define here an environment-friendly management as a Little Bustard-friendly management, characterized by restrictions on livestock density, fertilization, pesticides, and mowing dates.

in *Plaine de Niort* - calcareous valley, deep and shallow plain soils - with different agricultural potentials. They are represented on the grid (Figure 1) according to the ratio and layout observed. We considered 12 crop growing farms and 6 mixed dairy farms, both types being located on all types of soils and some of them having the possibility to irrigate a fixed set of contiguous fields. More details can be found on the description and the validation of the OUTOPIE model, as well as on the case study, in Bamière et al. (2011).

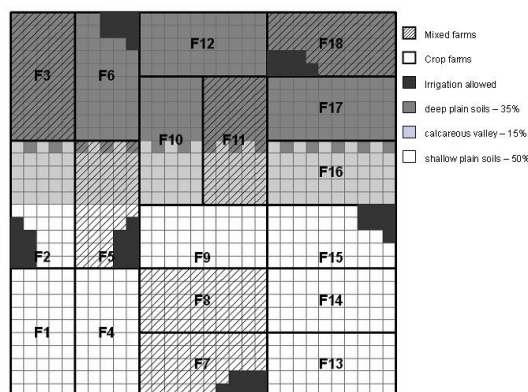


Figure 1: Model representation of the studied area (18 farms; 3 soil types)

In order to account for the spatial pattern of the obtained reserve, the model has been completed with a spatial indicator. According to some ecologist experts (Bretagnolles et al. 2009), the most suitable spatial pattern for the Little Bustard conservation is at least 15% of land covered by extensively managed grassland patches (3 ha being the ideal field size), randomly or regularly located within any radius between 100 and 1000 meters. As a consequence, we need to measure not only the size but also the shape of the reserve generated by the model. In order to do so, we use an indicator based on Ripley K and L functions (Ripley 1977, 1981). These functions measure both the density of the reserve and the distances between reserve sites. They are widely used in plant ecology (Haase 1995). Results can be interpreted as follows (see Figure 2 for two spatial distributions of the reserve and Figure 3 for the associated values of the Ripley function L): a) if L remains within the confidence envelope (dotted lines in Figure 3) then the spatial pattern of the reserve is significantly (Poisson) random; b) if L is above the upper limit of the confidence envelope, then the spatial pattern is clustered or aggregated.

More details are given on the Ripley indicator in Bamière et al. (2011).

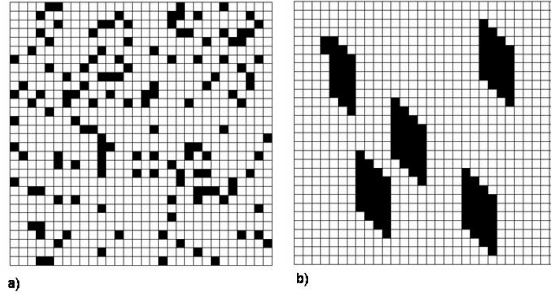


Figure 2: Spatial distribution of 135 reserve plots on a 900 plots grid: a) random, b) aggregated

3 A comparison of policy instruments

We now use our modeling approach to compare different policy instruments in order to reach a given environmental objective. This objective, consistent with ecologists' recommendation for the Little Bustard, is 15% of land covered with reserve.

The policy instruments are compared according to two criteria. First, we compare the total costs of reaching the 15% objective (cost-efficiency). Second, we examine the spatial configuration of the obtained reserve and whether reserve patches are randomly dispersed (i.e. whether the Ripley function is in the confidence envelop). We have chosen to consider both these criteria independently without giving a priority to one or the other⁶.

Regarding the total costs of the policy, we first consider the private costs. These are the sum of the opportunity costs - or forgone profits - incurred by farmers when converting their lands to reserve. These costs are minimized

⁶In order to give a priority to one objective or the other, we would have to write a social welfare function including the value for society of this bird's survival and expliciting the way the spatial pattern of reserve affects its probability of survival. This goes beyond the scope of our analysis.

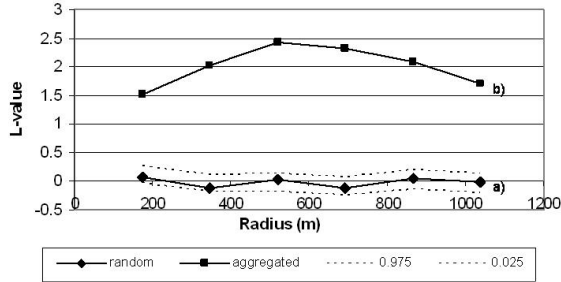


Figure 3: Ripley L function for the random (a) and aggregated (b) distributions

when converting first the less profitable lands, i.e. those with a lower associated gross margin. The three instruments we compare - namely a subsidy, an auction and a subsidy with agglomeration malus - are incentive-based instruments that let the farmers choose which parcels they convert to reserve. As the profit-maximizing farmer always chooses to convert first the cheapest parcels, we can show that total opportunity costs are automatically minimized. Therefore, the minimization of private costs is not a discriminatory criteria among the instruments we study.

We next consider the public costs of the policy. These are defined as the sum of the compensation payments to farmers. We assume we wish to compensate farmers for the opportunity costs of habitat conservation⁷. However, these costs are heterogeneous among farmers (due to different farm types, land qualities, etc) and, generally, the policy-maker does not know each farmer's costs. Moreover, farmers are not willing to reveal their real costs as, by communicating higher levels, they would increase their compensation payment (adverse selection). As a result, the public regulator cannot pay the exact amount compensating the farmers' costs. We will see how some instruments deal better than others with this issue.

The subsidy per hectare of reserve has been studied in Bamière et al. (2011). This instrument reaches the 15% objective with a total public cost

⁷This is consistent with the idea of remunerating them for an environmental service to society.

of **279 thousand euros**. Total payments to landowners exceed their real opportunity costs due to imperfect information (the subsidy is set so as to cover the cost of the most expensive parcel converted to reserve whereas some cheaper parcels have been converted). In total, farmers are compensated about 92% above their real costs, which shows tremendous cost inefficiencies. More generally, when uniform payments are used whereas costs are heterogeneous, payments must be high enough to ensure sufficient participation from the high-costs land-owners, therefore over-compensating the low-costs farmers.

Moreover, this subsidy does not reach a suitable configuration of reserves: the Ripley function is outside the confidence envelop (see Figure 5). This is linked to the fact that landowners choose to convert to reserve the parcels that represent the lowest opportunity costs. These opportunity costs are linked to the quality of the land, the farm type (mixed farms vs. crop farms) and/or the possibility to irrigate. These characteristics being partly aggregated (which is common on agricultural lands), the obtained reserve is partly aggregated.

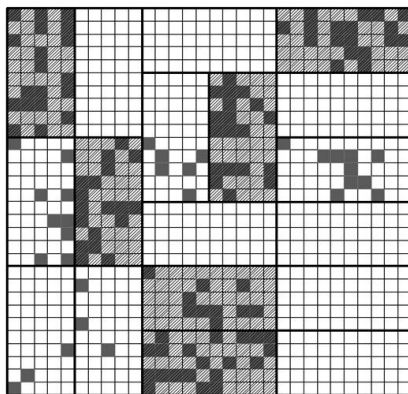


Figure 4: Reserve location with the subsidy per ha

We now consider other instruments that might perform better than the subsidy, either on its cost-efficiency (eg. the auction) or on the spatial objective (eg. the agglomeration malus).

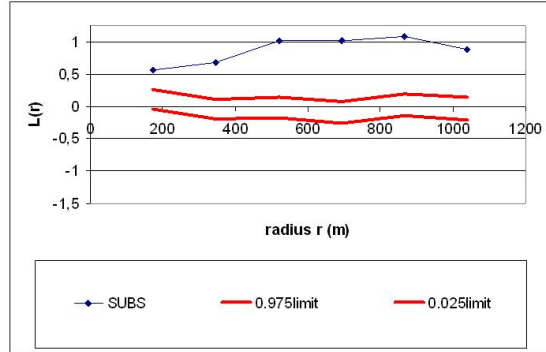


Figure 5: The Ripley L function with the subsidy per ha

4 The auction scheme

Auction schemes have increasingly attracted the attention of policy-makers to deal with agri-environmental regulation with incomplete information. Several real cases exist such as the *Conservation Reserve Program* in the United States (Kirwan et al. 2005), the *Bush Tender* in Australia (Stoneham et al. 2003) or some regional experiences in Germany (Groth 2005). According to many economists, this policy instrument, by favoring competition among farmers, helps minimize the payments to farmers even though they detain private information on costs (see Cason and Gangadharan 2004, Taylor and al. 2004, Reeson et al. 2011 and the references given in the introduction).

The auction we study here is a discriminatory-price sealed-bid procurement auction which works as follows. First, farmers submit their bid to the public regulator, i.e. they indicate the minimum payment they wish to receive to accept converting one parcel of their land to reserve. Their bid is sealed, meaning that the other farmers cannot observe it. Second, the regulator selects the best offer, i.e. the lowest amount, and pays this amount to the winning farmer against one additional parcel of reserve on his land. If several farmers bid at the lowest amount, they all win the bidding and receive this amount against one parcel of reserve. The operation is repeated until the total reserve reaches the desired size.

In the literature on auctions in conservation contracts, most contributions

are based on decision theory⁸ (Latacz-Lohmann and Van der Hamsvoort 1997, 1998; Rousseau and Moons 2006; Said and Thoyer 2007; Glebe 2008). This stream of literature has the advantage of being simple and tractable but its limit lies in the fact that it considers the threshold above which a bid is not accepted as exogenous, rather than resulting from the interaction among bidders. One of the main contributions of this article is that we model bidders' behavior and derive a formula for the optimal bid of a bidder i based on game theory.

We assume there are n farmers, all being risk-neutral⁹. Let us denote as Π_i^0 the profit of farm i without any commitment on its land-use and Π_i^1 its profit - not including the compensation payment - when farm i signs a contract with the public authority, committing to one additional parcel of reserve on its land. $v_i = \Pi_i^0 - \Pi_i^1$ represents the forgone profit of farm i (or opportunity costs) due to an additional parcel of reserve. Following the basic literature in game theory on auctions (see Klemperer, 1999), we assume that the values v_i are "independant private values", i.e. it is private information for each farmer i and it is common knowledge that each v_i is independently drawn from the same continuous distribution $F(v)$ on $[0, \bar{v}]$, with density $f(v)$. The assumption of independent private values is realistic in our case as opportunity costs are specific to each farm according to their type, land quality and irrigation equipment. Note that the lowest value for v is necessarily 0 as the opportunity cost cannot be negative for rational landowners who maximize their profit.

Given our assumptions, we can prove that the optimal bid of a farmer with opportunity cost v is given by the following formula

$$b^*(v) = v + \frac{\int_v^{\bar{v}} [1 - F(x)]^{n-1} dx}{[1 - F(v)]^{n-1}} \quad (2)$$

Proof. The optimal bid of player i of opportunity cost v is the expectation of the lowest of the remaining $(n - 1)$ values conditional on all these values being above v . Since the density of the lowest of $(n - 1)$ values is $(n - 1)f(v)[1 - F(v)]^{n-2}$ (expected value of v given that this value is inferior to

⁸Decision theory examines the decisions of rational individuals facing uncertainty but, contrary to game theory, it does not look into the strategic interactions among these individuals and how these interactions affect their decisions.

⁹This is a standard assumptions in the auction theory literature and in the conservation contracts literature. See Latacz-Lohmann and Van der Hamsvoort (1997) for a discussion on this assumption.

the $(n - 2)$ remaining values), the expectation of the lowest of $(n - 1)$ values is

$$\int_0^{\bar{v}} x(n - 1)f(x)[1 - F(x)]^{n-2} dx$$

The probability that v is inferior to the lowest of the $(n - 1)$ remaining values is then

$$\int_0^{\bar{v}} (n - 1)f(x)[1 - F(x)]^{n-2} dx$$

As a result, the optimal bid is

$$\frac{\int_0^{\bar{v}} x(n - 1)f(x)[1 - F(x)]^{n-2} dx}{\int_0^{\bar{v}} (n - 1)f(x)[1 - F(x)]^{n-2} dx} \quad (3)$$

After integrating the numerator by parts and simplifying, this yields formula (2). Our methodology is inspired from Klemperer (1999) but adapted to a procurement auction case ■.

Formula (2) describes the farmer's behavior which makes a trade-off between net payoffs and the acceptance probability. A higher bid increases the net payoff but reduces the probability of winning, and vice-versa. Each farmer's bid is then equal to his opportunity cost v (first term in (2)) plus a margin depending on v (second term in (2)). We can actually show that this margin is decreasing in v and we can easily see that for the farmer with the highest opportunity costs, i.e. with type \bar{v} , this margin is equal to zero. In other words, it is optimal for bidders to bid above their real costs in order to increase their gains. This phenomenon is amplified for low-costs participants (who can easily bid above their costs and remain competitive), whereas high costs participants are more likely to bid close to their costs in order to remain competitive. As a result, both the subsidy and the auction scheme may induce an over-compensation of farmers compared to their real opportunity costs.

In order to go further, we assume v follows a normal distribution on $[0, \bar{v}]$ with mean $E(v)$ and standard deviation σ . Note that another limit of the current literature on conservation auctions using decision theory is the use of a uniform distribution for the exogenous bid cap above which the bid is not accepted (Latacz-Lohmann and Van der Hamsvoort 1997). By using here a normal distribution for farmers' types, our model is more realistic as some opportunity costs levels are more common than others.

The formula for b^* in the normal distribution case is

$$b^*(v) = v + \frac{\int_v^{\bar{v}} [1 - \int_0^x \frac{1}{\sigma\sqrt{2\pi}} \exp(\frac{-(u-\frac{\bar{v}}{2})^2}{2\sigma^2}) du]^{n-1} dx}{[1 - \int_0^v \frac{1}{\sigma\sqrt{2\pi}} \exp(\frac{-(u-\frac{\bar{v}}{2})^2}{2\sigma^2}) du]^{n-1}} \quad (4)$$

In our model, it has been found that the highest possible value for the opportunity cost (the highest possible difference between the profit without any constraint and the profit when committing to one additional parcel in reserve) is $\bar{v} = 3320$ euros. We can then show through many simulations using *Mathematica* that, for a wide range of values of σ and v , b^* can be approximated by v , i.e. the second-term in (4) tends towards zero with a 10^{-1} precision (i.e. ten euro cents). In other words, in our case, the auction approximately allows to pay farmers at their real cost. This result is due to the value of \bar{v} in our case but it is shown to remain valid for many values for \bar{v} , v and σ as long as \bar{v} is not too small¹⁰.

Using this auction model, we introduce this policy instrument in the OUTOPIE model. Auction rounds are repeated until 15% of the zone is enrolled in the reserve. To limit learning effects and collusion among bidders, we assume there is no diffusion of information between two auction rounds (i.e. the amount of the winning bid and the identity of the winner are not revealed). As argued by Milgrom (1987), the advantage of a sealed-bid design is that it is less susceptible to collusion¹¹.

We find that the auction reaches the 15% objective with a total public cost of **145 thousand euros** which approximately corresponds to farmers'

¹⁰For example, the threshold value for \bar{v} above which bidders' margin is insignificant is $\bar{v} = 22$ when $\sigma = 500$ and $v = 0.5$. It is even lower for higher values for v . More details regarding these simulations are available upon request.

¹¹In multi-unit auctions or repeated auctions, there is a risk of collusion among bidders (Klemperer 1999). That is, if communication is possible and easy among farmers, they may agree to increase simultaneously their bid in order to improve their gain, which reduces the cost-efficiency of the auction for the public agency. However, bidders are also competitors and may be tempted to deviate from this type of agreement in order to lower unilaterally their bid and win the conservation contract (prisoners' dilemma). The literature in game theory shows that in a repeated game with finite horizon, the prisoners' dilemma persists and cooperation among players to collude is not stable (Fudenberg and Tirole 1991). Moreover, bids are sealed in our case, limiting the diffusion of information among bidders. As a result, we assume that no collusion occurs although the game is repeated. There may be, however, some learning effects due to the fact the auction is repeated; this has been studied in experimental economics (see Reeson et al. 2011) and remains an interesting scope for further research.

real costs of conversion. The auction therefore reaches a much better cost-efficiency than the subsidy, which was almost twice more expensive. This is due to the fact that as explained above, in our case, the auction is approximately cost-efficient.

Regarding the spatial configuration of the reserve, the auction does not reach the desired pattern (see Figure 7 where the Ripley function is shown to be outside the confidence envelop). As with the subsidy, in the auction scheme, the reserve is found to be partly aggregated due to the aggregation of low-cost-parcels. Let us now look into another policy instrument that explicitly takes into account the spatial issue.

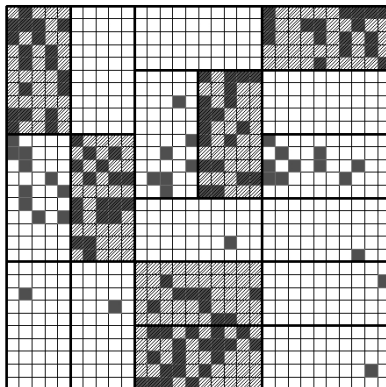


Figure 6: Reserve location with the auction scheme

5 The agglomeration malus

For many species, the spatial configuration of the habitat reserve - and not only its total size - is crucial for survival. There is no scientific consensus on the optimal spatial pattern of the reserve (which depends on the species) and only very few policy instruments have been developed to take into consideration these spatial issues. In the emerging literature on the topic, the most recurrent objective is to avoid reserve fragmentation. Parkhurst et al. (2002) and Parkhurst and Shogren (2007, 2008), for instance, examine an incentive mechanism called an agglomeration bonus, which awards landowners

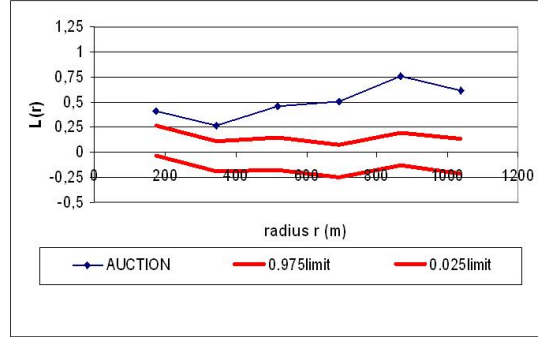


Figure 7: The Ripley L function with the auction scheme

bonus payments for the conservation of adjacent parcels¹². These authors use experimental economics to examine whether players are able to coordinate and reach the desired spatial configuration of land when facing such an agglomeration bonus.

We focus here on a similar instrument but reversed - an agglomeration malus - given that, on agricultural lands, it may be useful to avoid a too aggregated reserve, harmful to certain species such as the Little Bustard. We assume the farmers receive a payment per hectare of reserve but this payment is reduced when the remunerated parcel is adjacent to an existing reserve. We distinguish the parcels that are completely adjacent to the remunerated parcel from those having only one corner in common with this parcel. For example, if we assume a farmer receives a payment for the conversion of parcel 5 to the reserve (see Figure 8). He will pay the total malus if parcel 2, 4, 6 or 8 is in the reserve. And he will pay a lower amount - say half the malus¹³ - if parcel 1, 3, 7 or 9 is in the reserve, as these parcels only have one corner in common with parcel 5. The farmer pays the malus per adjacent

¹²A real-world application of an agglomeration bonus is Oregon's Conservation Reserve Enhancement Program (CREP), established in 1998 with the goal of assisting the recovery of salmon and trout species through the creation of riparian buffers along stream habitat (Grout 2010).

¹³A REVOIR Our spatial results are robust when changing this parameter from $1/2$ to any $\alpha \in]0, 1[$. This is due to the fact that, in the framework of our model, there are no adjacent parcels in reserve at the equilibrium so any positive value yields the same spatial pattern.

parcel in reserve (or half the malus per parcel with one corner in common with the remunerated parcel). In the example below, where parcels in grey are in the reserve, the farmer has to pay 2.5 times the malus when receiving the payment for converting parcel 5 to the reserve.

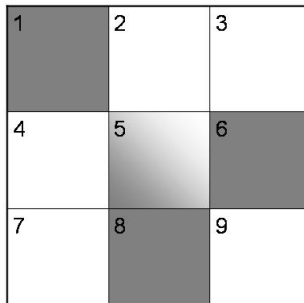


Figure 8: The agglomeration malus

We assume farmers can observe the existing parcels in reserve, as is consistent with reality. Moreover, we assume that when deciding which parcel to convert to reserve, they can communicate with their neighbors to coordinate in order to avoid an unexpected malus. In other words, farmers are aware of which parcels on neighbors' lands will be converted to reserve. This assumption is easily justified by the fact that, contrarily to the auction case where farmers are competitors, in the case of the agglomeration malus, farmers only have common interests to avoid the malus and obtain the greatest possible payment. Moreover, some experiments have demonstrated that, when it is in their interest, agents are able to coordinate facing an agglomeration payment (Parkhurst and Shogren 2007).

We find that this instrument reaches 15% of reserve with a total public cost of approximately **279 thousand euros**, which is the same amount as with the subsidy. This is not surprising given that, in our grid, farmers can locate the reserve patches so as not to pay the malus; they thus receive the same amount as with the standard subsidy. This instrument is therefore about twice more expansive than the auction scheme. However, it leads to the desired spatial pattern (see Figures 9 and 10): the Ripley L function is

inside the confidence envelope¹⁴.

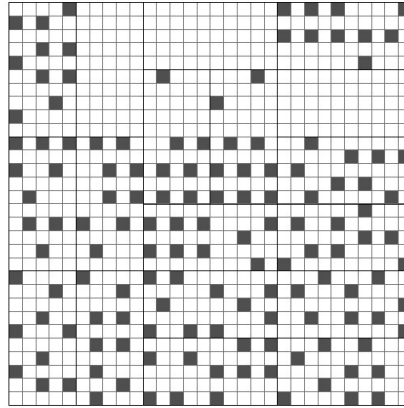


Figure 9: Reserve location with the agglomeration malus

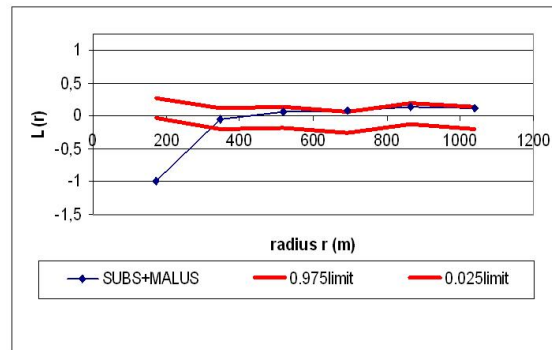


Figure 10: The Ripley L function with the agglomeration malus

¹⁴Except for the first point (200 meters radius): 200 meters corresponds to the maximal distance between any adjacent plots. The malus therefore generates over-dispersion at this level.

6 Summary and discussion

We have compared three incentive-based policy instruments - a subsidy per ha of reserve, an auction and an agglomeration malus - in order to reach a given size of reserve on agricultural lands, with reserve patches forming a random mosaic. In the framework of our model, the auction scheme has proven to be much more cost-efficient than the subsidy by reducing almost by half the public expenditures. The agglomeration malus is as costly as the subsidy and thus more costly than the auction but allows a better spatial pattern than both other instruments. As a result, we cannot rank the auction compared to the agglomeration malus as the former is more cost-efficient whereas the latter is more spatially efficient. We therefore have a trade-off between minimizing the public costs of the policy and reaching the desired spatial pattern of reserves.

Our work can be improved in many directions. The positive results on the auction's cost-efficiency must be mitigated for three main reasons. i) The specific characteristics of our case study leads to an insignificant margin in farmers' optimal bid, thus caricaturing the cost advantage of the auction. ii) The auction scheme may induce higher administrative costs than a standard subsidy due to a more complex procedure; data on the differences in administrative costs according to the instrument would be useful to incorporate this point in our analysis. iii) The fact that the auction is repeated may induce some strategic behavior and learning effects from the bidders, which could reduce the cost efficiency of this instrument.

Scope for further research includes introducing other policy instruments such as an heterogeneous payment scheme (based on mechanism design theory; see Wu and Babcock 1996 and Glebe 2008) or a reserve trading scheme, both potentially improving cost-efficiency. Also, we could improve the design of the auction scheme so as to deal more specifically with the spatial issue. This includes revising the scoring of bids taking into account a selection criteria which depends on the status of the adjacent parcel.

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