CONSOLE

CONtract Solutions for Effective and lasting delivery of agri-environmental-climate public goods by EU agriculture and forestry

Research and Innovation action: H2020 - GA 817949

Report on performance and design of result-based/outcome oriented approaches for AECPGs provision

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement GA 817949

Project	CONSOLE
Project title	CONtract Solutions for Effective and lasting delivery of agri-environmental-climate public goods by EU agriculture and forestry
Work Package	4 Simulations and performance of new contract solutions
Deliverable	D4.2
Period covered	
Publication date	Draft
Dissemination level	Public
Organisation name of lead beneficiary for this report	UNIBO
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1 Summary

This deliverable summarizes the findings generated by the models developed in "Task 4.3 Modelling result-based/outcome-oriented approaches for AECPGs provision". Four models, focusing on different aspects of the effectiviness of result-based schemes, have been developed in this task. The models suggest that result-based schemes do not necessarily provide effectivines improvement given the uncertainty in the rewards that they create. Specific design options (setting schemes based on *modelled* results) and technological improvements can increase their effectiviness.

2 Introduction

Deliverable D4.2. reports on the modelling exercises and results related to the task 4.3 Modelling result-based/outcome-oriented approaches for AECPGs provision. The main goal of the task is to assess the relative effectiveness and outcome of result/outcome oriented AECPG contracts under different conditions related to e.g. AECPG types. More specifically, the task objectives are to test: a) how results-based contracts solutions can work under different legal contexts and for different environmental results; b) to what extent "real" result-based outperform proxies (or the other way round); c) differences between compliance and result monitoring; d) how improved technological solutions (of different kinds) for monitoring and results measurement can improve the feasibility and performance of results-based contracts. The use of specific models aimed at simulating the environmental performances is a crucial component of the methods developed within the task.

Within the task 4 models have been developed, covering a range of different contractual parameters and AECPG types (Table 1). More specifically, CONSOLE has decided to concentrate the resources allocated to the tasks on the key aspects and design parameters of result-based modelling exercises. The focus of the models is the result of a selection process that mediates between feasibility, stakeholder inputs and novelties with respect to the existing scientific literature. More specifically, such a selection has taken into account a) the CONSOLE framework (deliverable D1.1 Preliminary framework), b) the results from the discussion regarding WP3 (and the results of the large-scale survey on the acceptability of the contract solutions among European landowners), c) input from stakeholders and from the CoP, with a final filter that considers the state of the art from

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the literature. Overall, the simulation models on result-based schemes developed within CONSOLE cover three of the most important AECPGS (soil erosion, carbon sequestration and biodiversity conservation). Moreover, all the models provide an assessment of the effectiveness of the result-based scheme with respect to the traditional design of AES (input-based). Finally, three key aspects are addressed. The first one is the effect of an ex-ante monitoring technology that enables to have a better prediction on the results that will be achieved. The second one is the design of result-based contracts whose payment are based on modelled results. The final aspect is the implementation of result-based scheme when the environmental processes depend on an area that is larger than the single farm. More details follow.

Table 2-1. Overview of the key characteristics of the modelling exercises.

Model code	AECPGS	Key aspects covered
RB_UNIBO_1	Biodiversity	Ex-ante monitoring technology and Environmental Extension Service
RB_UNIFE-UNIPI	Soil erosion	Simulated results based
RB_UNIBO_2	Carbon sequestration	Landscape scale environmental processes
RB_SGGW	Methane emissions	Optimal choice of instrument type

The first modelling exercise, RB_UNIBO_1, addresses the problem of the uncertainty linked to result-based schemes and whether such an uncertainty can be reduced through the use and adoption of technological improvements in the ex-ante monitoring. One of the key concerns on the formulation of result-based scheme is indeed the fact that, from the farmers point of view, the reward for the implementation of costly agri-environmental practices is dependent on their results, that in turn are the outcome of stochastic processes. The ultimate effect is that rewards are uncertain. The issue of the uncertainty of result-based schemes is not a novelty per se. However, what the literature has addressed is a situation where the level of uncertainty is given, and farmers are fully aware of the probability that a certain practice will succeed in achieving the target objectives. Advancing with respect to this framework, UNIBO addresses whether the existence of a technology operated by an Environmental Extension Service can reduce the uncertainty perceived by the farmer in the return from enrolment in a result-based scheme and ultimately allow the farmer to better choose on whether to enrol or not. The

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rough idea is that, before choosing to enrol in the scheme and implement the required environmental practice, farmers could have access to a monitoring technology managed by an Environmental Extension Service that can assess whether, given their farm-specific conditions, the implementation of the agri-environmental practice will indeed achieve the target results. The technology used by the Environmental Extension Service will not completely resolve the uncertainty, but will reduce it, leading farmers to take decisions with a higher degree of information. UNIBO models this problem through a Value of Information framework, widely used in other context, but to the best of the knowledge of the authors, never applied to the issue here at stake. The modelling exercise is numerically solved with data coming from the Emilia-Romagna region and using the results of the choice experiment developed in WP3. The model is applied to carbon sequestration as the AECPG targeted by the contract.

The second modelling exercise, by UNIFE and UNIPI, focuses on the effectiveness of a result-based contract based on simulated results to address the problem of soil erosion. The use of contracts that rewards simulated rather than actual results has been recently suggested as a mean to improve the effectiveness of Agri-Environmental Schemes and avoid the problem associated to the pure result-based schemes (Bartkowski et al., 2021). Indeed, as the previous paragraph has indicated, one of the main problems of result-based schemes is the uncertainty associated to the rewards for the farmers enrolling in such schemes. By moving from the pure to the simulated result-based scheme, the problem of the uncertainty is resolved from the farmers point of view, and enrolment is likely to be higher, holding everything else constant. The model is applied to a case study located in the province of La Spezia, an area extremely sensitive to the problem of soil erosion.

The third modelling exercise, RB_UNIBO_2, addresses the problem of assessing the effectiveness of result-based scheme under different environmental processes. More specifically, the modelling exercise focuses on biodiversity conservation when the targets species are characterized by different degrees of dispersal rate. The key feature of biodiversity conservation is that the outcome of an environmental process works at the landscape scale. If biodiversity conservation depends on the overall landscape composition, the plot-level biodiversity results depend not only on the implementation of agri-environmental practices in the given plots, but also on the implementation on the other plots in the landscape. In turn, if the landscape is subdivided among independent

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landowners, in such a condition, farmers enrolling in a result based would not only face the uncertainty caused by the stochasticity of environmental processes, but also the uncertainty related to the decisions taken by the other farmers. The overall effectiveness of the result-based scheme however will depend on the need of the target species to move around the landscape. UNIBO numerically implements the model on a number of randomized fictious landscapes and covering a wide range of parameters related to the environmental processes underpinning biodiversity conservation to assess whether result-based scheme improve AES in this context.

The goal of the fourth modelling exercise, RB_SGGW, is to evaluate what is the best instrument to deal with methane emission from dairy farms, and, in particular, whether is more effective to implement result-based schemes or input-based scheme. Such a goal is achieved through the combination of two methods. First, a Discrete Choice Experiments (DCE) has been implemented to evaluate the probability that farmers enrol in a wide range of hypothetical methane emission schemes. The results of the choice experiments is then introduced as an input and constraint in a mathematical programming model, that, given the probability of participation derived by the experiment, finds the optimal design of a methane emission scheme.

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3 Models' descriptions and results

3.1 Result based schemes and the value of information (RB_UNIBO_1)

3.1.1 Introduction

Despite the potential advantages (Matzdorf and Lorenz, 2010), result-based schemes face two main limitations compared to practice-based solutions: i) they are less attractive to farmers due to the associated uncertainty of reaching the environmental results and ii) they require an effective and legitimate measurement of results. These limitations engender three different kinds of risk for the farmers that hamper their enrolment in result-based contracts. Firstly, the need of coordinated efforts across different farms are relevant factors influencing results for some types of environmental parameters, such as the abundance of a species. Secondly, environmental results are often stochastic and non-linearly related with efforts. Third, farmers may lack the specific knowledge or skills needed to achieve the environmental objectives. In this paper, we focus on the latter issue and in particular on farmers' uncertainty regarding the choice of practices and the effort needed to achieve the target result.

The objective of this work is the assessment of the effect of the existence of a technology, operated by an Environmental Extension Service, for the ex-ante monitoring of the practices on the acceptability of result-based contracts. In doing this, we develop a theoretical model that is then applied to a case study region in Northern Italy. The value of information (VOI) approach is employed for the analysis of the farmers' decision to uptake a contract designed for increasing the carbon stock in agricultural soils. The VOI analysis is a decision analytic method for evaluating the expected increase in benefit from making better decisions through improved information. This framework provides an explicit evaluation of information in the context of regulatory decision making (Thompson & Evans, 1997) and it is simply estimated by calculating the difference between the expected utility with and without the information service (Yokota & Thompson, 2004). The basic assumption is that uncertainty can be reduced through better information, but the decision on the allocation of resources for information requires an assessment of the expected return of the economic investment on the information service. In other words, "*it is necessary to be concerned not only with the probabilistic nature of the uncertainties that surround us, but also with the economic impact that these uncertainties will have on us*" (Howard, 1966).

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3.1.2 Model description

3.1.2.1 Modelling framework

Assume that a regulator sets incentives for farmers to implement Conservation Agriculture (CA) practices able to improve soil organic matter (SOM) and therefore the carbon sink in the soil. The effectiveness of these practices is however uncertain as a range of factors such as soil type, climate variability, etc. affect the result in terms of SOM increase. Moreover, assume that CA practices entail higher (farm-specific) costs and no benefits for the farmers in in comparison to the regular agronomic practice (Pisante, 2007; SoCoProject, 2009). In this condition, farmers would implement the practices only if they are incentivized.

In designing the scheme, the regulator knows the distribution of the probability of SOM improvements and of the farmers' adoption costs, but she does not know the individual values. In this condition, she cannot tailor the scheme to the individuals. Call $\bar{C}$ the improvement in the SOM content that potentially is induced by the new practices. Call ρ_f the probability that the single farms f, once implemented the new practice, will reach $\bar{C}$. Furthermore, assume that if the practice is not implemented, there is no SOM improvement.

Three policy scenarios are investigated: a) an input-based scheme (I), b) a result-based scheme under uncertainty I, and c) a result-based scheme in case an Environmental Extension Service is available for farmers (E).

In the first scenario, the regulator designs an I scheme and set a payment. In an I scheme, farmers would enrol ($\gamma_f^I = 1$) in case $P^I - k_f \geq \pi_f$, with π_f being the profits in the no-enrolment case, k_f the costs associated to the implementation of the practice and P^I the payment attributed in case the practice is implemented. In such a scheme, enrolment in the scheme is only based on the opportunity costs, and the probability that the SOM will actually improve does not enter into the decision tree of the farms. The expected SOM improvement would then be $C^I = \sum_f \gamma_f^I \cdot \rho_f \cdot \bar{C}$, and the associated public expenditures would be $B^I = \sum_f \gamma_f^I \cdot P^I$.

In case of a result-based scheme (scenario R), the farmers that enrol receive a payment P^R only if an improvement in the SOM is detected ($C \geq \bar{C}$). The scheme is described by:

$$P^R = \begin{cases} > 0 \; if C \geq \bar{C} \\ = 0 \; otherwise \end{cases} \tag{1}$$

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Farmers have priors on the probability that the implementation of the practice will achieve a SOM of $C \geq \bar{C}$ in their farms: ρ_f. Facing the R scheme, farmers must decide on whether to enrol in the scheme ($\gamma_f^R = 1$) or not ($\gamma_f^R = 0$). Given these elements, the farm-specific expected value of enrolment in the R scheme is given by:

$$\mathbb{E}_f^R(\gamma_f^R = 1) = \rho_f \cdot (P^R - k_f) - (1 - \rho_f) \cdot k_f = \rho_f \cdot P^R - k_f \quad (2)$$

The decision to enrol is then based on the comparison between the expected value under uncertainty of enrolment and the profits they would obtain in the business-as-usual situation (π_f). Mathematically, farmers face the following maximization problem:

$$\max_{\gamma_f^R} \mathbb{E}_f^R = (\rho_f \cdot P^R - k_f) \cdot \gamma_f^R + (1 - \gamma_f^R) \cdot \pi_f \quad (3)$$

With $\gamma_f^R \in [0,1]$. Unfolding (3), farmers will participate in the R scheme under uncertainty (γ_f^{R*}=1) in case $\rho_f \cdot P^R > \pi_f + k_f$, i.e. when the expected value of enrolling is greater than the (direct and opportunity) costs associated to the practice.

In the third scenario, assume that the scheme is designed according to a result-based payment, but an Environmental Extension Service is available to inform whether the CA practices will enable to reach the expected SOM threshold. However, the service is imperfect and therefore affected by a standard probability of providing a correct information. Call for simplicity the Environmental Extension Service a *test*. Here, farmers need to decide on 1) whether it is convenient to purchase the test, and 2) given the result of the test, whether it is convenient or not to enrol in the scheme. The decision on whether or not to purchase the test is based on the Value of Information framework.

Call ψ the standard sensitivity of the test (e.g. 1- ψ probability of false positive) and ω the standard specificity of the test (1- ω probability of false negative). Given these parameters and the priors, the expected test outcome is given by:

$$\tau^+ = \rho_f \cdot \psi + (1 - \rho_f) \cdot (1 - \omega) \quad (4)$$
$$\tau^- = \rho_f \cdot (1 - \psi) + (1 - \rho_f) \cdot \omega$$

Where τ^+ is the probability that the test yields a positive (negative) result, i.e. that the application of the practice in the farm will actually improve the SOM content of the soil. τ^- indicates the opposite. Moreover, after the test is taken, farmers will update their belief

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according to the test result. Following a Bayesian pre-posterior analysis, $\rho_f^{c^+,\tau^+}$ and $\rho_f^{c^-,\tau^+}$ are respectively the updated belief that the SOM will reach the threshold or not given a positive test. $\rho_f^{c^+,\tau^-}$ and $\rho_f^{c^-,\tau^-}$ are respectively the updated belief that the SOM will reach the threshold or not given a negative test. According to the Bayes' Theorem, the pre-posterior belief is calculated as follows:

$$\rho_f^{c^+,\tau^+} = \frac{\rho_f \cdot \psi}{\tau^+} \tag{5}$$
$$\rho_f^{c^-,\tau^+} = \frac{(1-\rho_f)\cdot(1-\omega)}{\tau^+}$$
$$\rho_f^{c^+,\tau^-} = \frac{\rho_f \cdot (1-\psi)}{\tau^-}$$
$$\rho_f^{c^-,\tau^-} = \frac{(1-\rho_f)\cdot\omega}{\tau^-}$$

Given the pre-posterior belief (5), the expected value of enrolment is updated accordingly, and it depends on the result of the test:

$$\mathbb{E}_f(\gamma_f^E = 1, \tau^+) = \rho_f^{c^+,\tau^+} \cdot P^R - k_f \tag{6}$$
$$\mathbb{E}_f(\gamma_f^E = 1, \tau^-) = \rho_f^{c^+,\tau^-} \cdot P^R - k_f$$

Given (6), farmers will decide on whether to enrol or not, according to the results of the test:

$$\mathbb{E}_f^E(\tau^+) = max(\mathbb{E}_f(\gamma_f^E = 1, \tau^+), \pi) \tag{7}$$
$$\mathbb{E}_f^E(\tau^-) = max(\mathbb{E}_f(\gamma_f^E = 1, \tau^-), \pi)$$

The associated value of information is then the difference between the expected value under uncertainty ($\mathbb{E}_f^R(\gamma_f^R)$), and the expected value with the test, or: $V_f = \mathbb{E}_f^E - \mathbb{E}_f^R$, where $\mathbb{E}_f^E = \tau^+ \cdot \mathbb{E}_f^t(\tau^+) + \tau^- \cdot \mathbb{E}_f^t(\tau^-)$.

The test will be purchased if the value of information is positive, i.e. in case $\mathbb{E}_f^E(\tau) > \mathbb{E}_f^R(\gamma_f^R) + T$, where T indicates the cost of the test. Call $t_f \in [0,1]$ the decision

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on whether to purchase the test or not.[1] To evaluate the social expected value of the SOM improvement, note that the probability that a farmer will enrol once a test is purchased is:

$$\vartheta_f^E = \gamma_f^{E\tau^+} \cdot \tau^+ + \gamma_f^{E\tau^-} \cdot \tau^- \quad (8)$$

Under these circumstances, the expected carbon improvement is:

$$C^E = \sum_f t_f \cdot \vartheta_f^E \cdot \bar{C} \cdot \rho_f + (1 - t_f) \cdot \gamma_f^R \cdot \bar{C} \cdot \rho_f, \quad (9)$$

The first term in (9) is the expected SOM improvement in case the test is purchased and given the probability that the farmer will enrol (from equation 8). The second term is the expected SOM improvement in case the farmers will not purchase the test ($t_f = 0$) but will enrol under uncertainty ($\gamma_f^R = 1$).

3.1.2.2 Numerical implementation

Assessing the prior belief targets the mean expected belief of farmers about the effectiveness of CA practices and ultimately the probability to reach the 3% SOM threshold. Even though a diffused knowledge about the importance of organic matter for production can be expected, farmers' skills concerning the practices able to increase the SOM are typically heterogeneous. Also, it can be expected that the knowledge of farmers involved in schemes focused on SOM enhancement and periodic soil tests is significantly higher in comparison to the mean. To estimate the prior belief in the Emilia-Romagna region, we carried-out a choice experiment survey in 2021. The survey targeted farmers involved in soil-related measures (measure 10.1.03 "increase of soil organic matter" and 10.1.04 "conservation agriculture and increase of soil organic matter"; Rural Development Plan Emilia-Romagna 2014-2020) and, for comparison, farmers not involved in such measures. The choice experiment was designed to assess the preference towards different attributes of a hypothetical result-based contract targeting the increase of SOM in agricultural soils. One of the contract attributes was "technical support". Three separate conditional logit models (Aizaki & Nishimura, 2008) were applied to 1) the data set as a whole (n=38), 2) the cases not involved in soil measures before (n=22), and 3) the cases with experience in soil measures (n=16). The mean prior belief was estimated by comparing the differences of the model coefficients related to the technical assistance

[1] Call F^t the subset of the farmers population that would purchase the test, i.e. $F^t \subset F : \mathbb{E}_f^E(\tau) > \mathbb{E}_f^R(\gamma_f^R) + T$

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attribute between the three models. The estimation is based on the assumption that the technical assistance coefficient is a proxy of the necessity of information support and therefore of the level of uncertainty (i.e. the inverse of the belief) regarding the practices required to reach the SOM target. Even though the sample cannot be considered representative for Emilia-Romagna, that assumption was supported by the survey results as the technical assistance attributes resulted as -0.085 for experienced farmers (i.e. low interest in assistance) vs. 1.551 for non-experienced farmers (i.e. higher interest). Assuming that a *quasi*-perfect information can be related to farmers with past experience in soil measures ($\rho_f = 0.9$), and perfect uncertainty ($\rho_f = 0.5$) to farmers without past experience in soil schemes, then the mean prior belief is estimated as

$$\rho_{avg} = 0.9 - (A_d * U / A_D) \tag{10}$$

Where A_d is the average technical assistant attribute coefficient (whole set), U is the range between the maximum and minimum prior beliefs, and A_D is the difference between the technical assistant coefficient of the non-expert farmer set and the expert farmer.

The test is an expert support provided by consultants that inform about the potential effectiveness of CA practices and in particular about the possibility to reach the SOM threshold. The support takes into consideration the soil characteristics such as texture, SOM presence, etc. and on that base indicates if the SOM threshold will be reached or not. However, the test is imperfect and thus a probability of false positive or false negative affects the results. That can be related to different reasons such as inaccurate sampling or high heterogeneity of farm soil conditions and a consequent misinterpretation by the consultant. The Bayesian pre-posterior analysis allows to evaluate the influence of the test performance on the farmer management decision (Canessa et al. 2015), but the availability of test performance parameters including the possibility of consultant misinterpretations would need an ad hoc evaluation. For the purposes of this model, we assume a test mean sensitivity as 0.8 (i.e. 20% probability of test wrongly indicating that the SOM threshold will be reached) and mean specificity as 0.9 (i.e 10% probability of test wrongly indicating that the SOM threshold will not be reached). These parameters are in line to those reported in Canessa et al. (2015) for an environmental DNA test.

The opportunity costs related to CA practices have been estimated for Emilia-Romagna on the basis of the Rural development Plan cost analysis (RegEU n. 1305/2013, and Technical elements of agri-environment climate measure in the programming period

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2014 2020). In particular the average cost estimated for the measure 10.1.04 in Emilia-Romagna are employed (Università del Sacro Cuore, 2014).

3.1.3 Results

Figure 3-1 panel A shows the expected expenditures under the different scenarios and payment rate. Not surprisingly, in all the scenarios, an increase in the payment rate increases the expenditures. However, there are major differences among the scenarios. In the case of the I scenario, the expenditures rapidly increase after a 200€ rate. The rate of increase only depends on the heterogeneity of the farm-specific costs associated to the practice. Moreover, for any payment rate, the I scenario leads to the higher expenditures. The rate of increase and the overall level in the expenditures is lower in the R and E scenarios than in the I scenario. Indeed, in both these cases, the uncertainty related to the improvement in the SOM content is embedded in the farmers decision making, as the reward for the application of the practice depends on the achievement of an actual SOM improvement. Farmers weight the nominal payment rate by the probability of success, and hence for any nominal payment rate, a lower number of farms enrol. More specifically, only the farmers with the highest priors enrol.

Moreover, note that between about 200€ and 300€ payment rates, there is enrolment (and hence expenditures) in the E scenario but not in the R scenario. The possibility of purchasing a test result into a better refinement of the decision-making process. This ultimately causes a switch in the decision taken by some farmers from non-enrolment to enrolment. As we will show later, for a certain range of parameters, this will indicate that a test would improve the effectiveness of result-based scheme. Figure 3-1 panel B, showing the expected SOM for different payment rates, indicates similar patterns. At around 250€, in case all the farmers facing an I scheme enrol and reach the maximum expected SOM. The same level is reached at about 400€ in the case of the R scheme. Similar to the previous logic, the E scheme leads to a SOM higher than the R scheme in a range of payment rate between 200€ and 300€ and then it becomes lower. The difference is due to how the enrolment is assessed in the two scenarios. Despite the uncertainty in the rewards, in the R scheme the enrolment is certain as defined by equation (3). Instead, in the E scheme the enrolment is uncertain as it depends on the result of the test, and hence weighted by the probability that a test will yield a positive or negative result.

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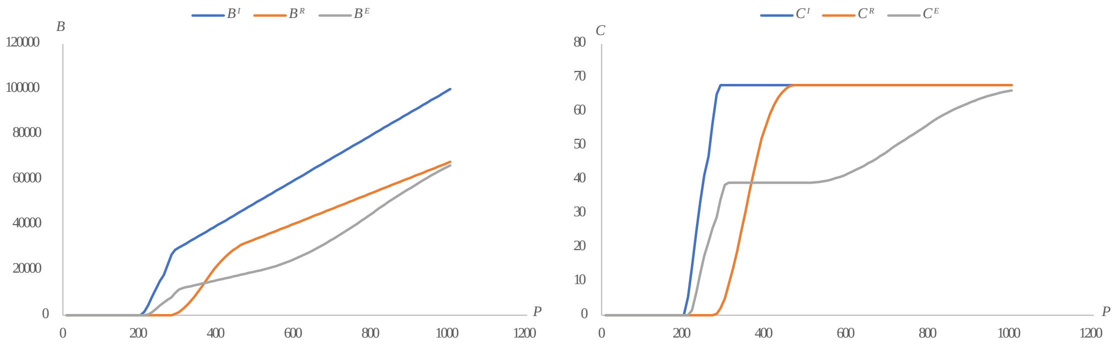

(A) *(B)*

Figure 3-1. Expected expenditures (A) and expected SOM improvement (B) in the input-based (blue), result-based (red) and Environmental Extension Service (grey) policy scenarios under different payment rate.

To evaluate the performance of the three schemes we build two indicators. The first one is the ratio between expected improvement in the SOM and the expected expenditures: C/B. Figure 3-2 panel A shows that for any payment rate, the two result-based schemes outperform the I scheme. Between about 200€ and 300€ payment rates, the E scheme is the most performative one, as in this range, in the R scheme no farmers enrol. After the 300€ threshold, the two result-based scheme yield the same results. Indeed, for high payment rate, the test will not refine the decision between enrolment or not, as farmers would enrol in any case.

The second indicator is the cost-effectiveness of schemes, here defined as the expected level of SOM improvement for the expenditure levels. Figure 3-2 panel B depicts the cost-effectiveness of the three schemes. Two are the main results indicated by the graph. First, the difference between the I and R scheme are rather small. For any payment rate, the I scheme yield more expected SOM improvement but also higher costs than the R scheme and the two effects cancel out when cost-effectiveness is taken into account. Second, the existence of Environmental Extension Service improves the cost-effectiveness of the result-based scheme for low level of expenditures. Indeed, up to around 2000€, the E scheme is the most cost-effective one.

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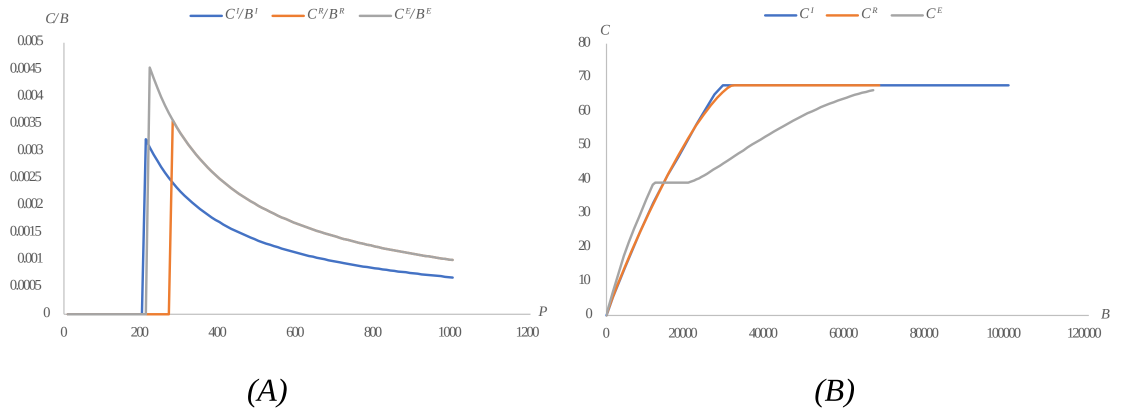

Figure 3-2. Benefit-cost ratio per payment rate (A) and expected SOM improvement per public expenditures(B) in the input-based (blue), result-based (red) and Environmental Extension Service (grey) policy scenarios.

3.1.4 Conclusion

Here we explore the role that an Environmental Extension Service could have in the performance of a result-based scheme. We simulate the participation of farmers into a result-based scheme, where the reward for the implementation of SOM improvement practice depends on the actual achievements and hence is uncertain. We add to this structure the possibility that farmers are helped in deciding whether to enrol or not by a technology operated by an Environmental Extension Service, and model this situation through a Value of Information framework. Finally, we compare the effectiveness of the result-based schemes (with and without the Environmental Extension Service) with a classic input-based scheme.

The preliminary results indicate that the major role of an Environmental Extension Service is when the payment rates and expenditures are low. In this situation, farmers are rather uncertain between enrolment in the scheme or not. The Environmental Extension Service is able to cause a switch in the decision for a number of farmers from business-as-usual toward enrolment. The ultimate result is that, under these circumstances, the result-based scheme assisted by an Environmental Extension Service is the most effective scheme.

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3.2 Modelling result based and assessing their effectiveness in case of reduction of soil by water erosion (RB_UNIFE-UNIPI)

3.2.1 Introduction

Many studies have investigated soil loss, and a majority of them focused on water erosion. Soil loss by water is an important environmental concern that generates an economic loss of approximately US$ 20 billion per year in the EU (Panagos et al., 2015). The amount of soil loss by water is uneven across regions, with 70% concentrated in mountainous and hilly regions that represent 10% of the EU areas. Despite the implementation of several measures, land degradation represents one of the major threats to sustainable development and is a major issue in the Mediterranean region (Barbayiannis et al., 2011). The protective actions should be made compulsory or, at least, strongly encouraged, especially in difficult territories. In the short run, technology allows yield increases despite high erosion rates, and some farmers do not even understand or care about environmental problems (Taguas and Gómez, 2015). In the past decade, extreme floods and landslide events have increased due to climate change. Media and institutions often raise the debate regarding hydrogeological instability only when a disaster occurs. This incorrect behaviour is often linked to the misconception that the triggering of storm/climate change events is the primary cause of the disaster, rather than the degradation of soils. In reality, the implementation of management practices and investment to protect soil has helped achieve a balance. For example, human activities have formed an important defence in mountainous and hilly areas where conditions are generally more difficult to manage because of the higher slopes. As a long colonisation process, the presence of dry-stone walls, terraces, and heroic agricultural farms, in general, has offered valuable support against surface erosion and landslides (Agnoletti et al., 2011). However, in other areas, the lack of soil-friendly management practices is exacerbated by the extremization of rain and wind events even today. In the past decade, the frequency of extreme flood and landslide events has increased owing to climate change. Several studies have attempted to determine the quantity of soil lost from water runoff and wind using diverse models and processes. It is commonly accepted that environmental measures act against this dangerous situation and often discourage or encourage certain agricultural activities. For example, modifying ploughing regimes and utilising cover crops can significantly reduce the quantity of eroded soil.

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Although soil erosion is a relevant concern, the contribution of environmental protection policies against soil erosion and landslides due to extreme weather events has not been sufficiently investigated. The EU Common Agricultural Policy (CAP) measures have been ineffective in protecting the environment from soil erosion and landslides (Früh-Müller et al., 2019).

Modelling the impact of policy activities on landscape conservation and restoration results would be important to increase the efficiency of EU funding. Against this backdrop, we test the introduction of results-based payments (with payments based on simulated results) in an area of Ligurian Region (Italy).

In Ligurian territories, small and hobbyist farmers produce a large percentage of environmental goods. Although actions implemented by single farmers seem insignificant because of the small farm dimension, collective actions from small farmers can improve land protection. However, the CAP measures often exclude them because of their failure to reach the minimum acreage or economic dimension requested. We analysed several agri-environmental commitments and how they affect the final quantity of soil erosion. We tested the introduction of different policy mixes considering a combination of the first and second pillar measures, including different contract types for Agri-Environmental Scheme (AES) payments (i.e. payments based on simulated results).

3.2.2 Model description

3.2.2.1 Model description

We apply a mathematical programming model to simulate the effectiveness of a results-based contract on reducing soil erosion by water. The model enables a simulation of farmers' behaviour in front of different types of payments for agri-environmental-climate practices and can simulate the impact on potential soil erosion. We utilised the revised universal soil loss equation to include the real variables that act in the process (Slope, crop factor, Erosion factor, Rain quantity) and we simulated different policy mix impacts on land demand using a mathematical programming model. The model enables the simulation of farmers' behaviour in front of a different combination of an environmental prescription under enhanced conditionality, eco-schemes, and agri-environmental schemes. We applied a dynamic mathematical programming model that optimises the Net Present Value of cash flow between the years 2022 and 2040. Formally,

$$\max NPV = \sum_t^T cf_t * (1-k)^{-t} \tag{1}$$

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$$cf_t = \sum_i^I \sum_j^J \pi_{t,i,j} * x_{t,i,j} + SFP_t + ECO * x_{t,i,j\in eco} + AES_t * x_{t,i\in aes,j} - tc_{eco} - tc_{aes} - cc - l_{in} * rent - tc_{in} + l_{out} * rent - tc_{out} \quad (2)$$

$$s.t. \ \sum_i^I \sum_j^J a_{t,i,j,h} * x_{t,i,j} \leq b_h \quad (3)$$

$$x_{t,i,j} \geq 0 \quad (4)$$

where

NPV = net present value between years 2022–2040

cf_t = annual cash flow for generic t year

k = discounted rate,

$\pi_{t,i,j}$ = profit of ith crop with jth farm practice

$x_{t,i,j}$ = area of ith crop with jth farm practice

SFP_t = decoupled payments received during generic year t

AES_t = agri-environmental-climate payments received during generic year t

tc_{aes} = transaction cost of participating in agri-environmental climate schemes

tc_{eco} = transaction cost of participating in eco-schemes

cc = cost of the enhanced compliance

$rent$ = land rental price

$a_{t,i,j,h}$ = scalar element of a generic h-th technical coefficient used by i-th crop with j-th farm practice during generic year t

b_h = vector of available resource quantities

In the absence of monitoring data that directly measure soil types in the regional agricultural systems, the potential impact of measures was estimated using the difference in the contribution to erosion reduction between holdings under commitment and holdings not participating in measures. Using the general formula, we have

$$\delta_{aes} = S_{p1} - S_{p0}$$

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S_{p1} = annual potential erosion per farm under commitment to a generic action aimed at reducing soil erosion

S_{p0} = annual potential erosion per farm without environmental commitment

The calculation of potential erosion was conducted by applying RUSLE, developed by Wischmeier and Smith (1978). The RUSLE equation allows the estimation of the annual tons of soil loss by erosion of a generic farm p by considering five factors:

$$S_p = R * K * LS * C \quad * P$$

The R-factor is the aggressiveness and leaching of rain and measures the kinetic energy and intensity of rain in the area associated with the run-off. It is worth noting that the parameter was the value of R, which is uniformly distributed between the current value of approximately 900 to 1500 (MJ mm/ha h year). The variability was simulated considering the projection from Panagos et al. (2021).

The K-factor expresses the susceptibility of a soil to erode and is computed by considering soil properties such as texture, organic matter, structure, and permeability of the topsoil.

The LS-factor represents the topographic parameters of soil erosion and integrates the effects of slope steepness (S-factor) and slope angle (L-factor) on soil loss.

The C-factor describes the land cover and management factor, measuring the combined effect of land use and management.

The P-factor describes the corrective factor in the case of an existing installation of erosion containment and control measures such as terraces, countering farms, stone walls, strip cropping, terracing, and grass margins.

The C and P factors are endogenous to the model simulation, whereas R, K, and LS are exogenous.

3.2.2.2 Empirical implementation

We assessed the model over representative farms in the Italian province of La Spezia and Genova, an administrative subregion of Liguria. We chose this area for the following reasons: a) its exposure to hydrogeological instability and the peculiarity of agriculture, which make the issue of soil erosion relevant; b) the area is an inner area; and c) the area shows very low activities in the land market. We selected the representative

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farms based on a list of ‘professional’, part-time, and hobbyist farmers. We conducted a non-hierarchical cluster analysis with a k-means algorithm and used the highest Calinski/Harabasz pseudo-F value as the ‘best clustering’ criteria. Two surveys were used to gather the data for the model. Farm total agricultural area, Farm usable agricultural area (UAA), and the number of direct payments were the three clustering variables. We ran the clustering procedure over three different areas of the region, given the importance of farm location, land slope, and farm specialisation for farming profitability and land-use-diversification potential. The 302 farms in the area fitted 12 representative clusters with well-defined features in terms of size, labour, and payment level (Table 3-1).

Table 3-1. Characteristics of representative farms

Farm	System	Weight (%)	Plots (#)	UAA (ha)	Arable crops (ha)	Permanent crops (ha)	Forest area (ha)	SFP (€ per farm)
1	olives	0.07	3	1.65	1.32	0.33	-	243.71
2	olives	0.07	4	2.49	1.76	0.73	-	433.00
3	olives	0.01	3	1.91	1.60	0.31	-	346.00
4	forest	0.30	3	4.66	0.52	-	4.13	196.23
5	forest	0.06	4	13.69	1.03	-	12.67	285.50
6	forest	0.01	7	551.00	0.05	-	550.95	-
7	forest	0.01	4	6.05	1.76	-	4.29	300.00
8	arable	0.26	5	14.27	14.27	-	-	713.04
9	arable	0.11	4	24.49	24.49	-	-	1,086.09
10	arable	0.04	4	69.20	69.20	-	-	3,221.00
11	arable	0.01	7	114.95	114.95	-	-	22,580.00
12	grapewine	0.06	4	5.72	3.84	1.89	-	348.50

3.2.2.2.1 Second pillar measures

In accordance with the ongoing debate on environmental regulation within the CAP post 2020 regulation, we limit our analysis to two AESs, which will go beyond the baseline set out by GAEC (total permanent grassing of the vineyards and olive oil crops) and the eco-schemes (winter soil cover and catch crops above conditionality, and agroforestry).

The two AES measures are as follows:

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AES1: Grassland conservation measure that provides a payment to avoid conversion or abandonment of permanent and semipermanent grasslands. This measure is currently included in the list of measure 10 of the Ligurian RDP.

AES2: Renaturalisation measure. This is a new measure that the regional administration would like to introduce during the new programming period. This measure integrates and promotes the combination of arable crops with significant areas of natural vegetation to increase biodiversity and introduce elements that can avoid soil erosion, such as wood, permanent crops, or other natural landscape elements.

Option A payments based on compensation costs (Action based payments)

The first option is the current payment calculation which is based on the compensation of participation cost, income foregone, and private transaction costs with the following:

Option B results-based payment on (simulated) results

We also simulated the introduction of results-based payments on (simulated) results to assess the change in soil erosion due to the introduction of different levels of payments. Formally, the parameter of AES payments ($AESpay$) is calculated as:

$$AES_t = \left(x_{t,j,i}K_1(1-r)\right) + (rV * \delta_{aes})$$

where

$x_{aes} =$ area under AESs

K_1 = compensative payment

r = share of payment based on the simulated results

V = economic value of reduced soil erosion (€ /t/ha year)

δ_{aes} = reduced soil erosion due to AESs

The results are presented considering different levels of r and V.

3.2.2.2.2 Exclusion criteria

Small and hobbyist farms characterise the Liguria region's agriculture situation. However, the current AES includes a threshold that makes the AES farmers below a threshold of three hundred euros and with an annual standard output below five thousand

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euros ineligible. This has the practical consequences of excluding hobby and part-time farmers by payments, although they are relevant in reducing soil erosion.

3.2.3 Results

Table 3-2 compares the cost-effectiveness of action-based and results-based payments. The cells take a positive value when a farmer participates in an AES or no value when the farmer does not. A positive value indicates that the amount of soil erosion reduced per 1000€ of payments (tons/ha/year).

The results show that AESs with payments based on compensation of participation costs (action-based payment, first columns) were profitable for seven of the fourteen farm typologies. Although this seems to be a relatively high number of adopters compared to the current diffusion of AESs in the region, it is worth noting that we simulated the introduction of additional measures which was found profitable for farmers with arable areas. Farmers who adopted such new measures were mainly farmers not specialised in arable crops (only two were specialised in arable crops), as they could easily implement the measure in the less productive portion of the farm. This is a very interesting result, as the new AESs can be considered profitable for non-arable farms and a relevant opportunity to maintain arable areas for farms specialised in other productions. Thus, a non-arable farming system has a lower opportunity cost to participate in AESs.

The results-based payment was simulated using two economic soil erosion values. The literature provides an average cost of soil erosion of 60.36 €/t/per year (Panagos et al., 2015b; Telles et al., 2011), and indicates a quite large variability, with the value spanning from 3€ to 300 €/t/per year (Panagos et al., 2015b). We considered two values of unitary benefit (V): low 45 and high 90 € per ton per year. We also parameterised the share of total AES payments based on the results.

The results show that the cost efficiency of AESs increased with a low value of V. Farms that participated in action-based payments engaged in AESs until the share of results-based payments remained low (0.25). This value indicates that the cost-effectiveness increased for six of the seven farms. We speculate that even a small portion of the results-based payment is enabled to reduce farmers' opportunistic behaviour due to adverse selections of AESs. The introduction of this small share of payments reduced the level of payments or encouraged the adoption of AESs around the farm, resulting in a higher reduction in soil erosion compared to the action-based results. With a share of

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payment based on 50% of results-based payments, the unitary payment will be lower than the compensation costs, and no farmer will adopt AESs.

When results-based payments were designed using a higher unitary value of the benefit (V= 90 €), two additional farms found it profitable to participate in AESs (farms 7 and 12).

Such a high value determines higher participation and payments level but, as payments are designed on simulated results only in three cases shows higher cost-effectiveness compared with action-based payments. Two of these cases, farms six and seven, had higher cost-effectiveness with full results-based payments.

Table 3-2. Effectiveness of results-based contract (change in amount of soil erosion per 1000€ of AES payment)

farm	Action Based Payment	Results based payment					
		Low economic value of reduced soil erosion		High economic value of reduced soil erosion			
		r=0.25	**r=0.50**	**r=0.25**	**r= 0.50**	**r = 0.75**	**r= 1**
1	0.5446	**0.7077**	-	0.5212	0.4998	0.4801	0.4619
2	0.5257	**0.6829**	-	0.5067	0.4890	0.4725	0.4571
3	-	-	-	-	-	-	-
4	0.6857	**0.8883**	-	0.7017	0.7183	0.7358	0.7541
5	0.6795	**0.8803**	-	0.6953	0.7118	0.7292	0.7474
6	0.3401	0.3456	-	0.3401-	0.3564	0.3650	**0.3740**
7	-	**-**	-	-	0.7129	0.7302	**0.7484**
8	-	-	-	-	-	-	-
9	0.5804	**0.6138**	-	0.5490	0.6208	0.4953	0.4722
10	-	-	-	-	-	-	-
11	0.6119	**0.7939**	-	0.6054	0.5991	0.7001	0.7280
12	-	-	-	-	**0.8260**	0.8225	0.7979

3.2.4 Conclusions

The combination of action-based and results-based payments, where the latter is based on simulated results, is applied to soil erosion. Our results suggest that the introduction of results-based payments should be carefully designed to consider both the environmental baseline and value of environmental benefits. The combination of results-based and action-based payments can increase the effectiveness of AESs. The model

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simply applies a payment based on the simulated results, a policy option that would also require low public transaction costs to design, implement, and monitor the measures.

In the future, we intend to include rain and extreme event simulations in the past model. This can improve the validity and accuracy of the model by including more environmental data and thus simulating results-based payments more effectively. In fact, the environmental data would help better simulate the external factors and improve sensitivity. In the future, extreme weather events will become more common, and the new CAP programming period must take this into account. Consequently, hydrogeological instability and catastrophic events will reach a higher diffusion. We cannot pursue a risk-zero scenario because extreme events can always occur; however, thanks to the cost-benefit analysis, we must guarantee good protection to the community. This is possible with an important level of information about weather phenomena to increase everyone's awareness regarding disastrous moments. Everyone should do something to achieve the predicted safety level, avoiding human loss and environmental degradation. Right remuneration can stimulate a virtuous circle of the custodians' actions.

The main limitations of this study can be related to the inaccuracy in the representation of the real scenario. Errors can occur in representing both the environmental (extreme weather events, run-off, crops, agricultural practices) and economic (farmers' behaviour) aspects. The model attempted to accurately simulate the average farm scenario, but external events could modify the average scenario. The results of the policy mix at the real level can be slightly modified from several factors and cannot be direct as in the simulation. In this model, we did not consider competitive agricultural prices which can represent a perturbation in the average farm situation balance. The prices of commodities, gross matter, and agricultural products can slightly modify the instruments related to the first and second pillars linked to crop production and ecosystem service provision. At the end of the study, we want to underline the importance of a practical analysis of future policies before real-level implementation. The process can save time, funding, and landscapes, avoiding ineffective policy projects that cannot guarantee positive effects for the farmers, regulators, and environment.

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3.3 Modelling results based and assessing their effectiveness for biodiversity conservation (RB_UNIBO_2)

3.3.1 Introduction

The economic literature on the effectiveness of result-based schemes, with some exception (Drechsler, 2017), has mostly focused on cases where the results in terms of biodiversity depend only on the individual actions of the farmers (Derissen and Quaas, 2013; White and Hanley, 2016). However, the ecological literature highlights how the environmental processes that underpin biodiversity conservation work at the landscape scale, on a territory that is typically larger than the one under control of an individual farm. In general, three factors affect the biota in a landscape: the extent of habitat, the composition of the mosaic and the spatial configuration of elements (Bennett et al., 2006). This implies that conservation efforts in one farm positively affect the probability of positive conservation outcomes in the other, neighbour, farms. In this prospect, from an economic perspective, the economic outcome of the individual participation in a result-based scheme depends on the actions of the other economic agents in a given landscape. Thus, the individual decision to enrol in the scheme depends on the expectation that each farm has on the decision of the other farms. In this situation, farmers decision face two levels of uncertainty. The first one relates to the stochasticity of species survival, the second uncertainty relates to the knowledge of the other farms opportunity costs, that in turn affects their conservation decisions and ultimately the overall species conservation success. Note that even if farmers would be fully aware of the opportunity costs of all the farmers in the landscape, a result-based scheme would create public good benefits under which individual participation would be sub-optimal.

The objective of this research is to model the enrolment in a result-based scheme and analyse its effectiveness in case conservation efforts provide positive spillovers. To analyse the effectiveness of the scheme, we compare the outcome of a result-bases scheme in terms of cost effectiveness (biodiversity level per level of public expenditures) with both a traditional, input based, payment and with a collective scheme (connectivity based) scheme.

With respect to the objective of “Task 4.3 Modelling result-based/outcome-oriented approaches for AECPGs provision” the model evaluates to what extent result-based schemes would perfume under different environmental processes.

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3.3.2 Model

3.3.2.1 Model description

Imagine a landscape composed by a number of plots $i \in I$. The plots are owned by a population of landowners. Call Ij the subset of plots that each farmer j owns. Each plot can either be allocated to habitat conservation (Xi=1) or agriculture (Xi=0). Each plot allocated to conservation contributes to the biodiversity of the area. The biodiversity of the area is defined as the number of individuals found in the area. The probability that a given plot hosts an individual depends on the entire landscape configuration according to:

$$\psi_i = X_i \cdot \dot{\psi}_i \cdot \sum_{k \neq i}^{J} X_k \cdot exp\left(-\frac{d_{ik}}{D}\right) \tag{1}$$

where D is the dispersal rate of the species under consideration, dik is the distance between the centroids of the two plots i and k, and $\dot{\Psi}_i$ is a scale parameter. Equation (1) adapts the ecological function for example used in Bareille et al. (2022) to yield a plot-level probability of survival success. Note that in such a function, only conserved habitat can host a species, i.e. if $X_i = 0$, then $\psi_i = 0$.

On the economic side of the problem, payoffs from agriculture are denoted by Π_i. There is no reward from conservation other than the subsidies provided by a regulator, and hence, in their absence there is no conservation. The regulator to increase the biodiversity of the area can set a scheme, choosing among a traditional input-based subsidy (*IB*), a result-based scheme (*RB*), or an agglomeration bonus (*AB*).

In the case of an IB scheme, the response of the farmers is evaluated through:

$$\max_{X_i} \Pi^{IB} = \sum_j P^{IB} \cdot X_i + P^{AG} \cdot (1 - X_i) \tag{2}$$

where P^{IB} is the subsidy level in case of the IB scheme. Being X_i a binary variable, a plot will be enrolled in the IB scheme in case $P^{IB} \geq P^{AG}$. With an IB scheme, the location and the number of plots conserved depends on whether, for each plot, the subsidy level is greater than the agricultural profits.

In case of the RB, a premium P^{RB} is granted if the species is found in the plot ($\Psi = 1$, $\Psi = 0$ otherwise). Mathematically:

$$P^{RB} = \begin{cases} > 0 \; if \; \Psi = 1 \\ = 0 \; if \; \Psi = 0 \end{cases} \tag{3}$$

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As the allocation of habitat does not necessarily lead to the presence of individuals in one plot, farmers facing an RB scheme take decisions in an uncertain environment. To account of this feature of the problem, we assume that farmers have a von Neumann-Morgenstern expected utility function combined with the Bernoulli utility function (Gollier, 2001). For each plot, the utility from conservation is given by:

$$U_i^{RB}(X_i = 1) = \psi_i \cdot \frac{(P^{RB}+P^{IB})^{1-\rho_j}}{1-\rho_j} \cdot X_i + (1-\psi_i) \cdot \frac{(P^{IB})^{1-\rho_j}}{1-\rho_j} \cdot X_i \tag{4}$$

where ρ_i is the risk aversion coefficient that is farmer specific and hence the same for any plot owned by farm i. Following Derissen and Quaas (2013), we include the possibility that the regulator sets a RB payment in addition to the classic action based payment (P^{IB}, in our model). Note Since we assumed that the probability to find an individual in an agricultural plot is zero, the payoff from agriculture is simply P^{AG}, or $U_i^{RB}(X_i = 0) = P^{AG}$.

If farmers enrol individually in the scheme, they face the following maximization problem:

$$\max_{X_i} \Pi_j^{RB} = \sum_{i \in I_j} U_i^{RB}(X_i) \tag{5.a}$$

$$\text{S.t. } X_k = \begin{cases} 1 \; if P^{IB} > \Pi_k \\ 0 \; otherwise \end{cases} \forall k \neq i \tag{5.b}$$

and equation (1). Equation 5.b. describes the expectations that farmers have on the land allocation of the plots that are not owned by them. We assume that farmers have only a limited knowledge on the behaviours of the others, and hence they consider that the other farmers will allocate land to habitat only in case the IB subsidy covers the opportunity costs. Note that setting $P^{RB}=0$ would collapse equation (5) to equation (2), that describes the simple input-based scheme.

Finally, in an AB scheme, in addition to a payment granted to each plot of lands allocated to habitat, there is a bonus for each neighbour plots that are also allocated to habitat. In such a scheme, the payoff for each plot allocated to habitat is given by:

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$$U_i^{AB} = P^{IB} \cdot X_i + \left(P^{AB} \cdot \sum_{\substack{k \neq i \\ k \in \Phi_i}} X_k \right) \cdot X_j \quad with \quad \Phi_i = \{k \in I | d_{ik} \leq \bar{d}\} \tag{6}$$

where Φ_i represents the subset of plots that are adjacent to the plot i.

We assume that farmers can enrol in the scheme as groups that present a collective conservation project. Following Bareille et al. (forthcoming), we model the response of landowners to the AB scheme using a coalition formation game with exclusive membership. The ultimate result of such a game is the set of stable coalition structures, the partition of farmers where no one has incentive to change group membership. Formally, we formulate a two-stage game and solve it by backward induction. In the second stage, for any group, farmers take decision on the location and number of plots allocated to habitat maximizing the aggregate utility of the group member. In the first stage, farmers decide on whether to become member or not of any given groups. In exclusive membership, the decision to join a coalition is subject to the approval of the member. The mathematical formulation follows.

In the second stage, land allocation is the result of the maximization of aggregate utility of coalition members, and it is described by:

$$\max_{X_{i \in I_j}} \sum_{j \in S} \Pi_j^{AB,S} \tag{7}$$

Where the utility of each coalition members is given by:

$$\Pi_j^{AB,S} = \sum_{i \in I_j} \left[P^{IB} \cdot X_i + P^{AB} \cdot X_i \cdot \sum_{\substack{k \neq j \\ k \in \Phi_j^S}} X_k + P_i^{AG} \cdot (1 - X_i) \right] \tag{8}$$

The result of the second stage is a vector of land use allocation for each plot for any possible group of landowners. Substituting we obtain $\Pi_j^{S,*}$

For the first stage, call Ω the configuration of a given coalition structure. Moreover, denote S and Z with $S \cap Z = \emptyset$ the composition of two coalitions being in the configuration of a given coalition structure Ω. Π_j^S the utility of farmer j being member of

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coalition S, and U_j^f the utility of farmer j behaving a singleton. The coalition structures that are stable, Π^*, meet the following conditions:

$$\Pi_j^S > \Pi_j^f \ \wedge \ \Pi_k^S > \Pi_k^{S-j} \quad \forall S \in \Omega \text{ and } \forall j, k \in S \tag{9}$$

$$\Pi_j^S > \Pi_j^{Z+J} \vee \Pi_k^Z > \Pi_k^{Z+J} \ \ \forall S, Z \in \Omega \tag{10}$$

The first part of condition (9) says that farmer j as a member of coalition S must find it more profitable than behaving as a singleton. The second part of condition (9) indicates that the other members of coalition S also find it profitable to accept j as a new member. Condition (9) should hold for any members of coalition S and for any coalition that compose a given coalition structure. Condition (10) indicates that player j, being a member of coalition S in the coalition structure Ω, is better off in coalition S than in coalition Z, or that the members of coalition Z would block her membership.

3.3.2.2 Empirical implementation

The model is run on a landscape composed by 7 farms, each of them owning 19 plots. Each plot is a regular hexagon of size 1 ha. The opportunity costs of habitat allocation are randomized according to a uniform distribution.

The benchmark scenario is defined by the following parameters. General to all the schemes analysed, we randomize the opportunity costs of habitat allocation creating 50 cost-randomizations. To randomize such costs, first we set the plot levels drawing values from a uniform distribution with a=50 and b=150. Second, to address farm specific productivity, we apply a farm-level drifter drawn from a uniform distribution with a=-50 and b=50. The dispersal rate is set at D=5, an intermediate level of species capacity to disperse. With respect to the RB scheme, we set PIB=0 and PRB up to the level that ensures that the full landscape is converted to habitat. Moreover, we assume a risk aversion parameter of $\rho_j = 0$, i.e. the farmers are risk neutral. For the AB scheme, we set PIB=0 and PAB up to the level that ensures that the full landscape is converted to habitat.

We run two sensitivity analysis. In the first one we change the RB scheme design. Two modifications are applied with respect to the benchmark scenario. First, we assume that farmers behave cooperatively as a single group. In such a case, farmers maximize the aggregate utility and there is no limited knowledge on the behaviours of the others. Mathematically, such a scenario is described by:

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$$\max_{X_i} \Pi^{IB} = \sum_i U_i^{RB}(X_i) \tag{6}$$

In this second case, the constraint described by 5.b does not apply: farmers have behaving as a group take decision together and there is no uncertainty on the behaviours of the others. Second, we vary the level of the PIB payment to observe whether this parameter affects the results of the RB scheme.

In the second scenario, we test the effectiveness of the different schemes according to the dispersal rate of the species under consideration. We re-run all the model under both D=10 and D=1. To interpret the results, consider that probability of species survival in the central plot depends on the habitat of the neighbouring plots by 6% in case D=10, 18% in case D=2 and 34% in case D=1. in other words, increasing the dispersal rate implies that a diffuser habitat configuration is needed for species survival.

3.3.3 Results

3.3.3.1 Benchmark

Figure 3-3 shows the habitat that is reached under the IB and RB schemes for different levels of payment. The results indicate that at a level of PIB=200, the entire landscape is converted to habitat in the case of the IB scheme. Much lower effect is obtained through the RB scheme, where a total payment of almost 500€/ha is needed to fully cover the landscape to habitat. Under the RB scheme, the per-hectare payoffs depend also on the actual presence of the species on the plot. In the case of the RB scheme, weight the nominal RB payment with the probability of species detection, that in turn depends on the entire (expected) landscape configuration. Hence a much higher payment is required to cover the opportunity costs than in the IB scheme.

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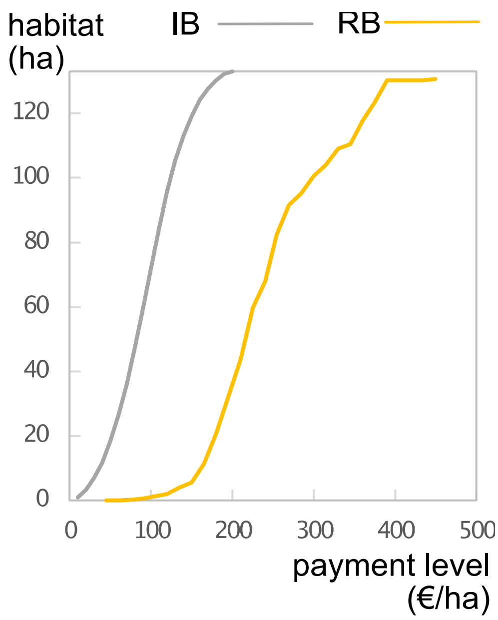

Figure 3-3. Habitat (ha) per different levels of payment levels (€/ha) in case of the RB (yellow) and IB (grey) schemes.

To further dig into the comparisons among the different schemes, Figure 3-4 shows habitat level (A), average opportunity costs (B), average connectivity (C) and biodiversity score (D) per public expenditures, under RB (yellow), IB (grey) and AB (violet) schemes. First, the comparison shows that the pure RB scheme performs much worse than the IB (as also the previous figure indicates) but also than the AB scheme in terms of habitat per expenditures. The AB and the IB schemes yield substantially similar results, with slightly higher habitat in the case of IB than in the AB for low level of public expenditures. Note that to fully convert the landscape to habitat, the RB scheme needs almost the double of public expenditures than the AB or IB schemes.

Bigger differences can be observed by looking at the average opportunity costs of the plots that each of the scheme manage to convert for different level of habitat. The AB scheme always selects more expensive plots than the IB scheme (on average). This result depends on the different target of the two schemes: the enrolment in the IB scheme only depends on the opportunity costs of the plot, while in the case of the AB, the payoffs depend also on the connections. As a result, the AB scheme leads to the selection of more expensive plots than the IB to implement the connections that are actually rewarded. Even the RB scheme, as its plot-level payoffs depend on the connectivity among the plots (given the assumptions on how the probability that the species is found in a plot), partially disconnects opportunity costs and enrolment. For low level of public expenditures, the

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RB scheme converts few plots (see previous discussion) but with on average the highest opportunity costs.

In terms of connectivity among habitat, the AB is the most performative scheme, reaching the highest level of connectivity for any level of public expenditure. Comparing it with the IB scheme (and recalling that show similar size of habitat) indicates that the AB does manage to cluster habitat. The least performative scheme is the RB, where the low connections are due to the low rate of conversion to habitat.

The overall result in terms of biodiversity per level of public expenditures shows a clear ranking. The most effective scheme is the AB, the IB scheme is slight less effective, while the RB scheme is substantially less effective. As we will see in the next section, this results however depends on how the RB scheme is designed and how the farmers enrolment is modelled.

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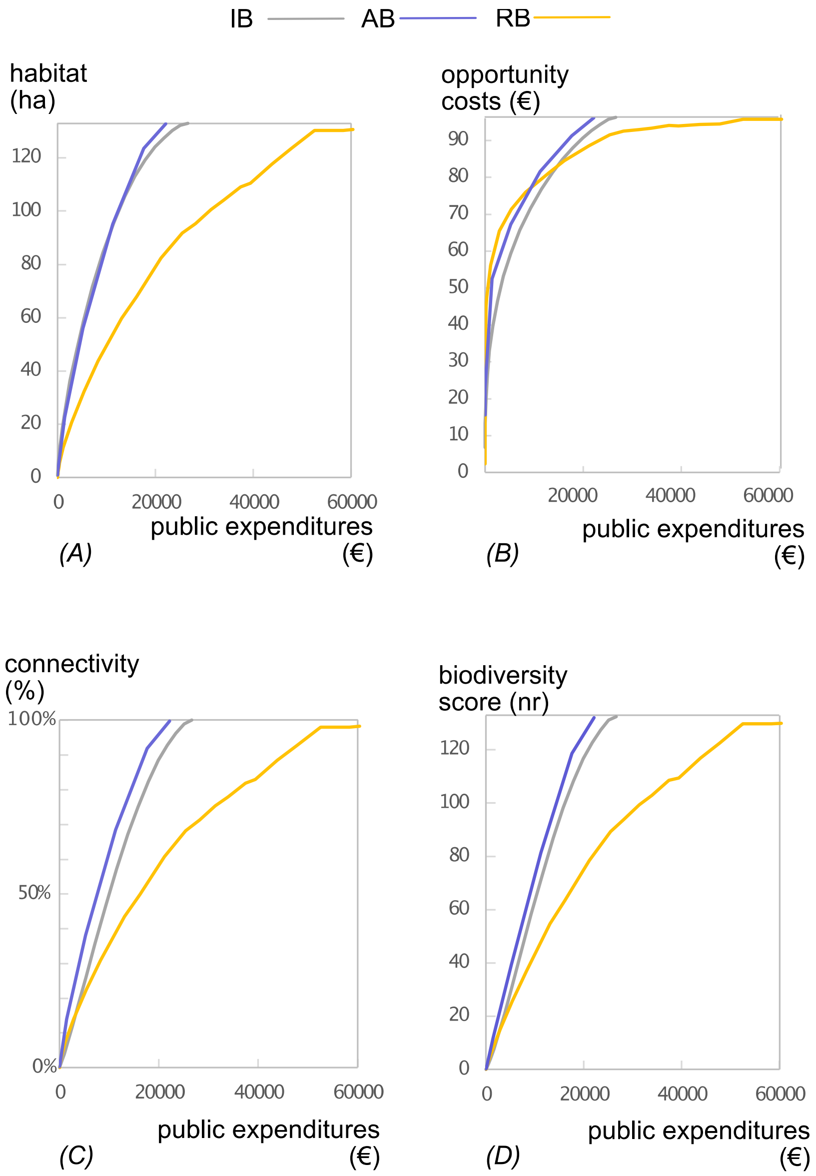

Figure 3-4. Comparison of the habitat level (A), average opportunity costs (B), average connectivity (C) and biodiversity score (D) per public expenditures, under RB (yellow), IB (grey) and AB (violet) schemes.

3.3.3.2 Sensitivity analysis: RB design and modelling.

Figure 3-5 compares the effectiveness of the IB and AB scheme with different designs of the RB schemes. More specifically, we change the level of the input-based payment within the RB scheme, and we also add the results of the RB scheme in case the farmers behave cooperatively in the decision to enrol (red lines in each of the graph). Increasing PIB causes a substantial improvement in the effectiveness of the RB scheme, while the overall ranking of the three schemes does not change. Moreover, the graphs indicate that if farmers cooperate on the RB scheme enrolment, such a scheme could

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become the most effective. When PIB=50, the Rb under cooperative enrolment outperforms any other scheme.

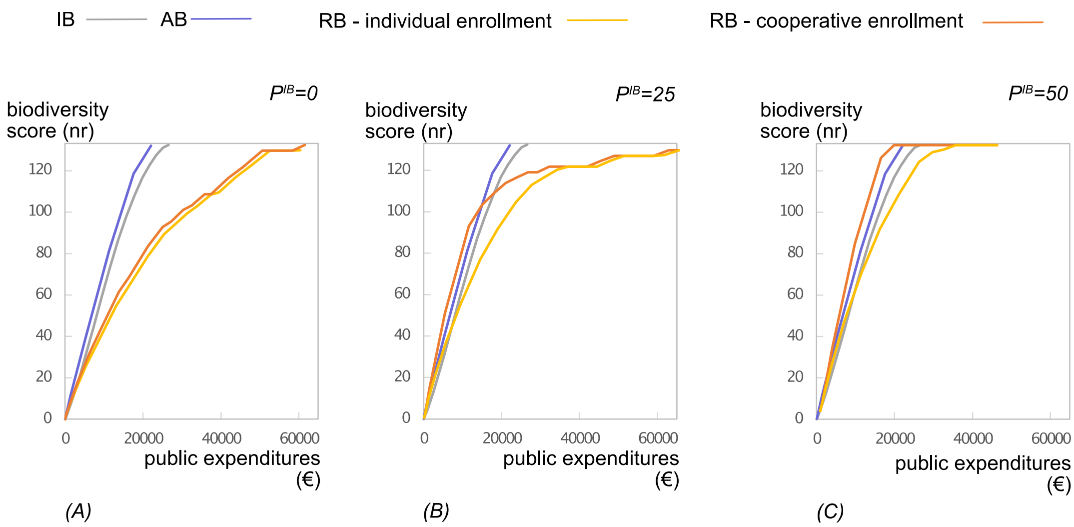

Figure 3-5. Biodiversity score per expenditures and for different designs of the RB scheme P^{IB}=0 (A), P^{IB}=25 (B), P^{IB}=50 (C). For comparison, also the results of the AB and IB schemes are displayed.

3.3.3.3 Sensitivity analysis: dispersal rate.

Figure 3-3 shows the habitat that is reached under the IB, AB and RB schemes for different levels of dispersal rate. The dispersal rate level affects all the scheme, albeit with different magnitudes. In the case of the IB and AB scheme, changes in the dispersal rate only affect the biodiversity score, but not land use and expenditures. As a result, differences in the effectiveness are not substantial, with a slight improvement in the AB with respect to the IB when the relative importance of neighbouring farms increases (higher dispersal rate). In the RB, the dispersal rate affects the overall results as the dispersal rate affect the probability of species survival, and hence expected payoffs. The results indicate that while the RB scheme remains the least performative options, its effectiveness increases with a reduction in the dispersal rate. Lower D entails an higher importance of neighbouring parcels, that in turn are more likely under control of the individual farms. Hence decreasing the dispersal rate reduces the dependence of the other farms, for which there is uncertainty on the land use allocation.

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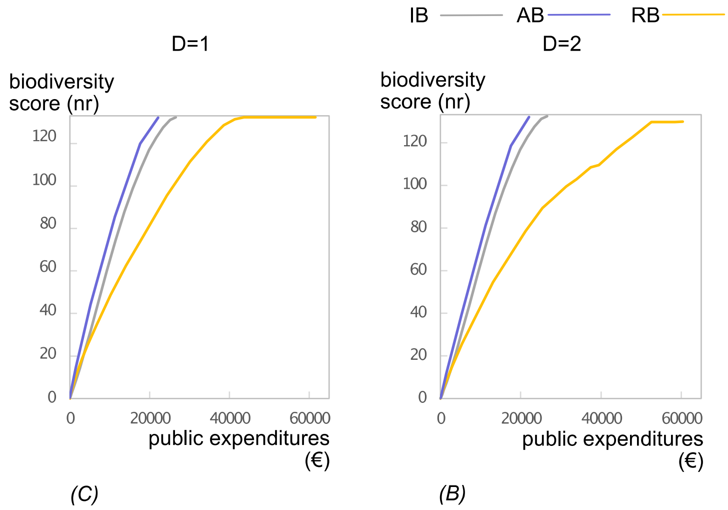

Figure 3-3. Biodiversity score per expenditures for different levels of dispersal rate D=0.1 (A), D=0.5 (B), D=0.9 (C).

3.3.4 Conclusions

The results indicate that when the local (plot-scale) biodiversity level is dependent on the entire landscape configuration, RB schemes are outperformed by both IB and AB schemes. In such a situation, collective schemes as the agglomeration bonus seem to be the most effective ones. The AB selects on average more expensive plots (in terms of opportunity costs), but by doing so create more connectivity among habitats ultimately leading to the highest effectiveness (biodiversity per level of public expenditures). The plot-scale nominal payments of the RB schemes are weighted for the probability of species survival success. If this depends on the actions of other farmers (for which only limited knowledge is available), very high nominal payments are required for habitat to become more profitable than agriculture. The overall result is then the low performance of result based. This general pattern is however reversed if farmers are assumed to behave cooperatively. In such a situation (and in case of a mix-instrument that combine result with input-based payments), the RB scheme becomes the most effective one. This points to future research focusing on mixed instruments combining the lessons from collective instruments with the one from result-based schemes.

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3.4 The optimal design of contracts aimed at reducing methane emissions from dairy farms (RB_SGGW)

3.4.1 Introduction

Mitigation of GHG emissions resulting from agricultural production is an important part of the debate on climate change. Cattle is considered the main source of agricultural methane emissions contributing to nearly half of GHG emissions from the Polish farming sector (NIR 2021). Each Member State of the EU is obliged to design AECM schemes to maximize the positive environmental impacts of the CAP. However, the programme's overall effect depends on the environmental efficiency of proposed measures and the share of farmers willing to participate. For the CONSOLE project we proposed a modelling exercise in which a set of specific measures orientated at reducing methane emission from dairy farms was considered. It is our own proposition of the agri-environmental measure constructed for the purpose of the study, which is not on the official list of the AECM schemes offered to farmers in Poland. In order to avoid confusion and linking it with the official Agri-Environmental Program in the further part of the paper we will call it a "Methane Mitigation Measure" – MMM. There are three actions reducing methane emissions included in this measure: (1) **dietary supplementation** (van Zijderveld et al. 2011), (2) **vaccination against Archaea** (Black et al. 2021), (3) **Biofiltration** (Melse, Van der Werf 2004).

The focus of the study is on assessing potential of result-based (RB) contractual arrangements to reduce methane emissions from dairy farms finding an optimal – the most cost-effective combination of defined MMM designs. The results for RB contract types were tested against model solutions for input-based (IB) contracts. The hypothesis set for the study is, that Result-Based contracts perform better in terms of cost effectiveness and have a higher potential to reduce methane emissions.

Analyzing various types of contracts for producing public goods by farmers, we attempted to model specific MMM designs that are the most cost-effective and have a potential of mitigating methane emission from dairy farms. Taking the perspective of public authorities, we attempted to find the design of MMM which would ensure reaching assumed environmental targets (reduction of methane emission) at the lowest taxpayer burden.

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The approach applied in the study combines the assessment of farmers' acceptance of methane mitigation instruments and the optimization procedure aimed at finding the most environmentally efficient structure of MMM providing assumed environmental effect. To investigate farmers' preferences, we designed and implemented a stated preference survey using the Discrete Choice Experiment (DCE), in which the following attributes have been included: type of contract (RB or IB), action to be applied (dietary supplementation, vaccination against Archaea and biofiltration), duration of the contract (1,5,10 years) and the payment rate.

These attributes were considered the most relevant (often classified as significant in the literature) and situationally representative (representing actual contractual characteristics at the time of the study).

The results of the logit regression model build upon the DCE results were used as constraints in the optimisation procedure aiming at defining an optimal set of MMMs assuring a given level of methane emission reduction achieved at the lowest possible cost.

Conclusions from the study will be presented to the Ministry of Agriculture in Poland with a suggestion of to add modelled measures to the Polish list of AECMs.

3.4.2 Model description

The modelling was carried out has been conducted in two stages. In the first stage farmers preferences were identified with the use of the Discrete Choice Experiment, allowing to estimate probabilities of specific choices to be made by farmers regarding methane reducing actions and preferred contractual arrangements.

For the second stage an optimization model providing the most efficient selection of MMMs designs was constructed.

3.4.2.1 Discrete Choice Experiment

To model farmers' preferences using modified discrete choice experiment data, logit model was applied with linear predictor:

$$\eta_{ij} = \boldsymbol{x}_i'\boldsymbol{\beta} + \boldsymbol{z}_{ij}'\boldsymbol{\gamma}; i = 1, \ldots, N; j = 1, \ldots, S$$

where vector $\boldsymbol{x}_i$ stands for respondent characteristics invariable across alternatives (i.e. number of cows at the farm) and vector $\boldsymbol{z}_{ij}$ represents characteristics which vary across alternatives (MMM design), N - number of farmers, S – number of MMM designs.

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It was assumed that the value of the linear predictor carries out the information that allows to determine the hierarchy of MMM alternatives reflecting their usefulness to the farmer. The estimated logit model was used for the calculation of probabilities of participation in MMM (j-th) for each farmer (i-th) in the sample. Probabilities were estimated with use of the following formula:

$$p_{ij} = \frac{\exp(x'_i\beta + z'_{ij}\gamma)}{1 + \exp(x'_i\beta + z'_{ij}\gamma)}$$

Calculated probabilities pij of participation in the program of the i-th farmer in the j-th MMM would be treated as constraints limiting the maximal share of farmers represented by i-th farmer that participates in the j-th MMM.

3.4.2.2 Optimisation model

The optimisation procedure is based on the linear optimisation model with the objective function to minimize total cost of the MMM's estimated for the given GHG emission reduction considering probabilities of making specific choices by farmers.

The objective function is as follows:

$$COST \rightarrow min = \sum_{i=1}^{N} \left(\sum_{j=1}^{S} F_i \cdot Q_{ij} \cdot \left(CPF_i + CC_i \left(PPC_j + CPC_j \right) \right) \right)$$

(Objective function)

Where:

F_i – number of farms in population represented be surveyed farm i

Q_{ij} – share of farmers represented by i-th farm decided to participate in j-th MMM

CC_i –number of cows per i-th farm

PPC_j – payment per cow for j-th MMM

CPF_i – cost per i-th farm (concluding contract costs, fixed costs of controlling farms)

CPC_j – cost per cow for j-th MMM (e.g. control costs)

The model assumes that, apart of payments for farmers, the total cost of the designed MMM program includes also transaction costs related to implementation of contracts and managing the programme (i.e. monitoring). Assumed transaction costs were

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divided into the fixed part – calculated for every farm taking part in programme and variable part - dependent on the number of enrolled cows.

Probabilities p_{ij} of the i-th farmer choosing specific MMM were used as a basic constraint in the optimisation model. It was assumed that the share of farmers represented by the i_{th} farm which would participate in the MMM have to be at the highest equal to the probability of participation estimated from the DCE. Thus:

$$Q_{ij} \leq p_{ij}$$

(1st constraint)

The total share of all farmers represented by the i-th farmer participating in all available MMM j=1,…,K were assumed not to be greater than the highest probability for all considered MMM measures (1..K for i-th farmer).

$$\sum_{j=1}^{K} Q_{ij} \leq \max(p_{i1}, \dots, p_{iK})$$

(2nd constraint)

This constraint keeps the total share of farmers participation in group of farms represented by i-th farm below the maximum achievable level. Using both constraints is necessary to ensure that each farmer in population will choose just one of offered MMM designs.

To make sure that the sets of MMM design with different payments rates (A, B, C) are represented adequately to probabilities of farmers participation reflecting respective rates and types of action (biofilters, vaccination, feed additives) the following constraints have been applied:

First type of action:

$$\sum_{j=1}^{K_1} Q_{ij} \leq \max\left(p_{i1}, \dots, p_{iK_1}\right)$$

(3rd constraint)

Second type of action:

$$\sum_{j=K_1+1}^{K_2} Q_{ij} \leq \max\left(p_{i(K_1+1)}, \dots, p_{iK_2}\right)$$

(4th constraint)

Third type of action:

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$$\sum_{j=K_2+1}^{K_3} Q_{ij} \leq \max\left(p_{i(K_2+1)}, \dots, p_{iK_3}\right)$$

(5th constraint)

There were three additional sets of constraints introduced to ensure that the sum of Q_{ij} shares for any combination of 2 types of actions is not greater than maximal probability for all MMMs with those types of actions:

Biofilters and additives:

$$\sum_{j=1}^{K_1} Q_{ij} + \sum_{j=K_1+1}^{K_2} Q_{ij} \leq max\left(p_{i1}, \dots, p_{iK_1}, p_{i(K_1+1)}, \dots, p_{iK_2}\right)$$

(6th constraint)

Biofilters and vaccines:

$$\sum_{j=1}^{K_1} Q_{ij} + \sum_{j=K_2+1}^{K_3} Q_{ij} + \leq \max\left(p_{i1}, \dots, p_{iK_1}, p_{i(K_2+1)}, \dots, p_{iK_3}\right)$$

(7th constraint)

Additives and vaccines:

$$\sum_{j=K_1+1}^{K_2} Q_{ij} + \sum_{j=K_2+1}^{K_3} Q_{ij} \leq \max\left(p_{i(K_1+1)}, \dots, p_{iK_2}, p_{i(K_2+1)}, \dots, p_{iK_3}\right)$$

(8th constraint)

Finally, the constraint which enforces a required minimal GHG reduction was added:

$$GHG_{red} \leq \sum_{i=1}^{N} \left(\sum\nolimits_{j=1}^{S} F_i \cdot CC_i \cdot GHG_j \cdot Q_{ij} \right)$$

(9th constraint)

The model presented above was aimed at selecting the most efficient set of MMMs designs to be implemented by farmers in order to achieve desired methane emission mitigation. From the perspective of farmers preferred choices would be most likely those with the highest probability of participation since it would correspond with MMM design with the highest utility. However, in this research we took a perspective of taxpayers represented by public authorities, offering MMMs to farmers in the most efficient way. Therefore, it was assumed that the basic criterion of choice is not the best utility for famers but the most cost efficient set the MMM designs offered. The procedure assumes calculating minimum costs of each possible combination of the considered MMMs at subsequent levels of the reduction of methane emission.

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3.4.3 Empirical implementation

3.4.3.1 Discrete Choice Experiment - revealing farmers preferences -

The initial plan included 54 MMM designs comprised of all possible combinations of attributes levels, differing in the type of action taken (3 options), the contract period (3), the method of determining the payment (2) and the rate of payment (3). The set of attributes and its level for DCE is presented in the table 3.4 1.

Table 3-4. Characteristics of DCE attributes and levels

Attribute	Levels
Type of action	feed additive (dietary supplementation)
	vaccine (vaccination against Archaea)
	biofilters (biofiltration)
Type of contract	Input Based – fixed payment
	Result Based - payment based on effect
Contract duration	1 year
	5 years
	10 years
Amount of subsidies	A- 80 EUR/t CO_2e
	B- 120 EUR/t CO_2e
	C – 200 EUR/t CO_2e

Payment per ton of mitigated emission was set at the levels of 80, 120 and 200 EUR/tonne of CO_2 equivalent (CO_2e). The rates of payments in the DCE were recalculated per cow for each type of the measure. In total 54 measures were designed being a combination of the above-mentioned attributes.

The plan of the DCE was prepared with 3 alternatives within each choice set:

- two of the three proposed actions (answers A or B);
- and a "no choice" option if for any reason farmer was not accepting A nor B choices.

An example of the DCE choice set as presented to the surveyed farmers is shown in the Table 3-5.

Table 3-5. Example of DCE choice set.

	Alternative A	Alternative B	
Type of action	Feed additive	Biofilters	NO choice
Type of contract	result based payment	constant payment	
Contract duration	1 year	10 years	

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Amount of subsidies	70 – 200 PLN/cow/year	860 PLN/cow/year	

In order to limit the redundancy and to simplify the experiment the number of choice sets was reduced with the use of the DB-error minimizing method. Applied coordinate exchange algorithm (CEA) implemented in the idefix package (R CRAN) allowed to prepare 36 choice sets. Each respondent was answering 9 choice sets selected randomly out of 36.

The experiment was run in 4 regions (NUTS 2) of Poland with the highest shares in the total country's milk production (Mazowieckie, Kujawsko-pomorskie, Podlaskie, Warmińsko-mazurskie), which covers nearly 60% of milk production in Poland. The field of observation was limited to farms keeping more than 20 cows. In total over 300 surveys were collected and used for modelling. It might be assumed that the sample represents about 25 thousand of farms with approximately 1 mln of cows.

The main goal of the DCE was exploring farmers' preferences regarding introduction of methane mitigation measures and identifying conditions under which farmers would be willing to conclude appropriate contracts for the production of public goods. Results of the experiment (answers A, B and C in each question) have been modified in the following way:

1. A binary variable Y (share) was created expressing the farmer's willingness to participate in a given MMM;
2. If the answer A or B was chosen, the variable Y was assigned the value 1, otherwise 0;
3. The variables describing the characteristics of MMM came from the chosen alternative A or B. If the answer C was chosen, it meant that neither of the answers A and B were chosen and thus for the value of the variable Y corresponding to alternatives A and B was 0. Consequently, in the case of If C was selected, two negative responses were obtained for A and B.

Based on the farmers responses collected from the DCE the logit regression model was estimated. The results of estimations are presented in the Table 3-6.

Table 3-6. Estimates of logit regression based on DCE results

.	Estimate	Std. Error	z value	p value
(Intercept)	0,7951	0,2679	2,968	0,003

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Action dietary supplementation	0,0026	0,2188	0,012	0,991
Action Vaccination against Archaea	-1,0194	0,2313	-4,406	0,000
Input Based payment scheme	-0,3845	0,0791	-4,859	0,000
Contract period	0,0063	0,0181	0,351	0,726
Payment rate B	0,5351	0,0990	5,405	0,000
Payment rate C	0,8438	0,0963	8,763	0,000
Farmers perception - no need for AECM	-1,5327	0,0960	-15,970	0,000
Dairy cows herd size	-0,0003	0,0023	-0,109	0,913
Number of workers	-0,1674	0,0480	-3,485	0,000
Farm financial standing	-0,4178	0,0573	-7,293	0,000
Farmers perception - methane impact on environment	0,3980	0,0393	10,117	0,000
Action dietary supplementation : contract period	-0,0876	0,0244	-3,591	0,000
Action Vaccination against Archaea : contract period	0,0029	0,0270	0,109	0,913
Action dietary supplementation : dairy cow herd size	-0,0085	0,0039	-2,181	0,029
Action Vaccination against Archaea : dairy cow herd size	0,0004	0,0034	0,120	0,904
Contract period : presence of farmers successor	0,0490	0,0163	3,005	0,003

Mc Fadden pseudo R-square 0.23

As it was presented in the model characteristics, the results of logistics regression was used to calculate probabilities of participation of every surveyed farmer in all considered MMMs, which created the matrix of 302 rows and 54 columns. Parameters from the matrix were used in the model's equations (constraints 1-8).

There were three main parameters of the objective function: assumed reduction of methane emission due to enrolling cow to the MMM, payments offered to the farmer and transaction cost of the MMM implementation.

Reductions of methane emission per cow were calculated based on the literature (Black et al. 2021, Van der Werf 2004, van Zijderveld et al. 2011).

For the Result Based MMM the possible effects were assumed based on the potential methane emission reduction for milk yields within the range 6000-10000 kg per cow per lactation. For the optimisation the average of minimum and maximum reduction value has been applied. The payments for farmers were calculated based on expected methane emission reduction and assumed payments rate in PLN per tonne of CO_2e. It was arbitrary assumed that for the Input Based MMMs the average methane reduction is 95% of the normative given in the literature, considering farmers have no incentive to increase effectiveness, as it is in the case of payments dependent on the results achieved. The assessments were made for the milk yield at the level of 6000 kg of milk per cow per

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lactation. Estimated transaction costs were allocated to contract types as presented in the Table 3-7.

Table 3-7. Allocation of assumed transaction costs to designed MMMs

Contract type	Result Based			Input Based		
Contract period [years]	1	5	10	1	5	10
Costs of establishing of the contract [PLN/ farmer/year]	400	80	40	200	40	20
Farm control costs [PLN/cow/year]	20	20	20	5	5	5
Farm control costs [PLN/farm/year]	100	100	100	100	100	100

The complete set of objective function parameters is presented in Table 3-8.

Table 3-8. Parameters for objective function in the optimisation model

Type of action	Payment rate	Type of contract	Contract duration [years]	Methane emission reduction [kg CO_2e/cow/year]	Payment for farmer [PLN/cow/year] PPC_j	Cost of MMM with variable implementation costs [PLN/cow/year] $PPC_j + CPC_j$
feed additive	A	RB	1	365.84	131.70	161.70
feed additive	A	RB	5	365.84	131.70	157.70
feed additive	A	RB	10	365.84	131.70	155.70
feed additive	A	IB	1	324.36	116.77	126.77
feed additive	A	IB	5	324.36	116.77	124.77
feed additive	A	IB	10	324.36	116.77	123.77
feed additive	B	RB	1	365.84	197.55	227.55
feed additive	B	RB	5	365.84	197.55	223.55
feed additive	B	RB	10	365.84	197.55	221.55
feed additive	B	IB	1	324.36	175.15	185.15
feed additive	B	IB	5	324.36	175.15	183.15
feed additive	B	IB	10	324.36	175.15	182.15
feed additive	C	RB	1	365.84	329.26	359.26
feed additive	C	RB	5	365.84	329.26	355.26
feed additive	C	RB	10	365.84	329.26	353.26
feed additive	C	IB	1	324.36	291.92	301.92
feed additive	C	IB	5	324.36	291.92	299.92
feed additive	C	IB	10	324.36	291.92	298.92
vaccination	A	RB	1	520.03	187.21	217.21
vaccination	A	RB	5	520.03	187.21	213.21
vaccination	A	RB	10	520.03	187.21	211.21
vaccination	A	IB	1	378.42	136.23	146.23
vaccination	A	IB	5	378.42	136.23	144.23
vaccination	A	IB	10	378.42	136.23	143.23
vaccination	B	RB	1	520.03	280.82	310.82

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vaccination	B	RB	5	520.03	280.82	306.82
vaccination	B	RB	10	520.03	280.82	304.82
vaccination	B	IB	1	378.42	204.35	214.35
vaccination	B	IB	5	378.42	204.35	212.35
vaccination	B	IB	10	378.42	204.35	211.35
vaccination	C	RB	1	520.03	468.03	498.03
vaccination	C	RB	5	520.03	468.03	494.03
vaccination	C	RB	10	520.03	468.03	492.03
vaccination	C	IB	1	378.42	340.58	350.58
vaccination	C	IB	5	378.42	340.58	348.58
vaccination	C	IB	10	378.42	340.58	347.58
biofiltration	A	RB	1	1084.60	390.46	420.46
biofiltration	A	RB	5	1084.60	390.46	416.46
biofiltration	A	RB	10	1084.60	390.46	414.46
biofiltration	A	IB	1	946.05	340.58	350.58
biofiltration	A	IB	5	946.05	340.58	348.58
biofiltration	A	IB	10	946.05	340.58	347.58
biofiltration	B	RB	1	1084.60	585.68	615.68
biofiltration	B	RB	5	1084.60	585.68	611.68
biofiltration	B	RB	10	1084.60	585.68	609.68
biofiltration	B	IB	1	946.05	510.87	520.87
biofiltration	B	IB	5	946.05	510.87	518.87
biofiltration	B	IB	10	946.05	510.87	517.87
biofiltration	C	RB	1	1084.60	976.14	1006.14
biofiltration	C	RB	5	1084.60	976.14	1002.14
biofiltration	C	RB	10	1084.60	976.14	1000.14
biofiltration	C	IB	1	946.05	851.45	861.45
biofiltration	C	IB	5	946.05	851.45	859.45
biofiltration	C	IB	10	946.05	851.45	858.45

3.4.3.2 Optimisation model – providing the most cost-effective methane mitigation measures' design

In the optimization procedure the initial set of 54 MMMs was reduced to 18 measures covering three actions, 3 contract period and the contract type (IB, RB) at payment rates at the levels A, B or C. Taking into consideration 54 measures in the Discrete Choice experiment was rational for identification of farmers' preferences expressed as maximal probabilities of participation. However, in reality only one, specific rate of payment might be offered at one time for one specific action. As each of the actions could be offered at the three different payment rates resulting with the maximum set of 27 combinations of MMM designs. The MMM designs were being introduced to the model subsequently, starting with those offered at the lowest rates (the most cost efficient, however with the lowest probability of acceptance by farmers). Thus in the first step

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farmers were offered MMMs with the payment rate A (A,A,A) for biofilters, vaccination, feed additives respectively, followed in next steps by all available combinations of payments (e.g. A,A,B; A,B,A), up to all sets with the highest rates (C,C,C). Each of the sets with a specific payment rates e.g. A,A,A, introduced to the model, contains K elements (different type of action, time of contract and type of contract). In the case of optimization limited to one type of the contract (IB or RB) K=9.

It was assumed that each i-th farmer in the sample represents specific number of dairy farmers form population. Therefore probabilities P_{ij} reflects maximal share of farmers represented by i-th farmer interested in participation in the j-th MMM. Thus in the model it was allowed to participate of i-th farmer in several designs of MMM (j=1,…,K).

For each set of the MMM design the optimization model was solved. The model for single MMM design set consisted of 5436 (32*18) decision variables and 7551 constraints (302*18 - 1st constraint; 302*7 – 2nd to 8th constraints +1 – 9th constraint). After solving models for all MMM sets the model results characterized by the lowest cost of implementation required emission reduction was selected.

The requested reduction of methane emission started from 20kt of CO_2e and was raised by additional 20 kt CO_2e in each model iteration until reaching the maximum methane emission reduction level. The total amount of the assumed reduction was achieved including farmers participating at the highest possible level of payments at the rates C for all types of actions. It was required to run 24 iterations in the case of IB types of contracts totalling with the reduction of about 480 kt CO_2e and 32 iterations in the case of RB types of contract (up to ~ 640 kt CO_2e).

After ranking the results of all the considered variants in terms of environmental performance, expressed as the average MMM for a given combination, at the cost of unit methane emission reduction, a correlation curve between the amount of public funds spent and the environmental effect was obtained.

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3.4.4 Results

The optimization was performed separately for RB (result based) and IB (input based) MMMs. Comparison of results is presented on diagrams. Modelling results show that the performance of both, the RB and IB types of contracts is similar at less ambitious reduction targets. In the case of reduction targets up to 340 kt of CO_2e the optimal costs of implementation MMMs is very similar. In the case of more ambitious reduction targets the RB type of contract performs better (Figure 3-6).

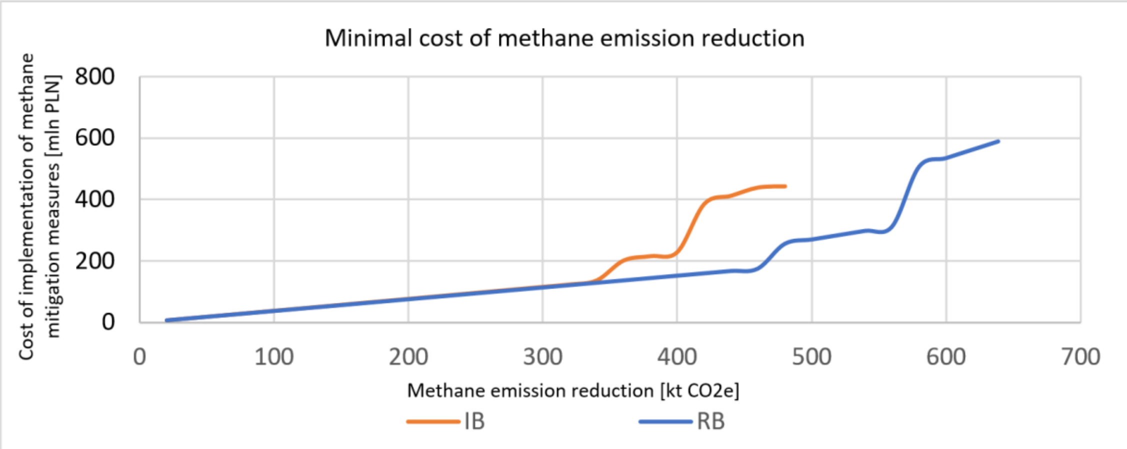

Figure 3-6. Costs and performance of methane emission reduction in Result Based and Input Based MMM.

Since the DCE results show a higher acceptance of RB type of contracts, also probabilities for participation in RB contracts are higher compared to the IB equivalents, assuming that other attributes of contracts are the same. The possibly higher participation of farmers in the MMM program influences the maximum reduction level which might be achieved. Within the adopted assumptions in the case of the IB type of contracts the reduction is slightly above 480 kt of CO_2e, while in the case of RB contracts the reduction reaches nearly 640 kt of CO2e. Because such specific measures have not been tested in reality in Polish conditions we may only hypothesize, that the RB payments provide a stronger incentive for farmers confident in their skills and abilities to achieve satisfying reduction in methane emissions.

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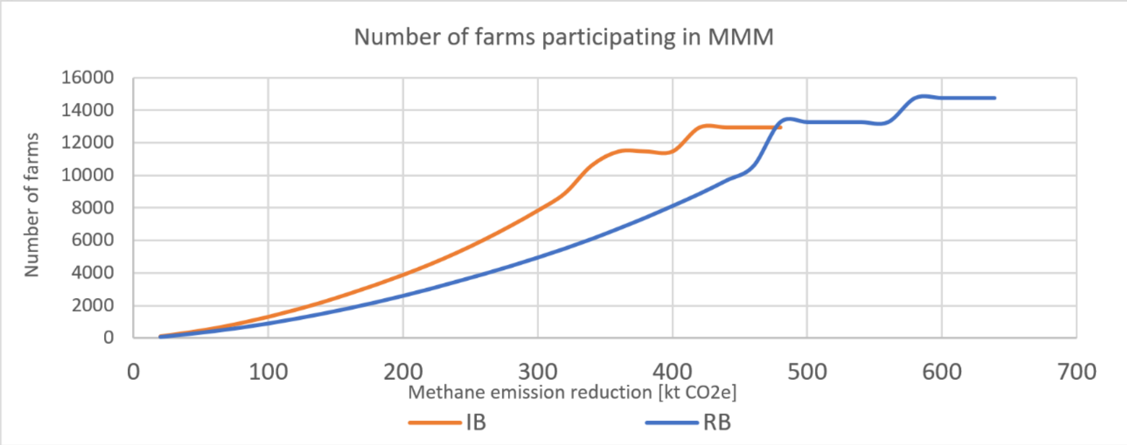

Figure 3-7. Number of farms participating in MMM.

The results presented on the Figure 3-6 correspond closely with the number of farms participating in the MMM (Figure 3-7). Due to the assumed lower efficiency of the IB type of contracts the higher number of farms participating in MMM is needed to achieve a requested methane mitigation emission. It needs to be pointed out, as elaborated in more depth in the next paragraph, that the farms participating in the IB scheme are on average slightly smaller. At the point of maximum reduction of emission for IB scheme the number of farms participating in RB contracts is similar, however due to higher probabilities of participation in the MMM, the maximum number of farms participating in RB programs is higher.

Comparing number of cows enrolled to MMM in RB and IB it in possible to point out that in case of RB the number of cows needed for reaching required methane emission reduction is lower. This is because of the assumption of the higher efficiency of methane emission reduction per cow in RB contracts. Thus for the same environmental effects more cows needs to be enrolled in IB than in RB contracts ().

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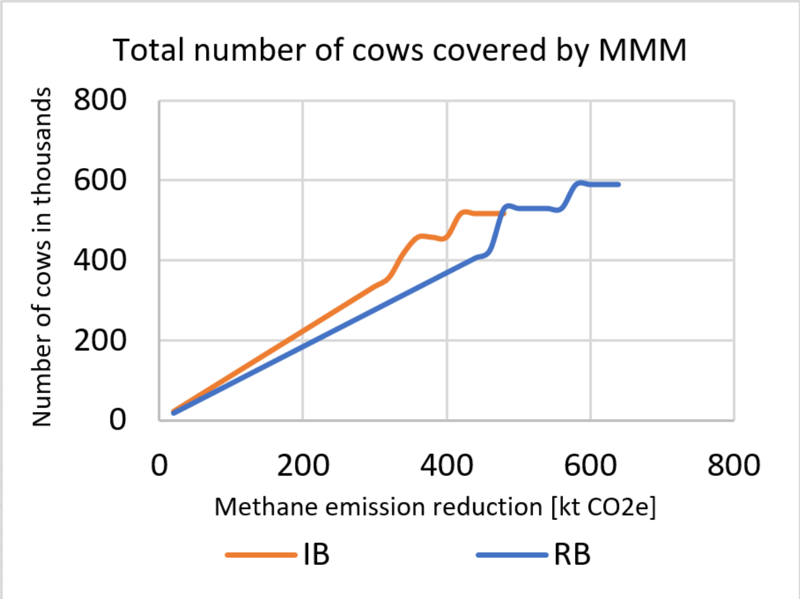

Figure 3-8. Number of cows in farms participating in MMM.

Comparing the average herd size in both types of contracts it could be noticed that in general the farms participating in RB contracts have bigger herds. Partly it could be explained by the assumption on transaction costs which, calculated per farm are higher in the case of RB contracts, but also by higher probabilities of participation in MMM resulting from the logit regression. Due to assumption on transaction costs calculated per farm, the model, in order to minimize the total costs of the methane reduction, starts to include the biggest farms from the very low methane emission reduction targets. As the probabilities of participation are on average higher in the case of RB contracts the greater number of big farms is participating, what results in the greater average herd size (Figure 3-9).

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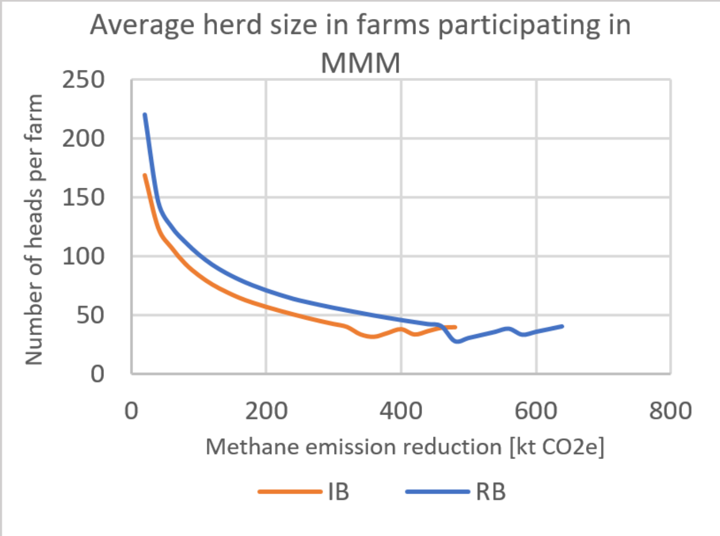

Figure 3-9. Average herd size in farms participating in MMM.

The optimal share of particular actions in model solutions differs between th Result Based and Input Based type of contracts. In both cases the results show biofiltration as the preferred and dominating type of action regarding number of cows covered by the MMM. In the RB contracts (Figure 3-10) biofiltration at higher ambitious emission levels is combined with vaccination against Archaea. High share of biofiltration in the model results could be explained by relatively high efficiency of this method according to the literature, and the results of the DCE, which show relatively high acceptance of farmers regarding this type of action.

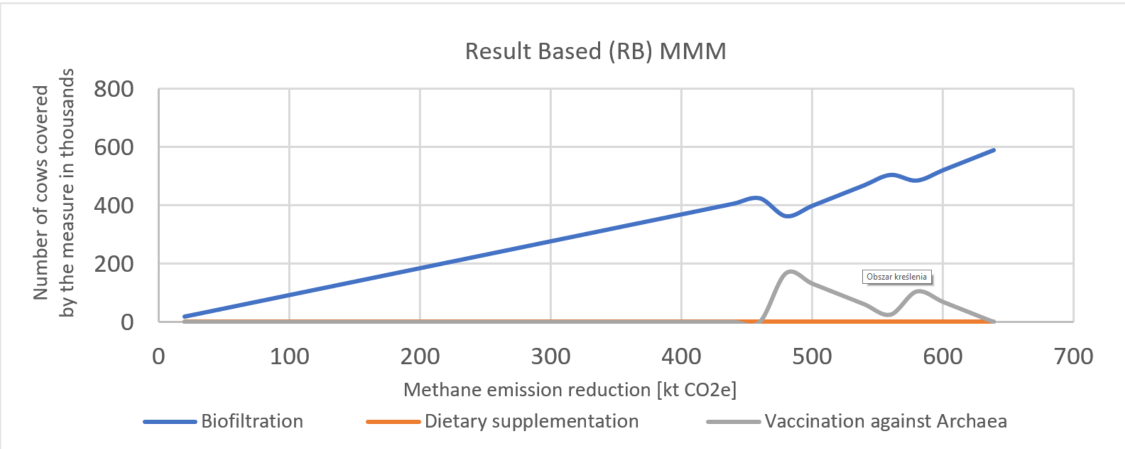

Figure 3-10. Number of cows in farms participating in Result Based MMM

Share of vaccinations in the model solution depends on the amount of the emission reduction which could be achieved at a given rate. It could be noticed that

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reaching the potential of biofiltration at a given payment rate results in the increase of the number of vaccinated cows. The share of vaccinations is growing until the total costs of MMM and requested methane mitigation reduction are justifying application of a higher payment rate for biofiltration. Reaching the maximum methane emission reduction level requires introducing biofiltration to its maximum extent, with the highest payment rates.

In the case of IB type of contracts the overall pattern of the optimal actions is similar to the patter characterizing RB contracts (Figure 3-11). Biofiltration is also the dominating action. However, it could be observed that in the case of reaching the maximum potential of biofiltration at the lowest payments rates both other actions are included in the optimal solution. This the case at the methane emission reduction level of 340 kt CO_2e.

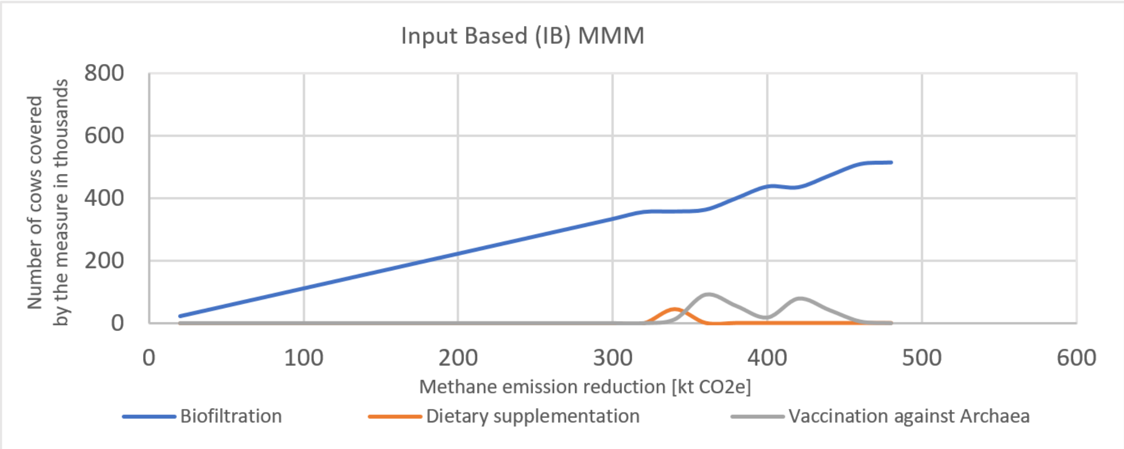

Figure 3-11. Number of cows in farms participating in Input Based MMM.

Moving towards more ambitious emission reduction rate the dietary supplementation share is decreasing to zero. This type of action is characterised by relatively low potential of methane emission reduction thus it is replaced at first by the vaccination and finally by biofiltration, which also in IB types of contracts is the only action allowing for highest methane reduction level.

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3.4.5 Conclusions

The results of the DCE reveal that farmers preferences to participate in MMM depends on the contract design, farmers perception and the farm characteristics. The strongest impact on the decision of participating in the MMM is farmers' perception of the impact of methane emissions on the environment. However also the elements of MMM design are influencing the farmers preferences, particularly: the type of action (biofilters, feed additive, vaccination), payment rates and type of contract (RB, IB). Duration of the contract itself does not differentiate farmers preferences, however duration of the contract in interaction of having a successor on the farm influenced farmers decisions. We also observed also that farm's financial standing has a strong negative impact on probabilities to participate in MMMs.

The proposed modelling approach allowed to create an optimal design of MMM to be offered for the farmers. The results of the model show that depending on the emission mitigation target the optimal set of MMM's to be offered is changing. The most efficient from taxpayers' point of view are biofilters supported by the Result-Based contracts. Having in mind the assumed transaction costs the most efficient are contracts with a longer duration. Input-Based contracts have an overall lower potential of methane emission mitigation.

The results of the research revealed several limitations of applied methodology. It could be pointed out that the real possibility of biofilters application, especially in smaller (< 50 cows) farms needs to be verified through a dedicated farm survey. Although the biofiltration is very efficient and the direct costs per cow are acceptable for farmers, the relatively high initial investment might be a barrier for a practical implementation in the case of smaller farms. It could be also concluded that a possibility of introducing selected MMMs, even with simplified procedure lowering transaction costs, might be considered also for farms with less than 20 cows.

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4 Discussion and Conclusion

The modelling exercises on result-based contract carried out in CONSOLE offer a wide overview on both the design of results-based schemes and their effectiveness. The main results by model are summarized in Table 4-1, while Table 4-2 shows the main messages by research question.

Table 4-1. Main results from the model exercises of task 4.3

Model	Issues analysed	Main messages
RB_UNIBO_1	Existence of an ex-ante monitoring technology for testing the probability of achieving target results	The e-ante monitoring technology is likely to increase enrolment and effectiveness of result-based scheme, especially at low level of public expenditures
RB_UNIFE-UNIPI	Performance of modelled result-based considering different value of public good	Designing a result-based scheme where results are modelled (rather than monitored) is likely to be more effective than traditional input based schemes
RB_UNIBO_2	Performance of result-based scheme in case of spatial spillovers among intervention sites	In the case of spatial spillovers among intervention sites, result based schemes are likely to be non-effective with respect to alternative instruments
RB_SGGW	Performance of results-based schemes in case of multiple contractual arrangements and prescriptions	Result-Based contracts perform better in terms of cost effectiveness and have a higher potential to reduce methane emissions.

Table 4-2. Main messages with respect to the main research questions in task 4.3.

Research questions	Main outcomes/results
How results-based contracts solutions can work under different legal contexts and for different environmental results.	Different mechanisms of environmental effect, in particular spatial spillover, can make result-based more or less effective and efficient than practice-based contracts. In the case of spatial spillovers among intervention sites, result based schemes are likely to be non-effective with respect to alternative instruments.
To what extent "real" result-based outperform proxies (or the other way round).	Designing a result-based scheme where results are modelled (rather than monitored) is likely to be more effective than traditional input-based schemes. Comparison with real result-based likely depends on conditions and reliability of proxy indicator and models assumptions .
Assessment of the difference between differences between compliance and result monitoring.	The difference between monitoring compliance or results itself has not been investigated. Difference between result-based and practice-based contracts show that depending on a set of variables one or

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	the other may be preferable in terms of effectiveness and efficiency.
How improved technological solutions (of different kinds) for monitoring and results measurement can improve the feasibility and performance of results-based contracts.	An ex-ante monitoring technology is likely to increase enrolment and effectiveness of result-based scheme. However, this depends on the level of knowledge of farmers and the budget available for the measure (it is more effective at low level of public expenditures).
How optimal results based contract should be designed?	Simulations indicate an higher efficiency of results-based contracts but their implementation should pay attention to the public transaction costs and the value of environmental public goods

Keeping in mind the general caveats that these exercises entail, the picture that emerges from the overview of the CONSOLE models seems to suggest that result-based schemes do not necessarily provide substantial improvements in the effectiveness of AES. Only in certain circumstances, defined by a combination of target AECPG, available technology and contract specific design, result-based schemes improve with respect to alternative contract design in terms of effectiveness.

Indeed, the model exercise RB_UNIBO_2 indicates that results-based schemes are outperformed by both input-based and collective schemes when the target result is the outcome of an environmental process that works at the landscape scale. In such circumstances, the collective approach seems the best instrument. The model exercise RB_UNIBO_1 indicates that the effectiveness of a result-based scheme is not substantially different from an input-based scheme, when the effectiveness is defined in terms of results per expenditures. Similarly, for low level of methane emission target, the model RB_SGGW shows that the costs of the measure of result-based are similar to those of an input-based scheme, whereas for high target result-based schemes are cheaper. This result is mostly due despite the lower participation rate of farms in a result-based scheme than in an input-based scheme.

However, this picture is changed under certain specific circumstances. First, the design of the instrument matters. The modelling exercise RB_UNIPI_UNIFE shows that a simulated result-based schemes does improve the effectiveness of AES aimed at reducing soil erosion. Such a design, at the same time, moves beyond the input-based contract types (creating a differentiation in the rewards for the practices implemented based on the value of the -simulated- results) and avoids the uncertainty that is likely to hamper the enrolment in *pure* result-based schemes. The modelling exercise RB_UNIBO_2 shows that a result-based scheme, if the input-based component of the nominal payment rate is relatively high and the farmers behave collectively, is the best

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instruments even in the case of biodiversity conservation. RB_UNIBO_1 indicates that if certain ex-ante monitoring technologies are available, result-based schemes are the most effective instruments in improving carbon sequestration by agriculture, in case of low expenditures.

More in general, the exercises show the difficulty of appropriate modelling and simulation of the response of farmers to results-based schemes and hence of assessing ex-ante their effectiveness and efficiency. On the other hand, this provides insights into relevant research gaps and pathways for future research in the field. There are three broad areas for further research emerging from this study.

First, behavioural aspects need to be better incorporated in modelling. Among the different behavioural aspects, in the case of pure result-based schemes, uncertainty is a crucial component of the analysis. As farmers' decision-making, when facing uncertainty, is likely to be affected by behavioural parameters such as risk aversion, modelling result-based schemes would certainly benefit from more reliable sources of risk-aversion estimates. More generally, modelling would highly benefit from improved empirical insights about preferences concerning contract aspects from e.g. experiment studies about farmers perception.

Second, more than for the simulation of traditional AES, modelling result-based requires appropriate mathematical descriptions of environmental processes, including impact and diffusion mechanisms, and of their relationship with farming practices. For example, spillovers, non-linearity and thresholds may be crucial here, letting alone the actual economic value of environmental improvement.

Finally, the details of the contract characteristics are very relevant for the final outcome. The literature and the modelling possibilities provide a limited set of cases and options compared with real-life solutions found. A wider investigation in this direction would allow to make models even more realistic and useful for practical decision-making.

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement GA 817949

6 Acknowledgment

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement GA 817949