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Research article

Economic efficiency of nature-based solutions: Theoretical framework and application to semi-natural habitat implementation

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ABSTRACT

The application of nature-based solutions to agriculture is promising because it allows the sustainable management of ecosystems and the reconciling of human well-being with the benefits of biodiversity. However, scientists lack robust economic arguments and concepts in the area of nature-based solutions that are well aligned with the expectations of the agricultural sector. This study addresses this gap by developing an interdisciplinary economic framework that integrates nature-based solutions and allows for an assessment of their efficient use. The conceptual framework is derived from a standard agricultural production model, making it possible to determine optimal levels of use and value. The framework is then applied to the establishment of semi-natural habitats, using econometric calibration and simulations based on agronomic, economic, psychological, and ecological data from a single case study in western France. The estimations show that the optimal semi-natural habitat coverage rate was 17.5% which was half the observed level, suggesting an underuse according to this framework. The present framework, which builds on standard economic efficiency models, demonstrates that ecosystems contribute to production similarly to conventional agricultural inputs, providing a productivity-based justification for their conservation.

1. Introduction

Nature-based solutions (NBSs), defined as actions to sustainably manage ecosystems and simultaneously support human well-being and biodiversity (Cohen-Shacham et al., 2016), are a promising approach to achieving the goal of feeding humanity while decreasing environmental degradation (IPBES, 2019; Dunlop et al., 2024). In the context of agricultural production, they correspond to productive and efficient strategies based on biodiversity and the use of ecosystem services (i.e., pollination, nutrient cycling, and pest control) and thus constitute alternatives to input-based conventional agriculture (Eggermont et al., 2015; Garibaldi et al., 2018). For example, implementing semi-natural habitat (SNH) as hedgerows or grassland is a well-known NBS, supporting natural enemy organisms that help control pests threatening crop yields, thereby reducing production loss (Albrecht et al., 2020; Faure and Mouysset, 2025), increasing pollinator abundance, and boosting insect pollination (Kremen et al., 2019). Although NBSs may safeguard food production while simultaneously providing environmental benefits, the slow pace of adoption by farmers needs to be accelerated (Hasler et al., 2022; Dunlop et al., 2024).

The current literature suggests that better scientific communication—in the sense of matching the narratives of scientists working on NBSs for agriculture with the language of the agricultural sector and policies would be helpful, but few economic arguments have been advanced for the adoption of NBSs (Velado-Alonso et al., 2024). Some economic ideas central to the concept of NBS, such as economic efficiency, have been excluded from the analysis in the context of agricultural production (Sowińska-Świerkosz and García, 2022). Economic efficiency, is a key concept in agricultural economics that reflects a farmer's ability to use inputs in optimal proportions given their respective prices (Hall and Winsten, 1959; Lau and Yotopoulos, 1971; Chavas and Aliber, 1993). To date, there has been no study that proves

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the economic efficiency of NBSs using standard economic methods. As a consequence, it is not clear how NBSs can be used to optimal effect alongside other inputs and how they contribute to well-being (i.e., their value; Paul et al., 2020). Answering these questions requires extending the standard agricultural modeling framework to integrate NBSs and thereby address their efficiency conditions.

One of the most commonly used agricultural production frameworks in contemporary research is that in Saha et al. (1997). This econometric framework is widely applied to quantify agricultural input efficiency with a high degree of accuracy (e.g., Zhengfei et al., 2005; Möhring et al., 2020; Tran et al., 2023; Devilliers et al., 2024). Specifically, the framework accounts for the fact that, in the presence of risk and risk-mitigating inputs (such as NBSs), marginal productivities can be overestimated, leading to biased estimates of input efficiency (Lichtenberg and Zilberman, 1986). However, consistent with the assessment by Paul et al. (2020), this study argues that the framework in Saha et al. (1997) is not suitable for studying NBS efficiency as it does not include ecological processes and dynamics and, as such, cannot capture retroactions between ecosystems and agricultural production (IPBES, 2016; Keesstra et al., 2018; Poggi et al., 2021, 2018). Nevertheless, as made by Chatzimichael et al. (2022) in a recent article about pesticides and health, this framework can be easily amended.

The objective of this article is to extend the modeling framework of Saha et al. (1997) by adding a model of ecological dynamics, and thus define precisely the economic efficiency of NBSs. This interdisciplinary approach bridges the disciplines of applied ecology and agricultural economics and provides a foundation for dialogue between the two. It also offers new economic-based narratives for scientists working on NBSs and prompts agricultural economists to reflect on sustainable agriculture. The study illustrates the efficiency of NBS by applying the extended framework to a case study in western France using empirical ecological, agronomic, economic, and psychological data and the econometric-process simulation model of Antle and Capalbo (2001). This involved first specifying and estimating empirical models before using simulations to represent farmers' decisions. The optimal use of NBS and their value in the form of SNH preservation and restoration, were then empirically estimated.

A methodological investigation was concurrently conducted to understand the consequences of alternative model specifications on NBS efficiency and value. Model-related choices regarding the specification of ecological dynamics may impact NBS efficiency conditions through the benefits considered. Therefore, NBSs were compared either when they encouraged only natural enemies (natural pest control service) or when they simultaneously encouraged pollinators (pollination service; Bengtsson et al., 2019; Albrecht et al., 2020). Finally, since NBSs influence the yield stochasticity through fostering natural enemy organisms, the study considered how the decision model under risk affected the efficient use and value of NBSs.

2. A framework for analyzing nature-based-solution efficiency

2.1. Theoretical model

This section introduces the framework in Saha et al. (1997) before setting out the proposed extension (see Fig. 1 for an overview). The model is developed in a stochastic context in which production (Box 2 in Fig. 1) is subject to a pest-related risk and another risk related to all other factors (Box 3 in Fig. 1). The pest-related risk depends on levels of infestation of the pest of interest, the associated damage, and the effectiveness of pest management solutions. The second type of risk includes risks related to crop growth conditions, mainly those of a meteorological nature, such as temperature and rainfall, and the overall pest risk due to pests other than the one of interest; this second type of risk is referred to here as "crop growth conditions" for simplicity. Saha et al.'s (1997) model of production at the field scale is given by the following:

$$y(X_{TBS}, \phi, \varepsilon) = f(X_{TBS}, \phi, \varepsilon) \tag{1}$$

where the yield y is a function of a vector of the crop growth conditions ϕ and the focused pest risk ε. It is assumed that output increases with better crop growth conditions and lower pest pressure. The yield is also a function of traditional agricultural inputs (such as pesticides or fertilizers), named technology-based solutions (TBSs), which are defined in contrast to NBSs in this study's framework, and denoted as X_{TBS}.

The extension, and hence the main difference with Saha et al.'s (1997) original framework, is that this study's framework includes a module in which the farmer can manage the focused pest risk using either TBSs or NBSs, denoted as X_{NBS}. Hence, Eq. (1) becomes,

$$y(X_{TBS}, X_{NBS}, \phi, \varepsilon) = f(X_{TBS}, X_{NBS}, \phi, \varepsilon) \tag{2}$$

Following Saha et al. (1997), the model is then asymmetrized, and the potential yield and pest damage are differentiated[1]:

$$y(X_{TBS}, X_{NBS}, \phi, \varepsilon) = h(X_{TBS}, \phi) \times (1 - d(X_{TBS}, X_{NBS}, \varepsilon)) \tag{3}$$

where $h(X_{TBS}, \phi)$ is the potential output (Box 2a in Fig. 1), and $d(X_{TBS}, X_{NBS}, \varepsilon)$ is the damage function (i.e., the proportion of crops damaged by the pest of interest; Box 2b in Fig. 1). In this framework, the NBS is considered a "pure" risk-abating input (Zhengfei et al., 2005). The innovation here is that multiple ecosystem functions can be considered simultaneously, and an NBS can thus be treated as a productive *and* risk-abating input. Indeed, NBSs usually promote multiple ecosystem services simultaneously (FAO, 2021; Manning et al., 2018). Within the multiple-service perspective, Eq. (3) then becomes

$$y(X_{TBS}, X_{NBS}, \phi, \varepsilon) = h(X_{TBS}, X_{NBS}, \phi) \times (1 - d(X_{TBS}, X_{NBS}, \varepsilon)) \tag{4}$$

The production function, in its single or multi-service definition, is then used to compute the gross margin gm (Box 4 in Fig. 1) as follows:

$$gm(X_{TBS}, X_{NBS}, \phi, \varepsilon) = p \times y(X_{TBS}, X_{NBS}, \phi, \varepsilon) - C(X_{TBS}, X_{NBS}) \tag{5}$$

where p is the output price and $C(\bullet)$ is the variable cost function related to the vector of farmer inputs (Box 5 in Fig. 1). Similar to the framework in Saha et al. (1997), in this study, the farmer's optimal decision is modeled (Box 1 in Fig. 1). This makes it possible to explore the effect of risk preferences through utility specification (Boxes 6 and 7 in Fig. 1). The farmer's decision module assumes the maximization of the expected utility (Gollier, 2004):

$$\max_{X_{TBS}, X_{NBS}} U = E[u(gm, \nu)] \tag{6}$$

where ν is the coefficient related to risk preference. In the framework presented here, the farmers are assumed to be either risk neutral or risk averse (Pennings and Garcia, 2001; Rommel et al., 2023). In solving Eq. (6), the computation of the optimal use level of NBS gives an estimation of the condition for NBS efficiency (Chavas and Aliber, 1993; Pindyck and Rubinfeld, 2018), the primary objective of this study (Box 8 in Fig. 1).

Efficiency arises from the marginal value attributed to NBS, that is, its contribution to well-being, which concerns the study's second objective (Box 9 in Fig. 1). This is referred to as the total value (V_T), which can be divided into the economic (V_E) value and the insurance (V_I) value (Baumgärtner and Strunz, 2014; Peled et al., 2020); the former is related to the contribution to average production and the latter is related to the contribution to risk reduction (Primmer and Paavola, 2021). Formally, V_E is defined as the marginal increase in gross margin resulting from a one-unit increase in input (Debertin, 2012) and V_I is defined as the marginal decrease of risk premium allowed by an

[1] Saha et al. (1997) proposed this distinction to account for the fact that some inputs, like insecticides, do not increase potential yield but rather decrease losses.

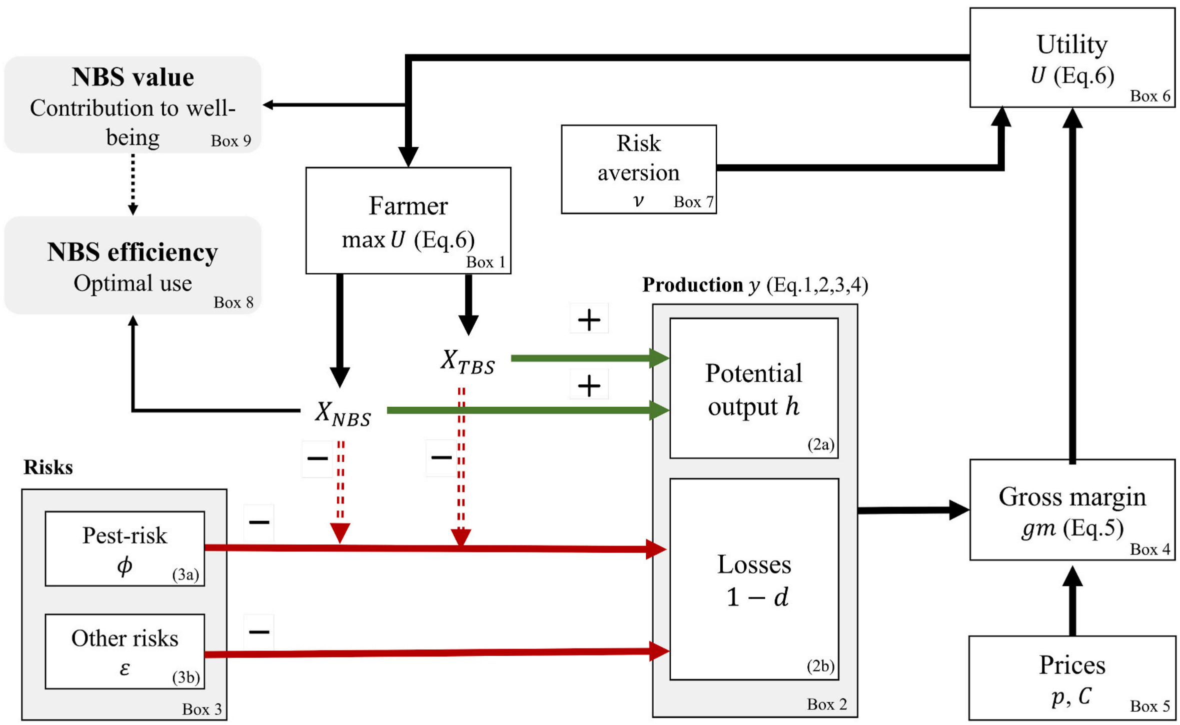

Fig. 1. Overview of the theoretical model. Solid arrows represent direct effects, while dashed arrows represent indirect effects. The final objective is to compute NBS efficiency and value.

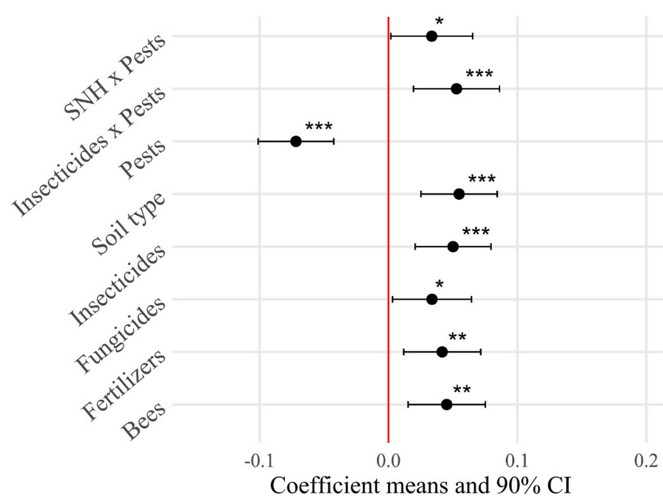

Fig. 2. Production model coefficient estimation. Data were ln-transformed and standardized. The points and lines represent the means and the corresponding 90% confidence intervals. The p-values of the t-tests, which compare the estimations with zero, are shown (*p < 0.1; **p < 0.05; ***p < 0.01).

incremental unit of input (Baumgärtner, 2007). Their sum gives the total value V_T. This definition implies that the total value is defined locally—that is, it depends on the extent of NBS use (X_{NBS}). Formally, the total value of input is given as follows:

$$V_T(X_{NBS}) = V_E(X_{NBS}) + V_I(X_{NBS}) = \frac{\partial gm}{\partial X_{NBS}} + \left(-\frac{\partial RP}{\partial X_{NBS}}\right) \quad (7)$$

The risk premium RP is defined as the amount of money that leaves the farmer indifferent between an alternative that offers certain wealth and another in which the wealth is risky (Zweifel and Eisen, 2012).

$$u(E[gm] - RP) = E[u(gm)] \\ \Longleftrightarrow RP = E[gm] - u^{-1}(E[u(gm)]) \quad (8)$$

2.2. Econometric specification

An application of the theoretical model is then proposed, using the econometric-process simulation model of Antle and Capalbo (2001), in which empirical models are first specified and then estimated. In this subsection, the specifications are presented in a way that remains broad and applicable to a wide range of NBS scenarios. The case-study estimations are detailed in Section 3. The same yield specification as Saha et al. (1997) and Möhring et al. (2020) was applied as follows:

$$y_i = F_i\left(X_{TBS_i}, X_{NBS_i}, \overline{X_i}, \beta\right) \times \exp(\phi) \times \exp\left(-A_i\left(X_{TBS_i}, X_{NBS_i}, \alpha\right) \times \varepsilon\right) \quad (9)$$

with $F_i(X_{TBS_i}, X_{NBS_i}, \overline{X_i}, \beta) \times \exp(\phi)$ being the production function for the i th field, $\exp(-A(X_{TBS_i}, X_{NBS_i}, \alpha) \times \varepsilon)$ being the damage function, and A_i the abatement function. Control variables such as meteorological or soilfertility factors were included in $\overline{X}_i$. For the specification of $F_i(\bullet)$, the simplified translog model was used[2]; that is, the quadratic terms were excluded (Debertin, 2012). The abatement function was assumed to decrease log-linearly with risk-abating inputs.[3] The generic econometric specification of the model for field i is thus given by the following:

$$\begin{aligned}\ln(y_i) = {} & c + \sum_{k_{TBS}} \beta_{k_{TBS}} \ln\left(X_{k_{TBS_i}}\right) + \sum_{k_{TBS}}\sum_{k_{TBS}} \beta_{k_{TBS}k_{TBS}} \ln\left(X_{k_{TBS_i}}\right)\ln\left(X_{k_{TBSi}}\right) + \sum_{k_{NBS}} \beta_{k_{NBS}} \ln\left(X_{k_{NBS_i}}\right) + \sum_{k_{NBS}}\sum_{k_{NBS}} \beta_{k_{NBS}k_{NBS}} \ln\left(X_{k_{NBS_i}}\right)\ln\left(X_{k_{NBS_i}}\right) \\ & + \sum_{k_{TBS}}\sum_{k_{NBS}} \beta_{k_{TBS}k_{NBS}} \ln\left(X_{k_{TBS_i}}\right)\ln\left(X_{k_{NBSi}}\right) + \sum_{k_{\overline{X}}} \beta_{k_{\overline{X}}} \overline{X}_i + \phi + \varepsilon \times \left[\alpha_\varepsilon + \sum_{k_{TBS}} \alpha_{k_{TBS}} \ln\left(X_{k_{TBS_i}}\right) + \sum_{k_{NBS}} \alpha_{k_{NBS}} \ln\left(X_{k_{NBS_i}}\right)\right],\end{aligned} \tag{10}$$

where ϕ is the vector of residuals linked to factors excluded from the specification, such as other stochastic events. Based on this identification, the model residuals are assumed to represent the logarithm of the crop growth conditions. This specification implies that ϕ follows a normal distribution and that the two risks are independent (zero covariance) because of the linear model assumptions. Regarding the pest risk, the logarithm of the observed values is denoted by ε, the pest-related risk factor. Contrary to other studies, such as Möhring et al. (2020), the framework used maximum likelihood estimation rather than assuming the theoretical distribution a priori. The stochastic gross margin per ha of the field i is given by

$$gm_i = p \times y_i - C_i, \tag{11}$$

where C_i is the variable cost function expressed as follows:

$$C_i = C_{base} + \sum_{j \in inputs} c_{j,i} X_{j,i}, \tag{12}$$

with *inputs* being the vector of inputs (i.e., the TBS and the NBS). Following the specification of the yield function, the utility function was specified. First, it was assumed that utility follows a constant relative risk aversion (CRRA) specification that makes it possible to represent farmers' risk preferences (Hadar and Russell, 1969; Apesteguia and Ballester, 2018). The risk aversion coefficient is denoted by ν_i.

$$u_i = \frac{gm_i^{(1-\nu_i)}}{1-\nu_i} \tag{13}$$

In combining Eqs. (8) and (13), the insurance value for this model was obtained as follows:

$$V_{I_i} = -\left(E[gm_i] - ((1-\nu_i)E[u(gm_i)])^{\frac{1}{1-\nu_i}}\right). \tag{14}$$

Eventually, the impact of modeling risk preferences was tested by assuming that the utility is equal to the gross margin and, thus, that the farmers are risk neutral.

$$u_i = gm_i \tag{15}$$

In this specification, the insurance value is zero (see Eq. (8)).

3. Case study in western France

3.1. Case study

The study area is an intensive agricultural landscape, the Zone Atelier Plaine and Val de Sèvre, located in the south of the Deux-Sèvres department in France. It is a 450 km^2 agricultural cereal plain comprising around 435 farms and 12,000 fields (Bretagnolle et al., 2018a). The main crops are cereals (~40% of the land use), oilseed rape (~10%), sunflower (~10%) and corn (~10%). The site belongs to the international network of long-term socio-ecological research platforms (LTSER; Singh et al., 2013). The research infrastructure includes detailed data on biodiversity—pests and wild and domestic pollinators—land use, farming practices, and economic factors, such as input costs or risk preferences (Bretagnolle et al., 2018a, 2018b; Gaba and Bretagnolle, 2021).

This study focused on the production of oilseed rape, which is a pollinated plant and the second-largest source of vegetable oil in the world, accounting for 39% of European biodiesel feedstock production (Flach et al., 2019). This crop is highly sensitive to pests (Zheng et al., 2020). The cabbage stem flea beetles (Genus: *Psylliodes*) that are the focus here were the main pests identified in the study area (Perrot et al., 2022).

The NBS in the model was represented by the preservation (or restoration) of SNHs; in this study, the SNHs are grasslands and hedgerows. The SNH proportion increases the abundance of natural enemies and ultimately supports pest mitigation (Albrecht et al., 2020; Bengtsson et al., 2019; Perrot et al., 2021, 2023). In addition, SNHs are multifunctional since they also increase bee abundance and, thus, pollination (Bengtsson et al., 2019). This makes it possible to test the effect of the ecological dynamics specification on NBS efficiency. However, in this study's data, hedgerows and grasslands are highly correlated (Pearson test: $\rho = 0.63$). Therefore, only the percentage of grasslands is used as the input linked to the SNH rate and to the use of NBS.

The empirical models are parametrized using the following databases: (i) a farmers' survey database containing information on yield and farming practices (e.g., fertilizers measured in $kg.ha^{-1}$; or pesticides measured by calculating treatment frequency indexes; see Möhring et al., 2019 for more details) and their associated costs in 294 oilseed rape fields surveyed in the study area from 2011 to 2018 (Catarino et al., 2019); (ii) a biodiversity database where bee and pest abundance were sampled in 124 fields from 2013 to 2018 (Perrot et al., 2022); (iii) a geographic information system for which soil characteristics and complete land use occupation (since 1994) have been recorded (Bretagnolle et al., 2018a); and (iv) a risk preferences database where the farmers' risk aversion coefficient distribution was evaluated in the study area using lottery experiments on 138 farmers (Couture and Gaba, 2021).

[2] While the Cobb–Douglas specification is commonly used in the literature, it has limitations because it restricts all elasticities of substitution to one, which may not accurately reflect the reality of the production process and the trade-off between technology-based and nature-based risk mitigation faced by farmers. A commonly used alternative specification is the translog, which has no a priori restrictions.

[3] The linear and quadratic specifications can also be used, but the log-linear specification simplifies the function by homogenizing its expression. In addition, using the case study data, linear and quadratic specifications were tested against the log-linear specification, but they did not show any statistical improvement over the log-linear specification (see Supplementary Material 4).

3.2. Production model

The production model (Box 2 in Fig. 1) was estimated in Eq. (10) by combining the three former data sets and employing 124 observations—ecological data were not available for all 294 fields from 2011 to 2018. All data were ln-transformed for parametrization, standardized, and analyzed using R Version 4.1.2 (R Core Team, 2018).

In the first step, the model was selected using Hendry's (1995) methodology: the general unrestricted model was defined and refined using an algorithm based on the Akaïke criterion (see Supplementary Material 1 for the detailed procedure). The model selection retained three TBSs (insecticides, fungicides, fertilizers; herbicides were excluded), the NBS (i.e., SNH proportion), as well as soil type and bee abundance (i.e., control variables; Fig. 2; Table S3). This suggests that extending Saha et al.'s (1997) model to NBSs was robust because two biodiversity-related variables were retained in the final model (SNH and bees).

The estimation of the model coefficients (Eq. (10)) shows that pests have a negative effect on crop yield, while the presence of bees, as well as the quantities of fertilizers, insecticides, and fungicides, have a positive effect (Fig. 2; Table S3 in Supplementary Material 2). Soil type also has a significant impact on crop yield, with clay soils leading to higher yields than calcareous soils. As expected, insecticides and SNHs both have a positive effect on crop yield through pest damage reduction. A linear hypothesis test regarding the equality of the two coefficients yielded a non-significant difference between the magnitudes of risk-abating inputs on average ($F = 0.37$; $p > 0.1$), suggesting that SNHs are as effective as insecticides in coping with pest risk. Surprisingly, pesticides do not have any noticeable impact on bees—the bee-pesticide interaction was not retained in the model selection leading to the final model (Fig. 2). Similarly, the SNHs–bee abundance interaction was not retained in the model selection procedure despite the supposed effect of SNHs on bees (Fig. 2; Table S3).

Given the observed positive impact of SNHs on bee abundance in the study area (e.g., Perrot et al., 2022), this effect was retained in the baseline model. A hierarchical multilevel model with a sub-model of bee abundance was constructed that includes the SNH proportion in the landscape, the estimate of which was then integrated into the production model at the field scale; additional information is provided in Supplementary Material 2. SNHs thus have the double role[4] of reducing the risk by killing pests through natural enemies while increasing yields by increasing bees.

3.3. Risks and decision model

Next, the economic and decision-making modules of the model (i.e., Eqs (11)–(13); Boxes 4, 5, 6, and 7 in Fig. 1) and the production risks (ϕ, ε in Eq. (10); Box 3 in Fig. 1) were estimated using the datasets described above. This approach is original in bioeconomic modeling because parameters—especially economic ones—are usually drawn from literature and not estimated from the same case study as the data used to estimate ecological parameters. The following provides a brief overview of the methods and estimation results; a comprehensive presentation is contained in Supplementary Material 3.

The two risk distributions were then specified and estimated with maximum likelihood estimation using the 2013–2018 database (i.e., 124 fields; see Section 3.1). This showed that the risk related to crop growth conditions (Box 3b in Fig. 1) was normally distributed, while the pest risk (Box 3a in Fig. 1) followed a Weibull distribution. This latter result is in line with previous studies; the Weibull distribution commonly fits aggregated pest distributions since it mainly describes survival curves (Wagner et al., 1984).

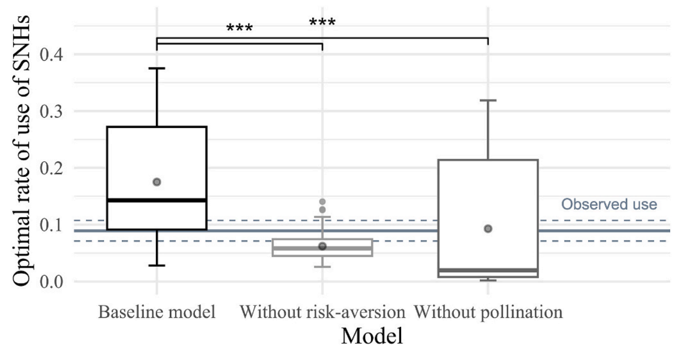

Fig. 3. Optimal rate of SNH use for the baseline model and the other two models (without risk aversion and without pollination). The points and lines inside a boxplot represent the mean and the median, respectively. The solid blue-gray line represents the observed rate of SNH use, while the dashed blue-gray lines are the corresponding 95% confidence interval.

The gross margin model and prices (Box 4 and 5 in Fig. 1) were then estimated using the economic database on oilseed rape production (i.e., 294 fields; see Section 3.1). The opportunity cost of implementing SNH was included in its total cost to account for the fact that cultivating arable crops would be more profitable. Finally, the decision models were parametrized using the risk preferences database (i.e., 138 farmers; see Section 3.1). The Couture and Gaba (2021) results confirm the use of the CRRA[5] specification (Eq. (13)) as the baseline decision model.

The specifications used in the model in this study were all validated through different dominance tests (see Supplementary Material 4). In addition, the production model output was validated by comparing the yields obtained with simulations to those observed; these were found to be significantly similar (Supplementary Material 4).

4. NBS efficiency, value, and impact of model specification

This section addresses the case study's two questions: "How should NBSs be used to maximize the well-being?" and "How do NBSs contribute to well-being?" This is achieved by using the model to simulate the efficiency condition, that is, the optimal rate of use of SNHs. Then, through simulations, the values attributed to SNHs by the farmers in the study sample were estimated. These two concepts were estimated using three versions of the model, allowing an assessment of how different modeling choices affect the final results.

The first version used for simulations was the one that best represented the reality of the case study. This baseline model is characterized by farmers' risk-averse behavior and the multiple-services perspective, the latter being related to modeling the impact of SNHs on both pest risk (natural pest control service) and bees (pollination service). The second version excludes risk aversion: the impact of risk preference choices was examined by modifying the CRRA specification (i.e., farmers are risk averse, Eq. (13)) to one in which farmers are risk neutral (i.e., farmers maximize their gross margin, Eq. (15)). The third version excludes pollination: the impact of ecological process modeling choices was then examined by removing the effect of SNHs on bees, that is, by eliminating the benefit of insect pollination to cro

p yield in Eq. S(1).

4.1. Simulation plan

The following simulation plan was executed to capture the heterogeneity in years, fields, surrounding landscape characteristics, and farmers' risk preferences. Each of the 124 observed fields was associated

[4] Using the terminology of the modeling framework, the study moves from a single service perspective (Eq. (3)) to a multiple-services perspective (Eq. (4)).

[5] The constant relative risk aversion specification states that farmers are risk averse and that this risk aversion depends on their revenue.

with five values of the risk aversion coefficient, sampled in uniform distributions calibrated using the aforementioned risk preferences experiments (see Supplementary Material 3 for details). These values were chosen arbitrarily to represent a reasonable trade-off between the variance of risk preferences and the computational time. This gives a total of $n = 620$ "field-farmer" pairs. The farmers' best decision (Eq. (6)) was then computed with the R package, *optim,* for each couple to determine the efficient level of SNH use (concurrently with optimal level of use of fertilizers, fungicides, and insecticides). The value of the SNH implementation was also investigated, and the values (Eq. (7)) were computed for each "field-farmer" pair. The outputs of each modeling context were compared using nonparametric paired comparison tests (i.e., Wilcoxon–Mann–Whitney tests).

4.2. Efficient rate of SNH use: how should nature-based solutions be used to maximize well-being?

The optimal rate of use of the SNHs was computed for the baseline model, the model without risk aversion, and the model without pollination. First, the simulations using the baseline model provided an optimal rate of SNH use of 17.5%, almost twice the observed rate of SNH coverage in the case study (Fig. 3). We show that risk-neutral preferences (i.e., model without risk aversion in Fig. 3) lower this optimal rate to 6%. We also show that not considering pollination in the model halves the optimal rate of use of SNHs compared to the model where both natural pest control and pollination are taken into account (Fig. 3). These last two results demonstrate that the modeling choices in terms of decision-making and ecological processes are crucial for determining the efficient rate of use of SNHs.

4.3. Total value, economic value, and insurance value of SNHs: how do nature-based solutions contribute to well-being?

Given that efficient use is implicitly guided by the value that farmers attribute to the SNHs, this is estimated from the sample. This total value is broken down by distinguishing the economic value—which quantifies the well-being gained through increased average production—and the insurance value—which quantifies the well-being gained through risk reduction. These values were computed for the observed levels of SNHs, depending on our different modeling contexts (Table 1). As expected, the economic value of the NBS was unchanged by the removal of risk aversion since the economic value belongs to the "certain-world" values and can be objectively defined (Paul et al., 2020). On the contrary, the estimations in this study show differing insurance values between the baseline model and the model without risk aversion. While the latter implies no insurance value, the former has significant positive insurance value. Adding insurance value significantly increases the total value, suggesting that models without risk preferences vastly underestimate the real value of NBS.

The estimations also show that the insurance value was not significantly modified by the number of ecosystem services considered (insurance value was not significantly different between Models 1 and 3; Table 1). In contrast, the economic value was deeply affected by the latter since not considering pollination makes the economic value drop from 120.7 €.ha^{-1} to − 86.8€.ha^{-1}. Modeling multiple ecosystem functions increases the total value almost fourfold, which demonstrates the impact of including an ecological perspective on NBS effectiveness measures.

Table 1
Means of value estimation (in €.ha^{-1}) of observed SNHs for the baseline model as well as the two other models (without risk aversion and without pollination). Standard errors are displayed in parenthesis (in €.ha^{-1}). Wilcoxon tests compare the simulated values between the baseline and each alternative model.

	Baseline model	Without risk aversion	Without pollination	p-value for Wilcox. test	p-value for Wilcox. test
	(1)	(2)	(3)	H_0: (1)−(2) = 0	H_0: (1)−(3) = 0
Economic value	€120.7 (€8.0)	€120.7 (€8.0)	−€86.8 (€1.8)	1	< 0.001
Insurance value	€155.9 (€12.7)	€0.0 (€0.0)	€158.4 (€12.8)	< 0.001	0.8
Total value	€276.7 (€16.3)	€120.7 (€8.0)	€71.6 (€12.9)	< 0.001	< 0.001

Note: Values are estimated using observed values of inputs.

5. Discussion

NBSs are promoted by scientists as a sustainable and desirable path for agriculture. However, scientists lack robust economic arguments and concepts to support NBSs that would better align with the expectations of the agricultural sector. This study aimed to fill this gap by integrating NBSs into a standard agricultural economics framework. A novel and innovative framework was provided by extending the original modeling framework of Saha et al. (1997) to include ecological dynamics, in this case, natural pest control and pollination. The NBS efficiency was then illustrated using a case study in Western France and employing empirical ecological, agronomic, and economic data to estimate a simulation model. The NBS in this study, SNH implementation, is one of the solutions that is most often advanced to support ecosystem services in agricultural landscapes.

The modeling framework developed here originates from a classical production econometric framework in Saha et al. (1997). This model was initially developed to avoid the overestimation of damage-abating input marginal productivity (Lichtenberg and Zilberman, 1986), but some studies applied the framework to environmental questions (e.g., Zhengfei et al., 2005; Möhring et al., 2020). However, they systematically focused on the estimation of traditional input efficiencies, leaving out any NBS. It should be mentioned that various ecological-economic modeling studies included NBSs in their analysis and estimated the efficiency of NBS fostering regulating services, including natural pest control (Martinet and Roques, 2022; Zhang et al., 2010) or pollination (Kleftodimos et al., 2021; Faure et al., 2023). However, their modeling frameworks are distinct from the framework presented here.

Even if existing frameworks include ecological dynamics, their simplistic modeling choices may have biased the estimations of NBS marginal productivity and, thus, of optimal use. More precisely, no study has simulated decisions in a stochastic context. Yet, we have shown how risk preferences impact efficiency: the optimal rate of NBS use is divided by three when risk aversion is not considered. This is consistent with the literature dealing with the influence of risk preferences on the optimal use of agricultural inputs (Chavas, 2018). Additionally, all existing studies have modeled a sole ecosystem service related to NBS use and biasing estimations. Indeed, when only natural pest control was considered, the optimal SNH use rate fell from 17.5% to 9%. Indeed, accurate modeling of the ecological processes is a key element of accurate biodiversity accounting (Paul et al., 2020). The Food and Agriculture Organization has recognized the potential of NBSs, citing the associated benefits allowed by the multi-service perspective (FAO, 2021).

Empirical applications have not used agricultural economics methods –econometrics—to estimate NBS efficiency. These models were calibrated using different case studies because of the lack of exhaustive data for a unique case study. The application in this study was thus unprecedented because it is site-specific and because it uses a combination of ecological data on ecosystem services, agricultural practices data, as well as production, economic, and psychological data. As specified by Antle and Capalbo (2001), the more site-specific the calibration, the more robust the model and its outcomes. With the increasing interest in LTSER platforms (Singh et al., 2013), applications of this study's framework will likely emerge for two main reasons. First, a broader panel of data, especially socio-economic data, will be collected; this is often the limiting factor in applied ecology research as practiced in these platforms (Kleijn et al., 2019). Second, these platforms will enhance their expertise, including in social sciences, by developing interdisciplinary and collaborative efforts, as promoted by the recent *eLTER* project supported by the European Commission.[6]

The NBS efficiency quantification in this study gave an optimal grassland coverage rate of 17.5%. In the case study, it was almost twice as high as the current percentage. The study's framework and empirical estimation thus support the conclusion that this NBS is underused and quantifies this underuse. The substantial underuse of grassland benefits should be looked at in the context of the continuous decrease of grassland areas worldwide (Queiroz et al., 2014). Interestingly, recent studies have advocated for coverage of a similar magnitude (15–20% SNH coverage rate) for the adequate functioning of agroecosystems (Eeraerts, 2023; Tscharntke et al., 2021; Garibaldi et al., 2021; Montoya et al., 2020). This study complements these ecology-based studies by adding production-based arguments: this was the aim of the framework presented in this study. The underuse of grassland may have many causes, including economic and cognitive factors that have been determinative in farmers' decisions (Dessart et al., 2019). Lack of knowledge about the role of grasslands in ecosystem services may be one of the first causes, as shown by Maas et al. (2021). The practical implications of our study are that it gives economic-based arguments that support NBSs and can be used to communicate with farmers about the role of ecosystems in agricultural production. This study, and more broadly, the conceptual framework, emphasizes that even from a productivity-focused perspective, ecosystem functions are crucial for production. In other words, natural elements should be preserved not only for biodiversity conservation or landscape aesthetics but also for their contributions to farmer's income and their stability.

Under the calibration in this study, the marginal total contribution to the well-being of the SNH is estimated at €276.7ha^{-1}($SD: \pm$ €181.5.ha^{-1}), with 44% coming from the production-related value and 56% coming from the insurance value. In terms of magnitude, our estimations are close to those in Finger and Buchmann (2015); the authors calculate the marginal benefit and insurance values of grassland species diversity in Germany, concluding that the NBS value is largely underestimated if insurance value is overlooked. We go further by providing the optimal rates with (~17.5%) and without (~6%) insurance value—including the insurance value resulted in a tripling of the efficient use rate. Methodologically, as shown by Saha et al. (1997) for pesticides, this illustrates how the model specifications shape the NBS efficiency estimations.

This study applied the framework with SHN implementation, but the framework can easily be adapted to other NBSs. However, because the magnitude of the effect of ecological functions on yield varies considerably depending on crop type or landscape, NBS efficiency is likely to vary across agricultural landscapes and according to the type and cost of implementation; for example, hedgerows have no direct impact on yield (Albrecht et al., 2020). Many factors contribute to the impact of ecological function on yields: ecological interactions, landscape spread, and confounding effects make it challenging to isolate the NBS impact on yield alone (Gagic et al., 2017). Moreover, the costs of NBSs can vary significantly, especially when they provide few benefits beyond their impacts on yield. For example, flower strips cannot be harvested like hay, potentially leading to optimal levels of zero, suggesting the framework's limits. Here, the concept of externalities is critical, and public policies like the Common Agricultural Policy should subsidize "unproductive" NBSs (Mennig, 2024). Other than SNH implementation, the framework is generally applicable to any NBS that contributes to the production function, either directly or indirectly, for example, grazing optimization or conservation agriculture (Iseman and Miralles-Wilhelm, 2021). However, NBSs aimed solely at carbon sequestration are not compatible with this model. Finally, this study's framework is fully extendable to multiple NBSs, allowing for a portfolio approach where they can be complementary or substitutable, similar to traditional inputs. Further research and empirical examples are needed on this point.

6. Conclusion

This study and its interdisciplinary approach contribute to two research fields. For agricultural economists, this framework addressed the pressing need for models for sustainable agriculture. Until now, research has focused exclusively on traditional agricultural efficiency, omitting NBSs. Here, a modeling framework is provided that quantifies NBS efficiency and offers insights into alternatives to traditional inputs to meet future challenges. In fact, the United Nations has recognized that NBSs can help countries achieve multiple targets of the 2030 Sustainable Development Agenda (FAO, 2021), revealing policymaker expectations concerning NBSs. Thus, integrating NBSs into standard production functions is essential to accurately identify the most efficient strategies. For applied ecologists, this approach addresses a critical gap. Despite the substantial evidence on biodiversity–agriculture win-wins, the agricultural sector has shown limited receptiveness to NBS adoption (Kleijn et al., 2019). In a recent article, leading researchers identified this issue as a mismatch between scientists' narratives and the language used in agriculture (Velado-Alonso et al., 2024): our framework directly responds to this challenge by adapting the narrative, offering a vocabulary and models that reflect agricultural sector concepts, particularly the notion of efficient input use. By treating NBSs as an input within the framework, it is possible to calculate their optimal use, demonstrating that NBSs are currently underutilized relative to their value and contributions to agricultural production.

Finally, this study also has implications for agricultural policies. The concept of NBS is increasingly being adopted in national and international policies (Sowińska-Świerkosz and García, 2022). For instance, the European Union has integrated NBS into its new framework programme for research and innovation, "Horizon 2020," providing a narrative that aligns biodiversity and ecosystem services with goals of innovation, growth, and job creation (Nesshöver et al., 2017). This political adoption has swiftly brought the concept of efficiency into focus. For example, the first comprehensive European Commission publication on NBS emphasizes that NBS should be resource-efficient, highlighting the importance of identifying the most effective and affordable solutions while considering alternatives (Sowińska-Świerkosz and García, 2022). In the context of agriculture, these alternatives often involve the use of chemical inputs. By presenting the first conceptual framework linking economic efficiency with NBS in agriculture, this study lays the groundwork for discussions on how funding should be allocated. It particularly highlights the productive and substitutive roles of NBS, providing insights for more targeted and effective policy strategies.

CRediT authorship contribution statement

Jérôme Faure: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Sabrina Gaba:** Writing – review & editing, Funding acquisition. **Thomas Perrot:** Writing – review & editing, Data curation. **Vincent Bretagnolle:** Writing – review & editing, Funding acquisition. **Lauriane Mouysset:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Competing interest and ethical considerations

We have no competing interest to declare. We have thoroughly considered all ethical aspects regarding the collection and use of the data in our study. All data were collected and utilized in accordance with relevant ethical guidelines, ensuring confidentiality and integrity

[6] https://elter-projects.org/.

throughout the research process.

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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. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123793.

Data availability

The authors do not have permission to share data.

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