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Technological innovations for biodiversity monitoring and the design of agri-environmental schemes[☆]

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ABSTRACT

Policymakers and scholars are increasingly interested in result-based schemes to improve the performance of biodiversity conservation policies. However, the availability and accuracy of monitoring technologies challenge a shift from traditional input-based incentives to result-based schemes. Inspired by recent technological developments, we develop a model based on a Bayesian framework to analyze the policy implications of potential improvements in biodiversity monitoring quality. Our numerical results suggest that improving monitoring quality increases the number of farmers enrolling in the scheme and their efforts. The availability of monitoring technologies with sufficiently high quality could make result-based schemes more performative than input-based ones. Monitoring developments might unlock the potential of result-based schemes and lead to their wider adoption.

1. Introduction

Biodiversity conservation policies need monitoring programs that accurately measure biodiversity trends and are affordable (Sommerville et al., 2011). Technological innovations applied to monitoring can improve the value of a biodiversity policy if they reduce costs and time/effort and overcome the need for technical expertise (e.g., taxonomists) that currently hamper the development of large-scale monitoring programs (Proença et al., 2017). Future perspectives in the advancements of monitoring techniques and approaches include citizen science (Ryan et al., 2018), DNA-based techniques (Hebert et al., 2016), automated image processing (Torresani et al., 2023) and automated passive acoustic monitoring (Biffi et al., 2024). In parallel, the recent developments of AI would enable the automation of processing the large datasets that monitoring technologies would create (Christin et al., 2019; Lahoz-Monfort and Magrath, 2021). These novel techniques will bring new possibilities for biodiversity monitoring and for the range of potential uses of biodiversity data. This technological advancement might also entail policy implications.

Traditionally, in agricultural landscapes, farmers have been incentivized to implement conservation practices through voluntary input-based payments (Hanley et al., 2012). For example, in the European Union Common Agricultural Policy, farmers may enroll in voluntary schemes to reduce the intensity of farming (either through a reduction of inputs or farmed land or through the establishment of seminatural elements) in exchange for a payment (Baylis et al., 2008; Gars et al., 2024). Often, these payments are based on the average opportunity costs, defined as the extra costs or loss of income involved in complying with the scheme. In such a case, biodiversity monitoring is mainly aimed at evaluating the policy impact and does not affect the potential farmers' efforts and decisions. Despite some positive results, these types of environmental subsidies have been criticized for not being capable of halting farmland biodiversity decline (Pe'er et al., 2022). One of their problems is that the reward for the farmers is not linked to any actual outcome in terms of biodiversity conservation. Thus, there is a high risk of spending money for no conservation results (Ferraro, 2008).

To solve these problems, the scientific literature has suggested the adoption of result-based agri-environmental schemes (Burton and Schwarz, 2013; D'Alberto et al., 2024; Derissen and Quaas, 2013; Drechsler, 2017; Herzon et al., 2018; Tanaka et al., 2022).[1] The idea behind this approach is to pay farmers not for their actions but for what they actually achieve in terms of conservation. Despite the apparent triviality of their rationale, implementing result-based schemes hides several challenges. One of the most relevant challenges is the uncertainty around the payoff for farmers enrolling in the scheme (Bartkowski et al., 2021; Derissen and Quaas, 2013; Drechsler, 2017). Indeed, result-

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[1] In the literature, result-based schemes are also alternatively called, for example, "outcome-based" (Tanaka et al., 2022), performance-based (Derissen and Quaas, 2013), or output-based (Drechsler, 2017).

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based payoffs are subject to two sources of uncertainty. First, the success of conservation is subject to environmental uncertainty due to, e.g., weather variations (González-Trujillo et al., 2023; Lindenmayer et al., 2019) and/or invasive alien species (McCann, 2000). Moreover, the effect of agri-environmental practices on biodiversity is not perfectly known (Duru et al., 2015). Second, result-based schemes inherently require monitoring activities to indicate whether a biodiversity target has been reached and consequently to gauge the payment on a measure of biodiversity. Monitoring, in turn, is subject to errors (Henry et al., 2008) that would hence further exacerbate the environmental uncertainty. For example, the malfunctioning of a passive acoustic monitoring device could prevent detecting a target species (Markova-Nenova et al., 2023). Such uncertainty creates an economic environment in which undertaking (costly) efforts to reach a biodiversity target could lead to unsuccessful outcomes that would not be rewarded in a result-based scheme. This uncertainty, in turn, might negatively affect the willingness to enroll in such a scheme.

Our paper aims to provide a framework to evaluate how monitoring quality affects agri-environmental schemes' design. Using a theoretical model, we show how monitoring quality affects farmers' decision to uptake a result-based scheme and, eventually, how it affects the agri-environmental scheme design. In detail, first, we analyze farmers' decisions on the intensity of effort to conserve biodiversity under a result-based scheme. We assume that farmers know the quality of monitoring, i.e., the probability that monitoring will correctly detect their success in conserving biodiversity (or, on the opposite side, to make mistakes). Second, we introduce farmers' reactions to the regulator's decisions to adopt better monitoring technologies and implement result-based schemes (rather than input-based ones). We model this second aspect through a Bayesian framework, in which monitoring quality is used to update the belief about biodiversity conservation success.

The novelty of this paper relates to the analysis of the impact of biodiversity monitoring quality on the performance of result-based agri-environmental schemes. The issue of uncertainty associated with result-based schemes has been analyzed for a long time (Bartkowski et al., 2021; Derissen and Quaas, 2013; Drechsler, 2017). However, to the best of our knowledge, the distinction between the uncertainty generated by environmental processes and by monitoring quality has not been addressed. The distinction is, however, important as the latter is an endogenous variable for policymakers (Zabel and Roe, 2009). More in general, while it has not been evaluated in terms of scheme design, monitoring has often been indicated as a challenge for the implementation of result-based schemes, and it is increasingly analyzed (Alblas and van Zeben, 2023; Granado-Díaz et al., 2024; Tanaka et al., 2022). Furthermore, in a recent survey, D'Alberto et al. (2024) reported that monitoring is a critical factor for the attitude of farmers toward result-based schemes. Also, Bayesian approaches for the assessment and design of monitoring biodiversity are not new (Runge et al., 2011). For example, Polasky and Solow (2001) apply it to the problem of site selection, and Drechsler (2000) suggests it (but does not analyze) to explicitly take into account the improvement in data to choose among different management options. However, it has not been used to evaluate the performance of result-based schemes.

The paper's results have a range of implications related to the formulation of biodiversity policy and, in particular, to the potential implementation of result-based schemes to improve agri-environmental policies. As our model suggests, the availability of monitoring technologies (their accuracy and their costs) affects the net value of biodiversity conservation created by result-based schemes. This ultimately determines the design of agri-environmental schemes targeting biodiversity (Gibbons et al., 2011), i.e., what type of incentive should be implemented. As we will see, result-based schemes provide a higher net expected value from biodiversity conservation than input-based ones, but only if monitoring accuracy is relatively high.

The paper proceeds as follows. Section 2 reviews the implications of improving biodiversity monitoring performance. In section 3, we describe the model and its results. Section 4 discusses such a result and concludes.

2. Background: An overview of biodiversity monitoring technologies, their performance, and their costs

Balmford and Gaston (1999) claimed that money spent on biodiversity data collection is worth its cost. However, quantitative evaluations of the cost-effectiveness of different sampling protocols are rare or based on significantly simplified cost estimations (Gardner et al., 2008). The costs of biodiversity monitoring depend on the objectives and use of the information provided (Caughlan and Oakley, 2001). Monitoring for policy compliance, targeting and evaluation, scientific research, etc., requires different approaches and protocols, thus incurring widely different costs. Moreover, for the same objective, strategies and, therefore, costs may vary considerably (Schmeller et al., 2015). Monitoring cost considerations are particularly critical when the condition for a voluntary monetary payment is linked to the provision of an environmental service (Gibbons et al., 2011). This is the case for payments for environmental services (Wunder, 2015), and more particularly for result-based schemes in which cost-effective[2] monitoring is important for their success in achieving conservation targets (Schaub et al., 2025).

The identification and development of indicators and monitoring approaches fitting to result-based schemes are the focus of several studies (Elmiger et al., 2023; Matzdorf et al., 2008; Pinto-Correia et al., 2022) because these are substantial in determining or hampering their acceptability and their successful implementation (D'Alberto et al., 2024). Indicators for biodiversity monitoring should be designed to be ecologically relevant and cost-effective according to the context (Cantarello and Newton, 2008). Therefore, generalization about cost and feasibility is difficult as different indicators have strikingly different costs and involve different protocol requirements for the measurement of parameters along with notable labor time differences (Carlson and Schmiegelow, 2002; Levrel et al., 2010; Targetti et al., 2014). Although cost differences are too wide to provide a consistent overview, general evidence converges to consider labor and the availability of taxonomic expertise as the critical resources for field-based indicator measurements (Gardner et al., 2008; Ji et al., 2013; Qi and Perry, 2008; Targetti et al., 2014).

In this prospect, several strategies have been suggested, such as data collection based on lower expertise (and thus low-cost) or innovative monitoring technologies relying on (semi)automatic identification that thus allows reduced labor time requirements. Levrel et al. (2010) and Oliver and Beattie (1996) suggested that inventories of terrestrial invertebrates generated by non-specialists (e.g., based on morphospecies) were potentially cost-effective. For instance, estimations point to potentially relevant cost reductions for biodiversity surveys if citizen scientists could be engaged. Breeze et al. (2021) report costs for different pollinator monitoring schemes, designed to identify trends in the abundance of insect pollinators in the UK, ranging between £6159/year for a low-intense volunteer scheme vs. £2.7 M/year for an intense professional-based monitoring network. Based on a European-level farmland biodiversity pilot sampling, Targetti et al. (2014) estimated up to 77 % cost saving for a farm-level biodiversity sampling in the case of volunteer-based fieldwork. Levrel et al. (2010) reported that up to 4.4 M EUR had been saved by the French administration thanks to the involvement of citizen scientists in the national-level butterfly and bird biodiversity monitoring. Note that cost savings are only some of the many advantages of citizen science approaches. This is particularly true in the case of farmland biodiversity monitoring, as the potential engagement of farmers in monitoring would disclose several additional

[2] We use the term *cost-effective* to indicate the cheapest option to obtain a desired level of accuracy, where accuracy can be measured in terms of statistical power (Beranek et al., 2024).

positive impacts on agricultural sustainability (Ryan et al., 2018).

Innovative technologies developed for biodiversity monitoring may have the potential to be employed for result-based schemes. Franco et al. (2007) found that a traditional bird transect survey was more cost-effective than telemetry, but targets and range influenced such a result. For instance, telemetry was the most cost-effective in poor access areas. Technical and data analytical advancements based on Unmanned Aerial Vehicles (UAV) make this option a valid alternative for monitoring biodiversity (Torresani et al., 2023). Results from on-ground comparisons of UAV and expert-based surveys of the presence of flowers as a proxy for pollinator abundance outline that UAV is not currently a 'game changer' for result-based schemes. Further research on standardized image elaboration is needed for real-life applications (Schöttker et al., 2023). Higher computation post-processing costs of UAV outweigh the reduced field-labor efforts. However, as a reduction of technology-related costs is expected, and as the lower unitary costs per area compared to field sampling allow economies of scale in the case of large-area monitoring, there is likely a relevant future potential for UAV monitoring.

Markova-Nenova et al. (2023) analyzed the cost/effort of bird monitoring based on passive acoustic recording to identify affordable monitoring solutions for result-based schemes. Results outline lower costs for human observation for 'normal' daytime monitoring. Acoustic monitoring had, on the contrary, a cost advantage in cases of monitoring of rare species that require more field trips or nighttime sampling. C.a. 250 EUR /ha per day and nighttime monitoring in human monitoring vs. c.a. 175 EUR /ha in case of passive audio monitoring were estimated. Attention is also growing on the development of DNA-based techniques, but available cost estimations show contrasting results. Gueuning et al. (2019) reported almost double costs for metabarcoding in comparison to species identification. However, the result was based on laboratory activities only, as the same fieldwork sampling served both parameter estimations. Opposite results are reported by Ji et al. (2013) for arthropod and bird monitoring. DNA sampling costs (from samples to taxonomies) were four times smaller in the three different countries of the study in comparison to the use of taxonomic expertise. The Centre for Biodiversity Genomics indicated significant cost reductions from bulk samples to species assessment (Secretariat of the Convention on Biological Diversity, 2021). The result was based on the consideration of decreasing analytical costs and a sequencing output of instruments approximately doubling every nine months. Such reports outline a range of potential advantages of metabarcoding, including laboratory skills that are more abundant than taxonomic expertise, the possibility to centralize the analysis in a few labs (a single instrument can currently process samples containing millions of specimens in a month), and availability of samples for third party verification. However, the use of DNA techniques in result-based schemes is conditional to the availability of databases fitting to the agro-ecological area and a future consistent reduction of reagent costs (Steinke et al., 2022). Bartkowski et al. (2021) suggested circumventing the monitoring problem for result-based schemes employing *models* instead of direct monitoring data. Such an approach would ensure a range of advantages, including minimizing risks for farmers and, thus, an expected higher uptake of environmental schemes. However, this would also give up several positive aspects of result-based schemes. Some advantages of result-based over input-based are, for example, the valuable provision of information about biodiversity status, the inclusion of farmers' knowledge in the process, and the stimulation of innovation connected to the 'production' of biodiversity.

Concerning the analysis of cost-effective monitoring solutions, results from several studies outline a non-linear relation between indicators requiring higher efforts for their measurement and their accuracy as biodiversity proxies (e.g. Gardner et al., 2008; Qi and Perry, 2008). Similarly, findings reported by Lüscher et al. (2014) and by Targetti et al. (2016) suggest that relatively low-cost parameters such as vegetation are accurate, economically feasible, and capable of conveying information to a range of users like farmers, administrators, and consumers. This is relevant for the setting-up of monitoring schemes for result-based schemes. Indeed, farmers need clear information about their capacity and/or probability of producing biodiversity, and therefore, intelligibility and trust in the measurement are of primary importance to facilitate the adoption of such contracts (D'Alberto et al., 2024; Gibbons et al., 2011). In this view, biodiversity monitoring for result-based schemes should not only provide reliable information on results but also inform farmers about their performances. This points to the relevance of including indicators that can reduce uncertainty for farmers and support their decision-making appropriately (Runge et al., 2011).

3. A framework for the assessment of different monitoring technologies

3.1. Model description

From the previous section, we understand that monitoring technologies vary in quality, costs, and the costs associated with improving accuracy. Building upon such findings, we now develop a model for assessing different monitoring technologies and their implications for designing result-based agri-environmental schemes. Our main intuition is that monitoring quality and its costs affect the net expected value of biodiversity conservation from result-based schemes.

First, we look at the perspective of the farmers. The key feature of a result-based scheme is that farmers who enroll are paid only if a specific conservation target is actually reached (and not for what they implement). As such, the economic environment in which farmers make decisions is subject to a double source of uncertainty. The first one is the natural stochasticity of environmental processes. The second one is the quality of monitoring, i.e., the accuracy of monitoring programs in detecting the success of conservation efforts if this is achieved. Here, we model monitoring quality as the probability of correctly identifying the achievement of a biodiversity conservation target. We embed monitoring quality in the farmer's program to evaluate its effect on their decision to enroll in a result-based scheme. Not surprisingly, increasing monitoring quality causes an increase in the farmers' enrollment and in the intensity of their conservation efforts. As accuracy is increased, for any given effort level, the probability of obtaining the payment is higher (while costs do not change), and hence, their payoffs are greater.

Second, we introduce these elements in the regulator programs. Once the farmers have decided on the efforts and a certain level of conservation is reached, monitoring provides a message on the status of the biodiversity. We model the regulator perspective through a Bayesian framework, in which the message is used to update the probability of conservation success and, hence, the expected value of the result-based scheme (the value of conservation minus the payments that are attributed to the farmers). As this computation depends on the accuracy of the technology that is used, the regulator maps different monitoring qualities to their expected values and confronts them with their costs. Based on this, she then chooses the monitoring quality level that leads to the highest net expected value. Finally, she compares the net expected value of result-based schemes with that of input-based ones to decide what mechanism to implement. Monitoring quality affects then the net expected value of result-based schemes through three mechanisms: by influencing the efforts of the farmers, by determining the accuracy of the messages regarding the status of biodiversity, and by its costs.

We now mathematically describe the problem at stake. Imagine that there is a certain number of farmers in a given landscape. Each farmer (indicated by the index i) decides on the conservation effort level (e_i). For simplicity, assume that they can implement "low" or "high" conservation efforts (respectively $e_i = e_i^L$ and $e_i = e_i^H$) in addition to no enrollment ($e_i = 0$). For instance, 'non-intervention' practices, such as the delay of mowing a grassland, require lower efforts than an active intervention, such as seeding a flower strip. Assume that the higher efforts entail both a higher probability of achieving a given conservation target and a higher cost. We use β_i^H and β_i^L to indicate respectively the probability of conservation success under the high and the low efforts ($\beta_i^H > \beta_i^L$); similarly, we indicate the costs by k_i^H and k_i^L, with $k_i^H > k_i^L$.

Imagine that a regulator formulates a result-based scheme. In such a scheme, farmers would be rewarded if they enroll and if a biodiversity target is achieved and detected. Use $P > 0$ to indicate the payment level that farmers would obtain if the target were detected as a result of the monitoring. The payment is not attributed if the target is not detected (i.e., $P = 0$). Call η the monitoring results, i.e., $\eta = 1$ if the conservation target is detected and $\eta = 0$ if not. We assume that the regulator bears the cost of monitoring. Thus, this is not part of the farmers' decision framework. As described in the previous section, monitoring is imperfect, and errors can be made. Assume that the probability of correctly detecting the biodiversity target if this is achieved is $0 < m < 1$. In other words, m is our measure of monitoring quality. On the opposite side, $1 - m$ is the probability of claiming that the biodiversity is not achieved even if this was the case (i.e., probability of incurring a false negative; this attains monitoring specificity). For simplicity, we neglect the possibility of having false positives, i.e., the probability of detecting the biodiversity target if this is not achieved is equal to 0. Despite this simplifying assumption, the model adequately describes the main features of the problem at stake.

3.2. Farmers enrollment

As mentioned above, farmers who enroll in the scheme face a double source of uncertainty. The first is due to the stochasticity of environmental processes, represented by the two probabilities β_i^L and β_i^H. The second one is due to the imperfect capacity of the monitoring technology to detect the success of conservation (the target is achieved), represented by m. The probability of obtaining the result-based payment is then differentiated by the effort the farmers implement. In case of low effort, such a probability is $\alpha_i^L = m \bullet \beta_i^L$, i.e., the probability that conservation success is detected times the probability that it is actually achieved. Similarly, the probability for the high effort is $\alpha_i^H = m \bullet \beta_i^H$. Given these uncertainties, farmers enrolling in the result-based scheme are unsure about the payoffs they would obtain (Derissen and Quaas, 2013; Drechsler, 2017). Such a payoff is only certain ex-post, after the efforts' implementation and monitoring outcome. Hence, the decision to enroll is based on the *expected* payoffs. We assume that a farmer is risk-neutral, and in case of low effort, the expected payoffs are given by[3]:

$$\pi_i^L = m \bullet \beta_i^L \bullet \left(P - k_i^L\right) + (1 - m) \bullet \beta_i^L \bullet \left(-k_i^L\right) + \left(1 - \beta_i^L\right) \bullet \left(-k_i^L\right) \tag{1}$$

The first term in eq. (1) is the expected payoff when the biodiversity target is achieved, and the monitoring detects the improvement; the second term is the expected payoff if the monitoring does not detect the biodiversity target even if this is actually achieved; the third term represents the case when the biodiversity target is not achieved. In latter cases, enrollment in the scheme would only lead to the cost *of* k_i^L. Eq. (1) simplifies to $\pi_i^L = \beta_i^L \bullet m \bullet P - k_i^L$. Similarly, the expected payoff from enrolling and implementing the high effort is given by $\pi_i^H = \beta_i^H \bullet m \bullet P - k_i^H$. Farmers would then decide by exerting the effort (no enrollment, low or high effort) that would lead to the highest expected payoffs.

$$\pi_i = \max_{e_i}\left(0, \pi_i^L, \pi_i^H\right) \tag{2}$$

The level of monitoring quality determines whether farmers enroll in the scheme or not, and if enrolled, the effort level, ceteris paribus. First, consider whether or not the low effort leads to a positive expected payoff. This is checked by solving for m the inequality $\beta_i^L \bullet m \bullet P - k_i^L > 0$. Such a condition is verified if $m > m_i^L = \frac{k_i^L}{\beta_i^L \bullet P}$. Intuitively, the enrollment in the scheme makes sense only if the monitoring quality is sufficiently high. Otherwise, the uncertainty of monitoring will make enrollment unprofitable for farmers. A decrease in the opportunity costs and in the probability of improvement, as well as an increase in the payment level, decreases such a threshold. The threshold for having positive payoffs in the case of high effort is higher than that of low effort, as long as the ratio cost/probability is higher than that of the low effort $\frac{k_i^H}{\beta_i^H} > \frac{k_i^L}{\beta_i^L}$. By comparing the expected payoff in the high and low effort, we determine the monitoring quality threshold that causes the switch toward the high effort. Such a threshold is $m_i^{H*} = \frac{k_i^H - k_i^L}{\left(\beta_i^H - \beta_i^L\right) \bullet P}$.

To summarize, in case of low monitoring quality, very few farmers (only those with very low costs) enroll in the scheme. Once the monitoring has improved, farmers enroll by implementing the low efforts; further improvements in the monitoring quality lead to the implementation of the high effort. Fig. 1 depicts these patterns using a simple numerical example, which is described in A1 Appendix to section 3.2.

3.3. Policy implications: The decision to adopt a better technology

We now analyze the conditions under which it is advantageous, from the policy point of view, to adopt a technology of higher quality. To do so, we build upon the results of the previous section, but we take into

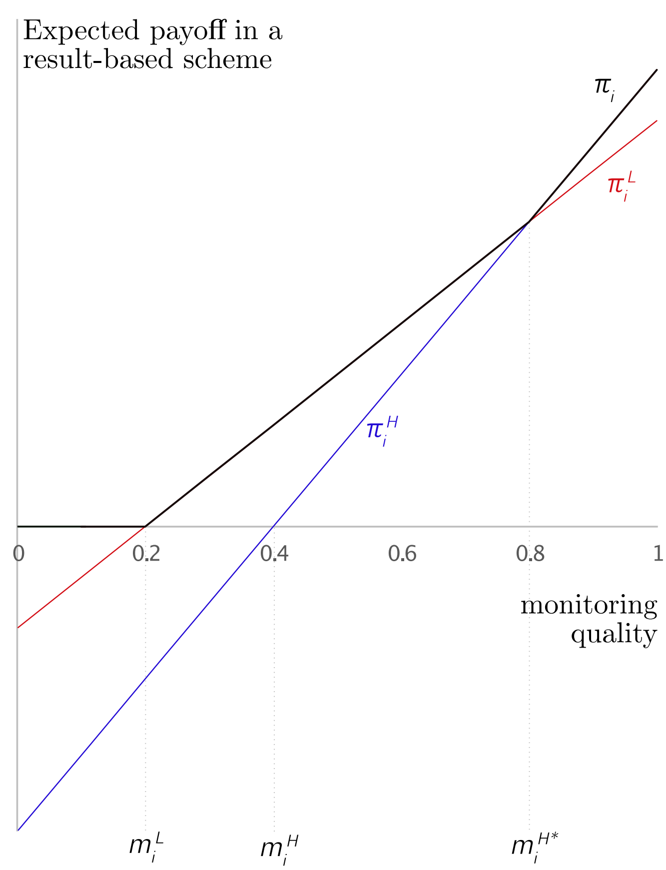

Fig. 1. Farmers' response to a result-based scheme under different quality of monitoring technology. The red line depicts the expected payoff if the farmer implements the low effort. In blue, the expected payoff is in case the farmer implements a high effort. The black line depicts the overall expected payoff implementing the optimal effort. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[3] Risk neutrality is surely a simplifying assumption (Iyer et al., 2020), but the model still captures the essential element of the issue at stake. Risk aversion can be included by, e.g., reformulating farmers' utility using a Bernoulli utility function, as in Drechsler (2017).

account a population of farmers rather than a single one. Moreover, we introduce a Bayesian framework to model a regulator's decision to adopt one of the available monitoring technologies, which are characterized by different quality (m levels) and costs. A critical but reasonable assumption is that the regulator knows the distribution of the relevant parameters (probabilities and the costs) across the farmers, but she is not able to define the parameter levels for each one of them. To evaluate the problem at stake, assume that there are only two monitoring technologies, one of low quality (m^l) and one with high quality (m^h), with $m^h > m^l$. High-quality technology is more expensive than low-quality technology, such as $C(m^h) > C(m^l)$. Intuitively, the regulator will adopt the high-quality technology if the expected value in terms of conservation generated by the scheme given the low-quality technology ($EV_{rb}(m^l)$) minus its costs is lower than the one provided by the high-quality technology ($EV_{rb}(m^h)$) minus its costs. Mathematically, adopting high-quality technology makes sense if $EV_{rb}(m^h) - C(m^h) > EV_{rb}(m^l) - C(m^l)$.

To compute $EV_{rb}(m^h)$ and $EV_{rb}(m^l)$, first, we assume that the regulator knows the behavior of the farmers given different monitoring qualities. In other words, for example, the regulator knows that farmers will start implementing the low effort only in case $m > \frac{k_i^L}{\beta_i^L \bullet P}$, as we have shown in the previous section. She also knows the distribution of the probabilities of reaching the biodiversity outcomes (β_i^L and β_i^H). To compute the values, first, it is necessary to update the probabilities of achieving the biodiversity target for each farm enrolling in the scheme, given the monitoring results (which are dependent on the monitoring quality) and the prior probabilities (which are β_i^L and β_i^H). Then, the expected value of biodiversity conservation (the economic value of biodiversity conservation minus the policy costs) for each possible monitoring result (detection or not of the conservation target) is computed. Finally, considering the total probabilities of the two possible monitoring results, the overall value is computed and aggregated over the entire farmers' population. The mathematical procedure is described in A2 - Appendix to section 3.3.

A simple numerical example, described in the appendix A2-b, illustrates the problem. For a given level of payment, moving from m^l to m^h entails an overall change in the farmers' responses. As shown in Fig. 2, increasing the monitoring quality causes an increase in the number of farmers that enroll in the scheme, with an effect greater for those farmers that have a higher prior of reaching the conservation target (to the right of both graphs). In our example, in the case of m^l, 879 farmers do not enroll, 50 farmers implement the low effort, and 70 farmers implement the high effort. In the case of high-quality monitoring, these numbers change to 656, 142, and 201, respectively. The amelioration in the monitoring quality causes an increase in enrollment and an improvement in the intensity of the effort, which enlarges the social value generated by the scheme. Overall, the RB scheme would enable obtaining $EV_{rb}(m^l) = 5876.16€$ and $EV_{rb}(m^h) = 13097.85€$ hence, the adoption of the high-quality technology makes sense if the difference in the cost between the high-quality technology and the low-quality one is lower than 7221.69€.

3.4. *Policy implications: Technology developments and the implementation of result-based schemes*

To investigate the issue further, we focus on the policy implications of the developments in monitoring technologies and examine how their associated costs are linked to improvements in accuracy. Imagine different monitoring technologies that are differentiated by the costs required to improve information quality. As an example, imagine that a monitoring technology is represented by expert-based sampling. Improving the quality of information would require, for instance, increasing the number of trips to the study site. Another technology might be the use of passive acoustic devices. Increasing the accuracy of the information would require increasing the number of such devices. In these two situations, the cost of monitoring a farmer is different for any given level of accuracy required. We model this notion by further qualifying the costs of monitoring. Assume that the costs of monitoring each enrolled farmer are a function of the monitoring quality and a parameter c. For simplicity, imagine a linear relationship. Call E the total number of farmers enrolled, i.e., those who exert a strictly positive effort as the eq. (2) solution. The monitoring cost of a result-based scheme is then $C = m \bullet c \bullet E$. Recall that the regulator bears such a cost, but the monitoring quality affects the total number of farmers enrolled.

We now explore the effect of advancements in monitoring technologies, represented by a reduction in the value of parameter c. In Fig. 3, we represent the simulations of the *net* expected value of the result-based scheme (the expected value minus the monitoring costs). We do so under two different monitoring technology costs, i.e., with $c^b < c^a$, with a fixed payment level (the numerical implementation is described in A2-b numerical examples). The decrease in the cost of monitoring quality (in Fig. 3, moving from the yellow to the blue curve) has two effects. First, the peak in the net expected value of the biodiversity conservation moves to the right, i.e., the optimal monitoring quality increases. Second, it increases the overall expected value of the biodiversity conservation generated by the result-based scheme. This second effect suggests that technology development might unlock the potential of result-based schemes, which would then provide a greater net expected value than input-based ones.

In an input-based scheme, farmers are offered a subsidy in exchange for a given effort in conserving biodiversity. Hence, in such a scheme, monitoring quality does not affect the farmers' response. Imagine that the scheme requires the implementation of a high effort at a payment P. Farmers enroll only if the opportunity cost is lower than the payment, i.e., if $P > k_i^H$. By aggregating all the efforts of the enrolled farmers, we obtain the resulting expected net value of the input-based scheme and compare it with the resulting value from the different result-based ones. One such comparison is depicted in Fig. 3, where the black line represents the expected net value of the input-based scheme. The graph suggests two main implications for the design of agri-environmental policies. First, there might be cases where the costs of the monitoring technology are so high that it is preferable to incentivize farmers through an input-based scheme. Second, there might be cases where the cost of a given technology would push the result-based scheme to yield the highest expected net value of conservation, but only if a minimum of monitoring quality is attainable. In the picture, if the monitoring quality is lower than about 0.6, the input-based scheme is the best performer.

4. Discussion and conclusion

Shifting to incentive schemes that pay farmers for what they achieve (i.e., result-based schemes) rather than for what they do (input-based schemes) is likely to improve the performance of biodiversity conservation policies (e.g. Meier et al., 2024). The relevance of such an approach is also highlighted in the Common Agricultural Policy (Regulation (EU) 2021/2115, 2024). However, among others, the poor performance of monitoring technologies (in terms of quality or costs) hampers the implementation of result-based schemes. Monitoring accuracy and cost are at the core of result-based schemes and have implications for their acceptability (D'Alberto et al., 2024; Granado-Díaz et al., 2024; Tanaka et al., 2022). A range of recent developments (e.g. Biffi et al., 2024) in monitoring technologies might have relevant effects on the design of result-based agri-environmental schemes in the near future. Inspired by recent technological developments, we provide a framework to analyze the policy implications of potential improvements in biodiversity monitoring quality.

Our framework is based on a theoretical model that we use to evaluate how an amelioration in the capacity to correctly assess the

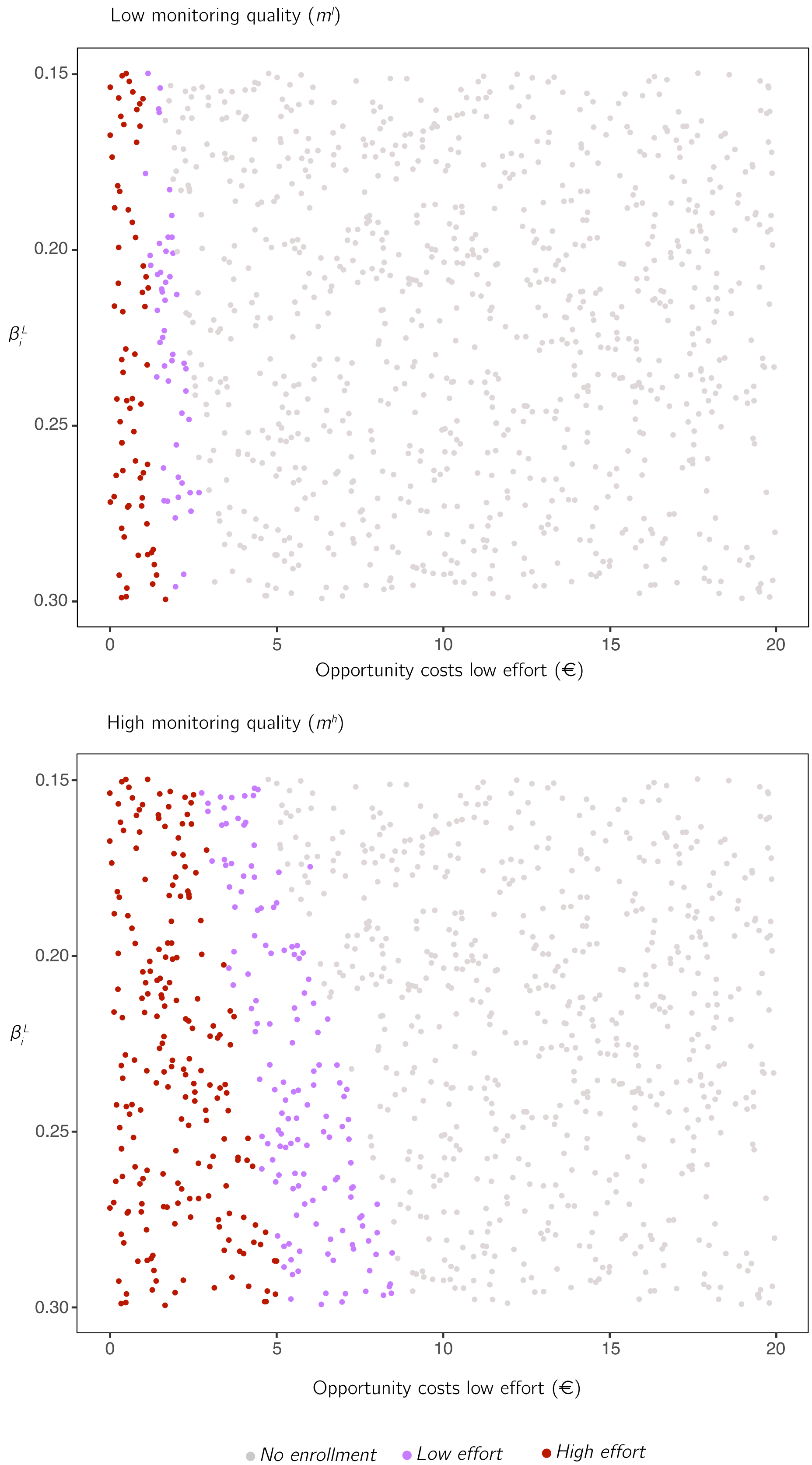

Fig. 2. Farmers' response to a result-based scheme in case of low (upper panel) and high (bottom panel) quality monitoring technologies. Each farmer is mapped by the probability of conservation success (β_i^L; y-axis) and by the opportunity costs (k_i^l; x-axis), both for the low effort. No enrollment is depicted in grey, and low and high efforts are shown in violet and red, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

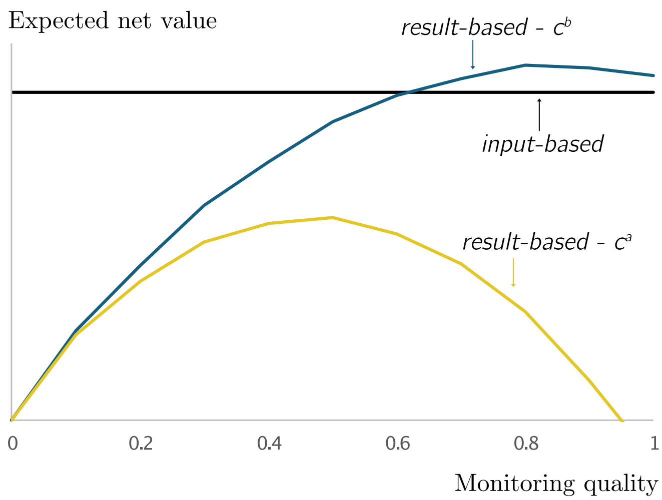

Fig. 3. The expected net value of two result-based schemes characterized by different monitoring cost levels ($c^a > c^b$, respectively in yellow and in blue) and the expected net value from an input-based scheme (in black). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

achievement of a biodiversity target affects the farmers' response in a result-based scheme. This result, in turn, is embedded in the regulator problem of selecting the monitoring technology and, ultimately, whether choosing a result-based or an input-based scheme. The results suggest that improving the monitoring quality increases the number of farmers enrolling in the scheme and their efforts. The improvement creates a higher expected value, in terms of biodiversity conservation, from the result-based schemes. Finally, if more precise or cheaper monitoring becomes available, result-based schemes are likely to improve the societal value of biodiversity conservation with respect to input-based ones.

The model relies on simplifying assumptions that deserve to be further explored. First, we do not address the possibility of having false positives resulting from monitoring. Their inclusion would influence the uptake of the result-based scheme as farmers' probability of getting the payment is increased. Presumably, this will also affect the decision on the expected effort invested by farmers. Second, the model assumes that monitoring quality is embedded in farmers' decisions. Likely, this is not straightforward in the real world, but the relevance of farmers' awareness and understanding of the indicators employed has been shown in a consistent body of literature (e.g. Elmiger et al., 2023; Pinto-Correia et al., 2022). This means that besides the monitoring quality, its capacity to convey information to farmers is of primary importance. Third, we assume that farmers are risk-neutral. Introducing risk aversion, as in Drechsler (2017), would undoubtedly enrich the analysis. Fourth, our approach relies on a monetary evaluation of biodiversity, which is necessary to compare the biodiversity outcome with the policy implementation costs. Despite the enormous literature on the topic (Bakhtiari et al., 2014; Nijkamp et al., 2008), and its importance in policy design (Dasgupta, 2022; Tienhaara et al., 2020), economic evaluation of biodiversity is a debated topic (Kallis et al., 2013; Nunes and van den Bergh, 2001). For example, most of the studies that evaluate biodiversity use proxies that do not fully account for the complexity of the issue (Bartkowski et al., 2015). Moreover, values might differ according to the provision scale (Hein et al., 2006). Finally, valuation depends on knowledge of the topic, which cannot be taken for granted (Spash and Hanley, 1995). For these reasons, the economic valuation of biodiversity should be taken cautiously. Further studies could extend the current framework in such a way that monetary evaluation is not necessary.

Despite the limitations, the results entail several policy implications. The recent developments in monitoring technologies -improving their accuracy and reducing their costs- can potentially change agri-environmental schemes' design and increase their performance (Biffi et al., 2024). More accurate monitoring technologies are important for designing result-based schemes as these allow for reducing costs and improving the quality of monitoring. Poor monitoring capacity has indeed so far hampered the adoption of result-based schemes (Bartkowski et al., 2021), and our results show that the choices on the scheme design depend on the monitoring technology. The availability of novel monitoring techniques, coupled with the advancement in other digital technologies (Ehlers et al., 2021; Wätzold et al., 2024), suggests the possibility of further experimenting with implementing results-based schemes. As such, policymakers should make an effort to review novel possibilities for biodiversity monitoring technologies frequently. From another perspective, this also means that the design of a biodiversity result-based scheme should involve an a priori consideration of the biodiversity targets that are of interest and that can be effectively measured.

CRediT authorship contribution statement

Matteo Zavalloni: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Stefano Targetti:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Davide Viaggi:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

A.1. Appendix to section 3.2

Basic algebra leads to the simplification of the farmer's expected payoffs. We represent eq. (1) for convenience: $\pi_i^L = \beta_i^L \bullet m \bullet P - k_i^L$. A farmer enrolls in the scheme and at least exerts a low effort if the expected payoff from such a decision is positive. Mathematically, we solve the following inequality:

$$\pi_i^L = \beta_i^L \bullet m \bullet P - k_i^L > 0 \tag{a1}$$

and hence: $m_i^L = \frac{k_i^L}{\beta_i^L \bullet P}$. Farmers with $m_i^L > m$ will implement the low effort. A parallel procedure leads to the definition of $m_i^H = \frac{k_i^H}{\beta_i^H \bullet P}$.

We now determine the conditions under which farmers would implement the high effort rather than the low one. This implies that the expected payoffs from implementing the high efforts are greater than those from implementing the low effort. Mathematically, we solve the following inequality:

$$\beta_i^H \bullet m \bullet P - k_i^H > \beta_i^L \bullet m \bullet P - k_i^L \tag{a2}$$

After rearranging (a2), we obtain $m \bullet P \bullet (\beta_i^H - \beta_i^L) > k_i^H - k_i^L$, or $m_i^{H^*} = \frac{k_i^H - k_i^L}{P \bullet (\beta_i^H - \beta_i^L)}$. If the monitoring quality is greater than $m_i^{H^*}$, the farmer would implement the high effort. An additional condition is that farmers would obtain positive expected payoffs. Mathematically this would entail that $m_i^{H^*} > m_i^H$, or that:

$$\frac{k_i^H - k_i^L}{P \bullet (\beta_i^H - \beta_i^L)} > \frac{k_i^H}{\beta_i^H \bullet P} \tag{a3}$$

After rearranging, (a3) becomes $\beta_i^H \bullet k_i^H - \beta_i^H \bullet k_i^L > \beta_i^H k_i^H - \beta_i^L \bullet k_i^H$, which, in turn, it simplifies to $\beta_i^L \bullet k_i^H > \beta_i^H \bullet k_i^L$, or to $\frac{k_i^H}{\beta_i^H} > \frac{k_i^L}{\beta_i^L}$. Hence, the ratio cost/probability determines the best course of action. In summary, a farmer starts enrolling and implementing the low effort if $m_i^L > m$. The farmer implements the high effort if $m_i^H > m$. This is shown in Fig. 1. Such a figure can be reproduced using $k_i^L = 2$, $k_i^H = 6$, $\beta_i^L = 0.2$, β_i^H=0.3, and $P = 50$, for each level of m from $m = 0$ to $m = 1$.

A.2. Appendix to section 3.3

A.2.1. Theoretical framework

We now show the steps to compute $EV_{rb}(m)$, given the Bayesian framework.

Using the Bayesian notation, the priors of our problems are defined by $\beta_i^* \epsilon [0, \beta_i^L, \beta_i^H]$, i.e., the probability of conservation success that is associated with the solution of the maximization problem described in section 3.2. For example, if the optimal choice for a farmer is $e_i^* = e_i^L$, then the prior is $\beta_i^* = \beta_i^L$. The monitoring quality $\theta(\eta|\nu)$ is the probability of detecting a successful conservation outcome ($\eta = 1$) or not ($\eta = 0$), given the status of biodiversity (if conservation is successful $\nu = 1$, otherwise $\nu = 0$). In other words, ν represents the true state of nature, i.e., whether the biodiversity target has been reached or not. η represents the monitoring message, which can be positive or not depending on the monitoring technology's intrinsic quality to detect the state of nature correctly. As explained in the text, we assume that $\theta(\eta = 1|\nu = 1) = m$, $\theta(\eta = 0|\nu = 1) = 1 - m$, $\theta(\eta = 1|\nu = 0) = 0$ and obviously $(\eta = 0|\nu = 0) = 1$. The probability of receiving a positive monitoring message given the prior belief of achieving the biodiversity target is, therefore, $\Psi_i(m, \eta = 1, \beta_i^*) = m \bullet \beta_i^*$, and the probability of receiving a negative message from monitoring (biodiversity target not detected) weighted on the prior belief of non-achieving the biodiversity target is $\Psi_i(m, \eta = 0, \beta_i^*) = 1 - m \bullet \beta_i^*$.

Given the results of the monitoring activities, the regulator updates her probability that the conservation target is actually reached. According to Bayes' theorem, the posterior probabilities depend on the prior belief of achieving the biodiversity target (β_i^*), the monitoring quality $\theta(\eta|\nu)$ (i.e. the probability of a positive message η, given the achievement of the biodiversity target ν), and the overall probability of receiving a positive message $\Psi_i(m, \eta = 1, \beta_i^*) = m \bullet \beta_i^*$ or a negative one $\Psi_i(m, \eta = 0, \beta_i^*)$=$1 - m \bullet \beta_i^* i$. The posterior probabilities, according to Bayes' theorem and using the notation of the model here described, are given by:

$$\Omega_i(m, \nu, \eta, \beta_i^*) = \frac{\theta(\eta|\nu) \bullet \beta_i^*}{\Psi_i(m, \eta, \beta_i^*)} \tag{a4}$$

In our simplified theoretical model, the posterior probabilities are therefore computed as follows. The posterior belief of achievement of the biodiversity target given a positive message is given by:

$$\Omega_i(m, \nu = 1, \eta = 1, \beta_i^*) = \frac{\theta(\eta = 1|\nu = 1) \bullet \beta_i^*}{\Psi_i(m, \eta = 1, \beta_i^*)} = \frac{m \bullet \beta_i^*}{m \bullet \beta_i^*} = 1 \tag{a5}$$

The posterior belief of non-achievement of the biodiversity target given a positive message is 0, as in our simplified model, we do not consider false positives; a positive message would shift the belief to certainty:

$$\Omega_i(m, \nu = 0, \eta = 1, \beta_i^*) = 1 - \Omega_i(m, \eta = 1, \nu = 1, \beta_i^*) = 0 \tag{a6}$$

The posterior belief of achievement of the biodiversity target given a negative message is given by:

$$\Omega_i(m, \nu = 1, \eta = 0, \beta_i^*) = \frac{\theta(\eta = 0|\nu = 1) \bullet \beta_i^*}{\Psi_i(m, \eta = 0, \beta_i^*)} = \frac{(1 - m) \bullet \beta_i^*}{1 - m \bullet \beta_i^*} \tag{a7}$$

The posterior belief of non-achievement of the biodiversity target given a negative message is:

$$\Omega_i(m, \nu = 0, \eta = 0, \beta_i^*) = 1 - \Omega_i(m, \eta = 0, \nu = 1, \beta_i^*) = \frac{1 - \beta_i^*}{1 - m \bullet \beta_i^*} \tag{a8}$$

We now compute the expected value generated by the farmer enrolling in the scheme once the monitoring positively detects the conservation target. This is given by:

$$\mathrm{EV}_i^{RB}(m, \eta = 1) = \Omega_i(m, \nu = 1, \eta = 1, \beta_i^*) \bullet (-P + B) - P \bullet [1 - \Omega_i(m, \eta = 1, \nu = 1, \beta_i^*)] \tag{a9}$$

The first term in equation (a9) is given by the multiplication of the probability of the achievement of the target (if the monitoring is positive) times the value of the biodiversity (B) minus the payment that is attributed to the farmer (P). The second term is the probability of actually not achieving the conservation target (despite the positive result from the monitoring) multiplied by the scheme's costs.

The expected value generated by the farmer enrolling in the scheme in case the conservation target is not detected is just represented by the value of biodiversity, as the payment, in this case, is not attributed:

$$\mathrm{EV}_i^{RB}(m,\eta=0)=\Omega_i\left(m,\nu=1,\eta=0,\beta_i^*\right)\bullet B \tag{a10}$$

We now combine equations (a9) and (a10) to have the overall expected benefit from the scheme generated by farmer i, multiplying $\mathrm{EV}_i^{RB}(m,\eta=1)$ and $\mathrm{EV}_i^{RB}(m,\eta=0)$ by respectively the probability that the result of the monitoring is positive or negative. This is the expected payoff attached to farmer i from his enrollment in the scheme, given the monitoring technology:

$$\mathrm{EV}_i^{RB}(m)=\Psi_i\left(m,\eta=1,\beta_i^*\right)\bullet\mathrm{EV}_i^{RB}(m,\eta=1)+\Psi_i\left(m,\eta=0,\beta_i^*\right)\bullet\mathrm{EV}_i^{RB}(m,\eta=0)$$

$$=m\bullet\beta_i^*\bullet\mathrm{EV}_i^{RB}(m,\eta=1)+\left(1-m\bullet\beta_i^*\right)\bullet\mathrm{EV}_i^{RB}(m,\eta=0) \tag{a11}$$

Finally, we sum over the farmers to obtain the aggregate benefits of the scheme: $EV^{RB}(m)=\sum_i\mathrm{EV}_i^{RB}(m)$.

A.2.2. *Numerical examples*

Here, we describe the numerical example we used to illustrate the theoretical framework. The parameters of the model are listed in Table 1.

Table 1
Parameter levels used in the numerical example.

Parameter	Description	Values
N	Number of farms	*999*
B	Societal value of biodiversity conservation	*100*
β_i^H	Farmer-level probability of achieving the conservation target in case of high effort	Drawn randomly from a uniform distribution with $a=0.5$, $b=1$.
β_i^L	Farmer-level probability of achieving the conservation target in case of low effort	$\beta_i^L=0.3\bullet\beta_i^H$
k_i^H	Farmer-level opportunity costs of biodiversity conservation in case of high effort	Drawn randomly from a uniform distribution with $a=0$, $b=100$.
k_i^L	Farmer-level opportunity costs of biodiversity conservation in case of low effort	$k_i^L=0.2\bullet k_i^H$
P	Payment levels	$P=[10,20,30,40,50,60,70,80,90,100]$
m	Monitoring quality	$m=[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]$
c	Cost of monitoring quality improvement	$c=[10,20,50]$

Fig. 2 is generated by considering $m^l=0.2$ and $m^h=0.6$, and $P=50$, representing the average value of the opportunity cost distribution. Fig. 3 illustrates the case where $P=50$, and $c^a=2500$, $c^b=5000$, $c^c=12500$.

Data availability

No data was used for the research described in the article.

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