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Natural insurance as a green alternative for farmers? Empirical evidence for semi-natural habitats and methodological bias

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ABSTRACT

Natural insurance based on the provision of ecosystem services is a promising tool for the future of agriculture. However, empirical evidence of the role it can play is lacking, and its integration into standard insurance strategies – for example, the use of pesticides or market-based insurance – has been understudied. To begin to fill this gap, this study developed an original conceptual framework to estimate the insurance value provided by semi-natural habitats in a crop production context. The framework was then applied to a case study in western France, focusing on the value of natural pest control provided by grassland areas in the context of oilseed rape production. We evaluated the insurance role of grasslands for pest control and estimated this at a value of €50 per hectare. However, this estimation varied greatly according to the farmer's risk-mitigation strategies considered. We found that omitting agricultural inputs (e.g. risk-mitigating inputs such as pesticides) overestimated the insurance value of grassland areas due to the substitution effect between different types of insurance tools. Despite this variation, the findings show that it is nonetheless always optimal for farmers to maintain grassland areas to manage risk. This study provides empirical evidence of the insurance role of semi-natural habitats in an agricultural production context and offers new arguments for the ecological intensification of agriculture.

1. Introduction

Agriculture is exposed to many environmental risks that are expected to increase in the next years due to global changes (Deutsch et al., 2018). Farmers have used to rely on risk management instruments to cope with pests, droughts or hail (Hardaker et al., 2015). The most traditional instruments are subscribing to market-based insurance (MI) and the use of risk-mitigating inputs (e.g. insecticides). While the former offers economic compensation for potential losses (Meuwissen and van Asseldonk, 2018), the latter tends to reduce variation in production by controlling the production context (Ehrlich and Becker, 1972; Pannell and D., 1991). Both types of instruments have adverse impacts on the environment. Market-based insurance may result in the intensification of agriculture with perverse impacts on the environment (Horowitz and Lichtenberg, 1993; Möhring et al., 2020b), while the use of inputs can directly negatively affect biodiversity and soil conditions (McLaughlin and Mineau, 1995; Sánchez-Bayo and Wyckhuys, 2019). Developing greener tools to reduce variability in revenues is thus at the core of current issues in agricultural development (Finger et al., 2024).

Natural insurance (NI), a tool based on the strategic use of biodiversity and ecosystem functioning, has recently appeared as a promising environmentally friendly risk-mitigating instrument that may reduce risk without destabilizing ecosystems (Dallimer et al., 2020; Primmer and Paavola, 2021). Natural insurance tools can be classified into two main types (Koellner and Schmitz, 2006). First, the diversification of species in crop rotations and crop genetics to make use of diversity against risks (Di Falco and Chavas, 2006, 2009; Baumgärtner and Quaas, 2010). Diversification makes an agroecosystem productive over a wider range of conditions (Naeem et al., 1994) and hedges risks including droughts, high temperatures and pests (Perrot et al., 2023; Renard et al., 2023). The second form of NI aims at stimulating the natural regulatory processes that mitigate risks through the management of semi-natural habitat (SNH; Baumgärtner, 2007). It is based on the implementation of grasslands, hedgerows, herbaceous strips, or other habitats that enhance regulation services (Bengtsson et al., 2019; Perrot et al., 2023). For instance, such habitats can host beneficial organisms that prey on pests that threaten crop yields, ultimately reducing production losses (Landis et al., 2000). Such habitats can also mitigate adverse effects of

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droughts and floods (Milazzo et al., 2023; Sánchez et al., 2010) and lead to co-benefits and positive externalities (Bengtsson et al., 2019; Holland et al., 2017), and even play a role in crop diversification, such as in the case of grasslands. In that context, some authors argue that these insurance tools are widely underused by farmers, as well as understudied by scientists compared to diversification methods (Faure et al., 2024; Schaak et al., 2023; Staley et al., 2023). We have identified two gaps that hinder widespread support from policymakers and adoption by farmers for risk management: a lack of empirical evidence demonstrating the risk mitigation role of semi-natural habitats, coupled with insufficient knowledge on how these habitats can be integrated alongside well-established insurance tools. (Kleijn et al., 2019; Paul et al., 2020). This study aims to fill these gaps by addressing the research question: do semi-natural habitats offer an alternative solution for risk mitigation?

Exploring SNH management as an alternative solution requires modelling risk-management strategies, which we refer to as portfolios. The modelling of risk-management strategies is well established; it is widely accepted that the availability of one insurance tool modifies the demand for others (Ehrlich and Becker, 1972; Markowitz, 1991). In the context of agricultural insurance, it has been shown that inputs and MI can either replace each other (Smith and Goodwin, 1996) or complement each other in some instances (Horowitz and Lichtenberg, 1993; Möhring et al., 2020b). Regarding the integration of NI tools based on diversification, it has been shown that they substitute for inputs and MI, reducing negative environmental impacts (Baumgärtner and Quaas, 2010; Di Falco and Chavas, 2006). Yet there is a knowledge gap regarding the use of NI based on SNH in risk-mitigation strategies: specifically, how this can replace or complement other tools. Most studies have focused on simplified insurance portfolios only considering MI (Baumgärtner, 2007; Quaas and Baumgärtner, 2008), overlooking inputs. However, not taking into account inputs in farmers' alternatives may bias the value of and the demand for NI, and ultimately the assessment of its efficient use by farmers (Finger et al., 2024; Paul et al., 2020) – a bias this study sought to evaluate.

We hypothesized that there may be two contrasting effects of integrating inputs on the economic properties of NI. Inputs and NI may substitute for one another as the use of pesticides or ecosystem services might both reduce production risks, as has been shown between MI and NI tools (Baumgärtner, 2007). On the other hand, inputs and NI could be complementary due to ecosystem complexity: enhancing one regulating service may increase the provision of others (e.g. pollination), leading to higher expected production. Furthermore, there are different forms of agricultural inputs: productive inputs (e.g. fertilizers) may enhance the expected production and so affect the insurance value and therefore the economic properties of NI. In this context, the overall effect resulting from adding agricultural inputs (risk mitigating and/or productive) is unpredictable and is likely to depend on the economic context, including price, effectiveness and risk distribution of alternative insurance instruments and inputs.

In this study we assessed, for the first time, the insurance value of SNH provided by the natural regulatory processes, when considering multiple insurance instruments and inputs – i.e. the possibility for farmers to conjointly use NI, MI, risk-mitigating and productive inputs to produce food and to cope with the environmental risks. We also assessed the methodological bias associated with considering certain instruments and not others. To do so, we developed an original conceptual framework that allowed the modelling of a farmer's portfolio in a risky crop-production context. The framework focused on a single crop in order to isolate each effect more easily, however, this prevented the integration of crop-diversification strategies. We applied the framework to a case study located in western France to empirically estimate three aspects of NI performance: the marginal effectiveness to increase and stabilize yields, the insurance value, and the optimal demand of NI. We used a model, estimated with econometric methods, where grassland areas can influence pest risk and various risk mitigation strategies can be employed.

In Section 2, a conceptual framework in which SNH insurance value can be evaluated is presented. Then, Section 3 presents the application with the case study and data. Section 4 presents the estimations of the insurance value, the optimal demand for SNH and the methodological bias. The concluding section discusses the implications of the results. Our estimates showed that grassland areas reduce risk through natural predation by beneficial organisms. We valued this service at 50 €/ha^{-1}, although estimates vary widely depending on the set of strategies considered. Regardless of the alternatives (i.e., chemical inputs and/or market-based insurance), our simulations demonstrated that the use of grassland areas is optimal and can partially substitute for other alternatives.

2. Conceptual framework

2.1. Economic farmer's program

A general graphical overview of the conceptual framework developed below is available in Appendix 1. Farmer's production takes place in a risky crop-production context defined as follows:

$$Y = F(X_{PI}, X_{RI}, X_{NI}) \times (1 - D(X_{PI}, X_{RI}, X_{NI}, \theta)) \tag{1}$$

where Y is the yield at the field scale, which depends on productive inputs (PI; X_{PI}), the risk-mitigating inputs (RI; X_{RI}), the inputs related to the role of natural insurance (NI; X_{NI}) implemented by the farmer in the landscape (here the SNH), as well as on the variable θ representing the production risks. In line with Saha et al.'s framework (1997), we distinguished the potential yield F, mainly impacted by X_{PI}, and the damage rate D, mainly impacted by X_{RI} However, depending on which risks are modeled or the interactions that can exist between the two types of inputs (see e.g., Möhring et al., 2020a; Möhring et al., 2020b), both can influence the two yield components. Furthermore, we used the extension developed by Faure et al. (2024), in which SNH can act on both risks and potential yield due to multiple ecosystem services. As a consequence, natural insurance X_{NI} also has an impact on the output F and on the damage D. Hence, in this framework – such as in Baumgärtner and Strunz (2014), Schaub et al. (2020) and Peled et al. (2020) – natural insurance might positively act on the farmer's expected income and negatively on the farmer's income risk.

This yield is then used to compute the gross margin gm, which is given by:

$$gm = p \times Y(X_{PI}, X_{RI}, X_{NI}) - C(X_{PI}, X_{RI}, X_{NI}, X_{MI}) + \psi(X_{MI}, D) \tag{2}$$

where p is the deterministic output price, C is the cost function, depending on inputs (X_{PI},X_{RI}), deterministic input and insurance prices, as well as natural and market-based insurance (X_{NI}, X_{MI}). ψ is the revenue function from the market-based insurance X_{MI} and the damage D. ψ is based on the model developed by Quaas and Baumgärtner (2008), who studied the relationship between NI and MI. They used a form of indemnity insurance where payouts are based on assessed losses, which is a common type of crop insurance (Bucheli et al., 2023).

The portfolio is defined as the vector of inputs and insurance tools $\mathscr{P} = (X_{PI}, X_{RI}, X_{NI}, X_{MI})$, which represents the whole decision set of the farmer. Portfolio A, denoted $\mathscr{P}_A(X_{NI}, X_{MI}, X_{PI}, X_{RI})$ is the portfolio in which all inputs and insurance tools are available: the *full* portfolio. To explore the effect of integrating PI and RI, three *reduced* portfolios can be defined: B ($\mathscr{P}_B = (X_{NI}, X_{MI}, X_{PI} = 0, X_{RI} = 0)$), C ($\mathscr{P}_C = (X_{NI}, X_{MI}, X_{PI} = 0, X_{RI})$) and D ($\mathscr{P}_D = (X_{NI}, X_{MI}, X_{PI}, X_{RI} = 0)$). Portfolio B is similar to the model usually studied in the literature on natural insurance, with X_{NI} and X_{MI} (e.g. Baumgärtner, 2007; Quaas and Baumgärtner, 2008), in which RI and PI are excluded. Portfolios C and D are variations of the full portfolio excluding either PI ($\mathscr{P}_C$), or RI ($\mathscr{P}_D$).

To represent the farmer's best decision concerning portfolios, the expected utility framework is used, to represent risk preferences vis-a-vis agricultural risk (Rommel et al., 2023). The farmer's program relies on an expected utility function which takes into account the farmer's risk preferences ν:

$$\max_{\mathscr{P}_p \mid p \in \{A,B,C,D\}} U = \mathbb{E}[u(gm, \nu)] \tag{3}$$

2.2. Model specification

Following Saha et al. (1997) and Möhring et al. (2020a); Möhring et al. (2020b), we specified the yield function in Eq. 1 as follows

$$Y = F(X_{PI}, X_{RI}, X_{NI}, \beta) \times exp(\phi) \times exp(-A(X_{PI}, X_{RI}, X_{NI}, \alpha) \times \varepsilon) \tag{4}$$

with $F(X_{PI}, X_{RI}, X_{NI}, \beta) \times exp(\phi)$ being a stochastic production function, and $exp(A \times \varepsilon)$ the damage rate with A the abatement function. We assumed that the potential yield F is subject to random crop growth conditions ϕ such as rainfall or temperatures, while the damage depends on pest abundance ε.

A quasi-Cobb-Douglas form is used to specify the production function F

$$F = exp\beta_0 \times \left(g_\beta(X_{NI})\right)^{\beta_N} \times \prod_{k \in \{PI,RI\}} X_k^{\beta_k} \times exp(\beta_c X_c) \tag{5}$$

with k representing the kth productive or risk-mitigating input, and X_c and β_c denoting the control variables and their respective coefficients. The impact of natural insurance on potential yield is indirect as it operates through a biodiversity-related vector (e.g., pollinating insects; Paul et al., 2020). Thus, the effect is conveyed by $g_\beta(X_{NI})$, with $g_\beta' \geq 0$, $g_\beta'' < 0$.

In line with Faure et al.'s model (2024), the damage decreases in a log-linear manner with risk-mitigating inputs. The abatement function A ($A \geq 0$) is thus given by

$$A = \alpha_0 + \alpha_N ln g_\alpha(X_{NI}) + \sum_{k \in \{RI\}} \alpha_k ln X_k \tag{6}$$

with $g_\alpha(X_{NI})$ representing the risk-mitigating effect of using natural insurance, with $g_\alpha' \geq 0$, $g_\alpha'' < 0$. Combining Eqs. (4, (5 and (6 provides the yield function Y (Table 1, Eq. A). While the complete yield model (Table 1, Eq. A) is associated to the full portfolio A defined above, we defined three reduced yield models (Table 1, Eqs. B, C, D) associated with portfolios B, C, and D respectively. Finally, we considered a utility function following a constant relative risk aversion (CRRA) specification. The risk aversion coefficient is denoted by ν.

$$u(gm, \nu) = \frac{gm^{1-\nu}}{1-\nu} \tag{7}$$

Table 1
Specifications of the yield function used to test the impact of the availability of agricultural inputs. Each model corresponds to a portfolio configuration. The notations of the coefficients are simplified by giving them unique notations regardless of the model. The estimates differ between reduced models (Clogg et al., 1995).

Yield model	Equation	Model	Portfolio
Full (with NI, RI, PI)	$lnY = \beta_0 + \beta_N ln g_\beta(X_{NI}) + \sum_{k \in \{PI,RI\}} \beta_k ln X_k + \varepsilon \times \left(\alpha_0 + \alpha_N ln g_\alpha(X_{NI}) + \sum_{k \in \{RI\}} \alpha_k ln X_k\right) + \phi$	(A)	$\mathscr{P}_A$
Reduced – No agricultural inputs (with NI, without RI, PI)	$lnY = \beta_0 + \beta_N ln g_\beta(X_{NI}) + \varepsilon \times (\alpha_0 + \alpha_N ln g_\alpha(X_{NI})) + \phi$	(B)	$\mathscr{P}_B$
Reduced – No productive inputs (with NI, RI, without PI)	$lnY = \beta_0 + \beta_N ln g_\beta(X_{NI}) + \varepsilon \times \left(\alpha_0 + \alpha_N ln g_\alpha(X_{NI}) + \sum_{k \in \{RI\}} \alpha_k ln X_k\right) + \phi$	(C)	$\mathscr{P}_C$
Reduced – No risk-mitigating inputs (with NI, PI, without RI)	$lnY = \beta_0 + \beta_N ln g_\beta(X_{NI}) + \sum_{k \in \{PI\}} \beta_k ln X_k + \varepsilon \times (\alpha_0 + \alpha_N ln g_\alpha(X_{NI})) + \phi$	(D)	$\mathscr{P}_D$

2.3. Natural insurance analysis

2.3.1. Natural insurance effectiveness

The elasticity of production of the NI in portfolio $\mathscr{P}_p$, denoted $\mathscr{E}_p(X_{NI})$, is given by combining Eqs. 4, 5 & 6:

$$\mathscr{E}_p(X_{NI}) = \frac{\partial ln Y^p}{\partial ln X_{NI}} = \beta_N^p \frac{\partial ln g_\beta(X_{NI})}{\partial ln X_{NI}} + \varepsilon . \alpha_N^p \frac{\partial ln g_\alpha(X_{NI})}{\partial ln X_{NI}} \tag{8}$$

where Y^p is the yield function associated with portfolio $\mathscr{P}_p$, and β_N^p and α_N^p are the model coefficients in portfolio $\mathscr{P}_p$. The first term $\beta_N^p \frac{\partial ln g_\beta(X_{NI})}{\partial ln X_{NI}}$ is the NI productive effectiveness linked to the contribution of natural insurance to the potential yield. The second term $\varepsilon . \alpha_N^p \frac{\partial ln g_\alpha(X_{NI})}{\partial ln X_{NI}}$ is the risk-mitigation effectiveness of NI.

2.3.2. Insurance value

The insurance value of NI is defined as the marginal decrease of risk premium allowed by an incremental unit of X_{NI} (Baumgärtner, 2007). Thus, the insurance value is measured in units of income, and can be interpreted as the well-being the farmer benefits from due to the reduction of uncertainty, allowed by an incremental unit of NI. The insurance value thus has a subjective dimension: the more risk averse the farmer, the higher the value (Baumgärtner and Strunz, 2014). Formally, the insurance value of NI at the use level X_{NI} is given by:

$$V_I(X_{NI}) = -\frac{\partial RP}{\partial X_{NI}}(X_{NI}) \tag{9}$$

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

$$RP = \mathbb{E}[gm] - u^{-1}(\mathbb{E}[u(gm)]) \tag{10}$$

The insurance value of NI can be computed both at the observed and at the optimal use levels of inputs.

2.3.3. Optimal demand for natural insurance

From the program in Eq. 3, we derive the *optimal demand for NI*. It is formally defined as:

$$X_{NI}^* = \underset{X_{NI} \geq 0}{\mathrm{argmax}} U \tag{11}$$

which describes how the farmer will optimally use the natural insurance within the insurance portfolio.

3. Application

3.1. Case study and data

We applied the framework to a case study located in western France, which is a typical intensive agricultural landscape, the Zone Atelier Plaine & Val de Sèvre. This is a 450-km^2 cereal crop plain that includes about 435 farms and 12,000 fields (Bretagnolle et al., 2018a). The site is part of the international network of long-term socio-ecological research platforms (LTSER; Singh et al., 2013). The model in our study focused on oilseed rape, which is the second-largest source of vegetable oil in the world (USDA, 2023), accounts for 39 % of European biodiesel feedstock production (Flach et al., 2019), and is one of the riskiest crops, with highly variable yields (Zheng et al., 2020). It should also be noted that oilseed rape yields are partly dependent on pollination (Woodcock et al., 2019). We modeled two agricultural risks. First, an endogenous pest risk related to flea beetles, which can severely damage oilseed rape crops. The exogenous second risk included crop growth conditions, mainly meteorological conditions such as temperature and rainfall, and the overall pest risk due to other pests such as weeds or other insects.

In the model, the farmer could increase production potential through fungicide and fertilizer application, both considered productive inputs (X_{PI} in Eq. 4). The risk-mitigating input was associated with insecticide application (X_{RI} in Eq. 4). The farmer could increase the portion of semi-natural habitats (SNHs; i.e. grassland areas and hedgerows) in the landscape, which have proven benefits for natural enemies of pests and for bees (Albrecht et al., 2020; Bengtsson et al., 2019), as they are compatible with natural enemy and bee nesting and rich in melliferous resources. As SNHs are associated with the natural insurance tool, their proportion in the landscape was therefore denoted $X_{NI} \in [0, 1]$. In this model, we assumed that the natural insurance role of grassland areas was limited to pest risk, excluding the possibility of substituting for oilseed rape (diversification) and treating other risks as exogenous. Lastly, the farmer could choose a fraction X_{MI} of the crops to cover by market insurance.

In this case study, we used three databases: (i) a farmers' survey database containing information on yield and farming practices (e.g. fertilizers or pesticides) as well as the associated cost of these practices from 294 oilseed rape fields surveyed in the study area from 2011 to 2018 (Catarino et al., 2019), (ii) a biodiversity database containing bee and pest abundance sampled in 124 fields from 2013 to 2018 (Bretagnolle et al., 2018b; Perrot et al., 2022), and (iii) a Geographic Information System containing complete land use occupation recorded since 1994, as well as soil characteristics (Bretagnolle et al., 2018a). The description of the data is available in Supplementary Material 1. All data was ln-transformed and standardized for estimations. The NI – that is, the SNH use rate – corresponded to the percentage of grassland areas within a buffer zone automatically selected by the *siland* package in R (Carpentier and Martin, 2021).

3.2. Parameter estimations and simulation plan

Testing the impact of portfolios on insurance value and optimal demand involved simulating decisions that are outside the range of observed data and strategies within the case study. In that respect, we used the process established by Antle and Capalbo (2001), in which the data collected in the case study was used to estimate econometric production models, and then incorporated into a simulation model that represented the decision-making process of the farmer. This protocol allowed decision-making to be simulated in a way that is consistent both with economic theory and with site-specific biophysical constraints and processes. We adapted it to our analysis, which focused on NI.

Following Faure et al. (2024), we specified the yield (Table 1; Eq. A) as follows:

$$lnY = \beta_0 + \beta_1 lnBees + \beta_2 lnFung + \beta_3 lnInsc + \beta_4 lnFert + \beta_5 Soil + lnPests \times (\alpha_0 + \alpha_1 lnSNH + \alpha_2 lnInsc) + \phi \tag{12}$$

where *Bees* and *Pests* represent the abundance of bees and pests. *Fung*, *Insc* and *Fert* are respectively the use of fungicide, insecticide and fertilizer. *Soil* stands for the soil quality, and *SNH* is the SNH implementation rate. The reduced yield functions (Table 1; Eqs. B, C, D) are built in the same way as Eq. 12 (Supplementary Material 2). We assumed that bee abundance is impacted by the SNH use rate (Bengtsson et al., 2019). To account for this, we built a hierarchical multilevel model, with a sub-model of bee abundance that includes *SNH*, the estimate of which was then integrated in the production model (more details in Supplementary Material 3).

The parameters of the yield functions (Eq. 12, S1, S2, S3) as well as the gross margin model (Eq. 2; results reported in Table S2) were estimated using ordinary least squares (OLS) regression (using R version 4.1.2; R Core Team, 2018) in combining the datasets described in Section 3.1. All linear model assumptions were checked.

The four estimated yield models (Table 1) were then used, in combination with the site data, to simulate farmers' optimal decisions, including the optimal demands for NI. The simulations were designed to capture the heterogeneity between years, fields, and surrounding landscape characteristics, as well as risk preferences and the resulting spatial variation of economic behaviour in the case study. We associated each of the 124 observed fields (obtained with a combination of datasets [i], [ii] and [iii]) with five values of risk aversion coefficient[1] (Faure et al., 2024). The latter were sampled in the empirical distribution of risk preferences in the case study, collected in experiments on 128 farmers in the area. This gave a total of 620 'field–farmer' pairs. The pest risk distribution ε was simulated through a Weibull distribution, which is common for modelling pest levels (Wagner et al., 1984). The risk distribution is known from farmers. The risk associated with crop growth conditions ϕ was assimilated to the residuals of each model. Finally, we represented the variation in the MI loading factor by sampling a random number across a uniform distribution $\mathscr{U}(0.15, 0.30)$ calibrated with Hartell et al. (2006). We carried out two sensitivity analyses on prices of RI (insecticides) and MI (crop insurance), which simulated a doubling of the prices of other insurance tools and the impact of this on the optimal demand for NI.

3.3. Statistical assessments of natural insurance performance and methodological bias

To determine the natural insurance role of SNH, we evaluated for the complete portfolio (Model A) the three performance indicators presented in Section 2.3: effectiveness, insurance value, and the optimal level of SNHs. We used observed data to evaluate the first two indicators (Eqs. 8–9), and used the simulated data defined in the previous section to estimate optimal demand (Eq. 11).

We also evaluated the methodological bias, by comparing the impact of the three other portfolios on both the productive and risk-mitigation effectiveness of NI, both defined in Section 2.3.1. These comparisons were made for given levels of pests ε and X_{NI}. Thus, comparing productive effectiveness was equivalent to studying the difference $\widehat{\beta_N^{p_1}} - \widehat{\beta_N^{p_2}}$ for each portfolio pair $\mathscr{P}_{p_1}$ and $\mathscr{P}_{p_2}$, where the hats are the estimates of the model coefficients. Similarly, we studied the difference $\widehat{\alpha_N^{p_1}} - \widehat{\alpha_N^{p_2}}$ to compare risk-mitigation effectiveness. Each difference was compared to zero. The standard errors of these differences were calculated using the method developed by Clogg et al. (1995) for comparing nested models.

Comparing portfolio B (Table 1, Eq. B) with portfolio A assessed the impact of considering RI and PI optimal demand, while the comparison between A and portfolios C and D (Table 1, Eq. C and D) assessed the marginal impact of adding either risk-mitigating (RI) or productive inputs (PI) respectively.

[1] This value was chosen arbitrarily to represent a reasonable trade-off between the variance in risk preferences and the computational time.

Since most of the simulated data did not follow standard distributions, we used non-parametric statistical tests for the analysis. Wilcoxon-Mann-Whitney tests were used to compare all pairs of samples on quantitative variables (i.e. estimated insurance value of NI and optimal demand for NI). The tests were paired because the field-farmer pairs were the same across two samples. All statistical analyses were carried out with R software.

4. Results

In this section, we first present the evaluation of SNH effectiveness and its insurance value in our case study. Next, we present the results of the optimal demand simulation, illustrating how an NI tool could be integrated into the risk-mitigation strategy. Additionally, we discuss the methodological bias related to simplified portfolios, evaluating them using the same units as the performance indicators.

4.1. Effectiveness and insurance value

Firstly, our estimation of the parameters of the production function (Eq. 12) confirms that SNHs play a role in natural insurance by mitigating the negative effect of pests on yield (Table 2; Model A). While pest abundance has a significantly negative effect, this effect is mitigated by the interaction between these pests and SNHs. We suspect that the underlying phenomenon is the predation of insect pests by their natural enemies. The translation of this natural insurance role into value is shown in Fig. 1. This insurance value is estimated at approximately €50. ha^{-1} for our case study with the complete model (Model A).

The study of methodological bias was independently conducted for each indicator. Firstly, our estimates show that it is robust to include inputs in the models, as the *F*-ratio between Models A and B (Table 1) is 7.517, which is significant at less than the 0.001 threshold. This indicates a better fit with the data in the former model than in the latter. In other words, $\mathscr{P}_A$ is a more realistic portfolio than $\mathscr{P}_B$, and agricultural inputs (RI and PI) must be included in the analysis of natural insurance to explain real decisions.

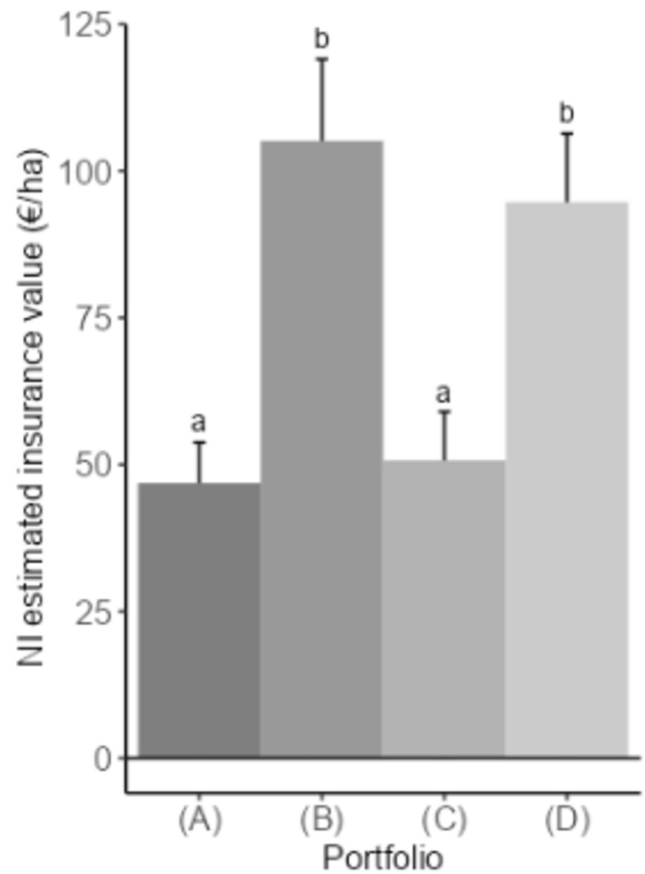

Fig. 1. Estimated insurance value of NI (semi-natural habitat implementation) in the observed levels of inputs in each portfolio. Letters of significance of Wilcoxon tests are shown.

Table 2
Estimations of the yield models. All data is log-transformed, endogenous variables are standardized. The specifications are those presented in Table 1. Standard errors are in parentheses.

	Yield			
	Specifications relative to portfolios			
	(A)	(B)	(C)	(D)
Bees (SNH)	0.045**	0.059***	0.057***	0.045**
	(0.018)	(0.019)	(0.018)	(0.019)
Fertilizers	0.042**			0.050***
	(0.018)			(0.019)
Fungicides	0.034*			0.035*
	(0.018)			(0.019)
Insecticides	0.050***		0.049***	
	(0.018)		(0.018)	
Soil type	0.055***	0.063***	0.062***	0.056***
	(0.018)	(0.019)	(0.018)	(0.019)
Pests	−0.072***	−0.060***	−0.066***	−0.067***
	(0.018)	(0.019)	(0.018)	(0.019)
Insecticides × Pests	0.053***		0.064***	
	(0.020)		(0.020)	
SNH × Pests	0.034*	0.063***	0.039**	0.052***
	(0.019)	(0.020)	(0.020)	(0.019)
Intercept	1.317***	1.321***	1.317***	1.321***
	(0.017)	(0.019)	(0.018)	(0.018)
Observations	124	124	124	124
R^2	0.395	0.237	0.343	0.306
Adjusted R^2	0.353	0.211	0.309	0.270
Residual Std. Error	0.192 (df = 115)	0.212 (df = 119)	0.199 (df = 117)	0.204 (df = 117)
F Statistic	9.377*** (df = 8; 115)	9.217*** (df = 4; 119)	10.183*** (df = 6; 117)	8.594*** (df = 6; 117)

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Then, the comparison of the SNH-related coefficients (Bees β_1 and SNH-Pests interaction α_1) between the full model (Eq. 12) and each reduced model (Eq. S1, S2, S3) shows that omitting agricultural inputs implies methodological bias. Table 2 shows that the coefficients α_1 and β_1 in Model A (Eq. 12; see details in Table S3) are significantly lower than those in Model B (Eq. S1). This indicates that considering agricultural risk-mitigating and productive inputs in the production model significantly reduces both the mean yield (Bees) and variance (SNH × Pests) effects of SNH natural insurance. Comparing the coefficients of Models C and D with those of Model A (Table 2, Table S3) indicates that while the mean effect is explained by the presence of productive inputs in Model A, the variance effect is explained by the presence of risk-mitigating inputs in Model A. In sum, considering the availability of agricultural inputs for farmers to deal with environmental risks systematically diminishes the production and the risk-mitigating effectiveness of NI. As a consequence, these results suggest that simplified yield models and insurance portfolios may have overestimated the capacity of ecosystems to mitigate agricultural risks.

This methodological bias also affects the natural insurance value, which is doubled and thus significantly overestimated in the absence of all agricultural inputs in the yield models (comparing portfolios A and B). Analyses of portfolios C and D suggest that the overestimation is caused by the presence of risk-mitigating inputs, since there is no significant difference between portfolios A (full) and C (with risk-mitigating inputs and without productive inputs). Hence, similar to effectiveness, considering risk-mitigating inputs systematically depreciates the insurance value of NI.

Table 3
Optimal demands for NI in the portfolios: $\mathscr{P}_A$ (complete), $\mathscr{P}_B$ (without inputs), $\mathscr{P}_C$ (without productive inputs) and $\mathscr{P}_D$ (without risk-mitigating inputs). Simulations are conducted with two additional calibrations to the initial calibration (i): with a doubled price of insecticides (ii, risk-mitigating input) and a doubled market insurance price index (iii).

—	(i) Initial calibration		(ii) High price of RI		(iii) High price of MI	
	Mean	SD	Mean	SD	Mean	SD
$\mathscr{P}_A$	0.102	0.037	0.068	0.028	0.131	0.047
$\mathscr{P}_B$	0.177	0.035	0.177	0.051	0.176	0.031
$\mathscr{P}_C$	0.156	0.052	0.098	0.041	0.189	0.057
$\mathscr{P}_D$	0.125	0.038	0.123	0.044	0.139	0.036

4.2. Optimal demand and relationships with other inputs

Table 3, col. (i) reports the simulations of the optimal demands for NI in portfolios A, B, C and D. This allows highlighting the effects of agricultural inputs on the economic performance of SNH in an efficient productive context, and thus to determine whether SNH substitutes for or complements synthetic inputs. First of all, we observe that integrating inputs drastically reduces the optimal demand for NI: the demand drops by 75 % between the reduced portfolio B without agricultural inputs compared to the full portfolio A (Table 3; col. [i]). This suggests a substitution effect between agricultural inputs and SNH. Interestingly, this substitution is observed regardless of the type of agricultural input. Demand decreases from 17.7 % (portfolio B: without agricultural inputs) to 15.6 % (portfolio C: with risk-mitigating inputs; Table 3; col. [i]). It drops even further (to 12.5 %) when productive inputs are marginally added (portfolio D). These results suggest that both risk-mitigating and productive inputs decrease the interest for NI, which may be due to the loss of effectiveness both in the forementioned increasing mean and decreasing variance.

Table 3, col. (ii) highlights the impact of an increase in the price of risk-mitigating inputs (i.e. insecticides) on optimal demand for NI. Unexpectedly, we observe that a higher price for insecticides deepens the decrease in optimal demand that follows the consideration of agricultural inputs in the portfolio (from 17.7 %±5.1 % in portfolio B to 6.8 %± 2.8 % in portfolio A). It suggests that the demand for insecticides and for NI are positively linked, showing that these two risk-management inputs are complementary rather than substituting for one another. Additional analyses indicate that this result is caused by the dual role (i.e. simultaneous productive and risk-reducing roles) played by SNH in our study (Supplementary Material 4), since when the productive role is muted, the two become substitutes.

Table 3, col. (iii) highlights the impact of an increase in the price of MI on optimal demand for NI. A higher price for MI globally increases the optimal demand for NI, showing that the two act as substitutes for risk management. Interestingly, doubling the price of MI reverses the marginal effect of risk-reducing inputs, as the optimal demand shifts from 17.6 % (±3.1 %) to 18.9 % (±5.7 %), suggesting that NI and risk-mitigating inputs become substitutes rather than complements. Overall, an increase in other insurance tool prices mitigates – but does not eliminate – the lower performance caused by the addition of agricultural inputs in the portfolio.

5. Discussion

5.1. The insurance value of semi-natural habitats

Natural insurance tools based on regulatory processes and stimulated by the implementation of semi-natural habitat (SNH) seem promising for the future of agriculture. However, empirical evidence of its insurance role and value is required to promote its implementation. To date, very few studies have evidenced the role of SNH for production and farmer well-being (but see Pywell et al., 2015), and to our knowledge only Colloff et al. (2013) have evidenced that farmers benefit from an insurance value of natural pest control resulting from SNH (in the context of citrus orchards). One reason for the scarcity of such empirical evidence is the high cost of simultaneously collecting ecological, agronomic and economic data. In this study, we considered the case of Zone Atelier Plaine & Val de Sèvre, a long-term interdisciplinary monitoring platform that includes data on all these areas (Bretagnolle et al., 2018a). Such platforms are expected to develop in coming years, especially with the establishment of the eLTER network at the European level,[2] which might boost empirical studies on the natural insurance role of SNHs. A second reason is that the effect of SNHs on natural enemies, pests and yields is not straightforward and can largely depend on the specific context (Albrecht et al., 2020; Chaplin-Kramer et al., 2011; Tscharntke et al., 2016).

In our case study, we converted the risk-mitigation role into a monetary value and found an insurance value of approximately €50. ha^{-1}. This value is significantly lower than the one estimated by Colloff et al. (2013), which ranged between €1700 and €5600.ha^{-1} for citrus orchards. The first thing to note about this discrepancy is that the authors considered the avoided cost of pesticides as the insurance value while citrus is a highly treated crop. Second, their calculation method may have overestimated the value compared to other definitions (including ours; Logar and van den Bergh, 2013). In addition, our model may underestimate the insurance value because it does not include all the benefits of risk mitigation provided by SNHs. For example, we did not estimate the role of grassland areas in flood regulation, erosion prevention, and climate regulation (Bengtsson et al., 2019; Milazzo et al., 2023). Excluding these other types of risks from the model and the effect of natural insurance on them might underestimate the effectiveness and insurance value of grassland areas. However, these effects are difficult to evaluate, especially at a localized scale like in our case. In addition, it is entirely conceivable that farmers may substitute some of their crops with grassland areas, as seen in the model by Faure et al. (2023), for example. In this case, grassland areas would provide additional insurance value, as they would allow for diversification of the portfolio. All these aspects show that further research is needed to clarify how to estimate insurance value with the available data, and the debate is still open on the most accurate value (Dallimer et al., 2020). Nonetheless, our estimation of insurance value contributes to addressing the need expressed in the field of applied ecology for studies that demonstrate that pest regulation management produces net agronomic and economic benefits (Kleijn et al., 2019). Only a few studies have shown this to date, and there is significant anticipation from economists, as such data is necessary to motivate the adoption of SNHs.

5.2. Evidencing ecological intensification

There is a growing need to better understand how farmers can balance various risk-mitigation tools, including nature-based instruments (Finger et al., 2024). By examining different portfolios, in this study we show that SNH could partially replace traditional insurance tools such as insecticides or market-based insurance. This aligns with findings on the integration of other forms of natural insurance, such as diversification. For example, some authors have shown that genetic diversity can substitute for pesticide use (Di Falco and Chavas, 2006). Our findings also indicate that SNH could substitute for productive inputs such as fertilizers, particularly through other regulatory functions such as pollination. These results support the hypothesis of ecological replacement rather than ecological enhancement (Bommarco et al., 2013). In that respect, the results allow new insights in favour of ecological intensification (Bommarco et al. (2013), which has been lacking in empirical evidence (Kleijn et al., 2019; Paul et al., 2020).

[2] Integrated European Long-term Ecosystem and Socio-ecological Research: https://elter-ri.eu

Our contribution in showing the potential benefit of ecological intensification also includes quantifying the impact of omitting inputs in the measurement of insurance value, as in previous scientific studies. Our results show that both the insurance value and the optimal demand for SNH have been significantly overestimated, suggesting that the marginal benefit is smaller than expected. This aligns with recent debates on methodological choices in the empirical evaluation of sustainable risk-management solutions (Finger et al., 2024). Our conclusions align with Paul et al. (2020), who conducted a comprehensive study on the impacts of synthetic inputs in evaluating biodiversity value. The authors explained that omitting inputs in decision-making implies that biodiversity and value are linked by a positive monotonic relationship (such as in Baumgärtner's, 2007 seminal paper). On the other hand, considering inputs in decision-making alters biodiversity-related benefits, including insurance value, towards a non-monotonic relationship between biodiversity and value. This is a good illustration of the perceptual differences that can sometimes exist between scientists and farmers regarding the role of ecosystem services in production (Maas et al., 2021). It confirms that representing over-simplified decisions may not reflect the reality farmers face (Finger et al., 2024).

5.3. Generalizations and limitations

Although we considered that grassland areas in an arable crop area regulate pests of oilseed rape, a similar insurance role of SNH can be expected in different agricultural landscapes where the benefits of pest regulation have already been proven. For example, grassland areas also increase seed predation of weeds and predation of aphids in cereals (Perrot et al., 2021); and other types of SNH, such as flower strips, play a similar role in natural pest regulation (Albrecht et al., 2020). However, it is difficult to generalize the positive value of this natural insurance beyond the context of a specific crop. The effects of SNHs and pollination services vary strongly depending on the landscape (Batáry et al., 2011), and therefore natural insurance might have a null or negative value function in an agroecosystem of interest.

Our study also has some limitations that should be mentioned. Firstly, since decision modelling is at the plot level, it does not account for diversification possibilities at the farm level to reduce risks (Baumgärtner and Quaas, 2010). It would be interesting to explore this possibility and any changes in risk-management scale. Additionally, mixing oilseed rape varieties, with some maturing earlier to attract pests, could reduce risk at the field scale, providing another form of natural insurance besides SNHs, although few farmers currently practice this as its benefits are unproven. Furthermore, our model does not include stochasticity in prices. Recent events of input price volatility have shown that risk reduction based on chemical inputs can actually be economically risky (Mustafa et al., 2024). It would be interesting to see if price volatility affects the substitution between artificial insurance methods and insurance solutions based on natural regulatory processes. Another limitation is that although we simulated an entire landscape with many heterogeneous farmers, we did not model certain positive externalities provided by SNHs such as cultural value or broader support services they offer (Bengtsson et al., 2019; Montgomery et al., 2020). Nor did we model negative externalities of using agrochemicals (Tudi et al., 2021). We did not consider the long-term benefits of agriculture relying on good ecosystem functioning, which is known to contribute to ensuring resilient landscapes for the future (Baumgärtner and Strunz, 2014; Bennett et al., 2021; Folke et al., 2010). So our field-focused results need to be nuanced, as they do not reflect a comprehensive understanding of all the benefits provided by nature.

6. Conclusion

Our results have shown that it is profitable and efficient for farmers to partially rely on the natural insurance role provided by grassland areas for risk regulation of oilseed rape. To directly address our research question, semi-natural habitats do indeed offer an alternative solution for risk mitigation. This finding aligns with the broader concept of ecological intensification, which posits that ecological functions and synthetic inputs can substitute for each other. Although empirical evidence remains limited, it is beginning to emerge. For example, Frank (2024) demonstrated that pest control provided by bats in the United States could have been replaced by insecticides.

Despite these empirical proofs of the effectiveness of ecosystems in reducing risks, this may not necessarily lead to widespread adoption by farmers for several reasons. Firstly, they may be unsure about the relevance of general recommendations from scientific studies for their specific farms (Kleijn et al., 2019). Moreover, besides economic considerations, a range of non-economic determinants, such as social interactions and risk perception, also play a role (Klebl et al., 2023). Secondly, when generalizing to other 'non-productive' SNHs such as flower strips or hedgerows, farmers would bear the full cost without any direct economic return from production. In this context, since the insurance function of ecosystems is a public good, it is crucial to find solutions for the governance of the insurance value of SNH, as the costs cannot be fully recovered by the farmers themselves (Paavola and Primmer, 2019).

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CRediT authorship contribution statement

Jérôme Faure: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Lauriane Mouysset:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Appendix

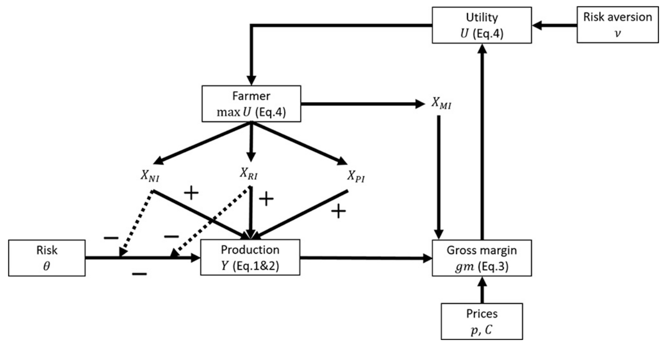

Fig. A1. Conceptual framework overview.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108415.

References

Albrecht, M., Kleijn, D., Williams, N.M., Tschumi, M., Blaauw, B.R., Bommarco, R., et al., 2020. The effectiveness of flower strips and hedgerows on pest control, pollination services and crop yield: a quantitative synthesis. Ecol. Lett. 23, 1488–1498. https://doi.org/10.1111/ele.13576.

Antle, J.M., Capalbo, S.M., 2001. Econometric-process models for integrated assessment of agricultural production systems. Am. J. Agric. Econ. 83, 389–401. https://doi.org/10.1111/0002-9092.00164.

Batáry, P., András, Báldi, David, Kleijn, Teja, Tscharntke, 2011. Landscape-moderated biodiversity effects of Agri-environmental management: a meta-analysis. Proc. R. Soc. B Biol. Sci. 278, 1894–1902. https://doi.org/10.1098/rspb.2010.1923.

Baumgärtner, S., 2007. The insurance value of biodiversity in the provision of ecosystem services. Nat. Resour. Model. 20, 87–127. https://doi.org/10.1111/j.1939-7445.2007.tb00202.x.

Baumgärtner, S., Quaas, M.F., 2010. Managing increasing environmental risks through agrobiodiversity and agrienvironmental policies. Agric. Econ. 41, 483–496. https://doi.org/10.1111/j.1574-0862.2010.00460.x.

Baumgärtner, S., Strunz, S., 2014. The economic insurance value of ecosystem resilience. Ecol. Econ. 101, 21–32. https://doi.org/10.1016/j.ecolecon.2014.02.012.

Bengtsson, J., Bullock, J.M., Egoh, B., Everson, C., Everson, T., O'Connor, T., et al., 2019. Grasslands—more important for ecosystem services than you might think. Ecosphere 10, e02582. https://doi.org/10.1002/ecs2.2582.

Bennett, E.M., Baird, J., Baulch, H., Chaplin-Kramer, R., Fraser, E., Loring, P., et al., 2021. Chapter one - ecosystem services and the resilience of agricultural landscapes. In: Bohan, D.A., Vanbergen, A.J. (Eds.), Advances in Ecological Research, 64. Academic Press, pp. 1–43. https://doi.org/10.1016/bs.aecr.2021.01.001.

Bommarco, R., Kleijn, D., Potts, S.G., 2013. Ecological intensification: harnessing ecosystem services for food security. Trends Ecol. Evol. 28, 230–238. https://doi.org/10.1016/j.tree.2012.10.012.

Bretagnolle, V., Berthet, E., Gross, N., Gauffre, B., Plumejeaud, C., Houte, S., et al., 2018a. Towards sustainable and multifunctional agriculture in farmland landscapes: lessons from the integrative approach of a French LTSER platform. Sci. Total Environ. 627, 822–834. https://doi.org/10.1016/j.scitotenv.2018.01.142.

Bretagnolle, V., Berthet, E., Gross, N., Gauffre, B., Plumejeaud, C., Houte, S., et al., 2018b. Description of long-term monitoring of farmland biodiversity in a LTSER. Data Brief 19, 1310–1313. https://doi.org/10.1016/j.dib.2018.05.028.

Bucheli, J., Conrad, N., Wimmer, S., Dalhaus, T., Finger, R., 2023. Weather insurance in European crop and horticulture production. Clim. Risk Manag. 41, 100525. https://doi.org/10.1016/j.crm.2023.100525.

Carpentier, F., Martin, O., 2021. Siland a R package for estimating the spatial influence of landscape. Sci. Rep. 11, 7488. https://doi.org/10.1038/s41598-021-86900-0.

Catarino, R., Bretagnolle, V., Perrot, T., Vialloux, F., Gaba, S., 2019. Bee pollination outperforms pesticides for oilseed crop production and profitability. Proc. R. Soc. B Biol. Sci. 286, 20191550. https://doi.org/10.1098/rspb.2019.1550.

Chaplin-Kramer, R., O'Rourke, M.E., Blitzer, E.J., Kremen, C., 2011. A meta-analysis of crop pest and natural enemy response to landscape complexity. Ecol. Lett. 14, 922–932. https://doi.org/10.1111/j.1461-0248.2011.01642.x.

Clogg, C.C., Petkova, E., Haritou, A., 1995. Statistical methods for comparing regression coefficients between models. Am. J. Sociol. 100, 1261–1293.

Colloff, M.J., Lindsay, E.A., Cook, D.C., 2013. Natural pest control in citrus as an ecosystem service: integrating ecology, economics and management at the farm scale. Biol. Control 67, 170–177. https://doi.org/10.1016/j.biocontrol.2013.07.017.

Dallimer, M., Martin-Ortega, J., Rendon, O., Afionis, S., Bark, R., Gordon, I.J., et al., 2020. Taking stock of the empirical evidence on the insurance value of ecosystems. Ecol. Econ. 167, 106451. https://doi.org/10.1016/j.ecolecon.2019.106451.

Deutsch, C.A., Tewksbury, J.J., Tigchelaar, M., Battisti, D.S., Merrill, S.C., Huey, R.B., et al., 2018. Increase in crop losses to insect pests in a warming climate. Science 361, 916–919. https://doi.org/10.1126/science.aat3466.

Di Falco, S., Chavas, J.-P., 2006. Crop genetic diversity, farm productivity and the management of environmental risk in rainfed agriculture. Eur. Rev. Agric. Econ. 33, 289–314. https://doi.org/10.1093/eurrag/jbl016.

Di Falco, S., Chavas, J., 2009. On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. Am. J. Agric. Econ. 91, 599–611. https://doi.org/10.1111/j.1467-8276.2009.01265.x.

Ehrlich, I., Becker, G.S., 1972. Market insurance, self-insurance, and self-protection. J. Polit. Econ. 80, 623–648. https://doi.org/10.1086/259916.

Faure, J., Mousset, L., Gaba, S., 2023. Combining incentives with collective action to provide pollination and a bundle of ecosystem services in farmland. Ecosyst. Serv. 63, 101547. https://doi.org/10.1016/j.ecoser.2023.101547.

Faure, J., Gaba, S., Perrot, T., Bretagnolle, V., Mousset, L., 2024. Evaluating the efficient use of ecosystem processes for agricultural production: an empirical analysis of the implementation of a nature-based solution in intensive crop systems. https://doi.org/10.21203/rs.3.rs-3852888/v1.

Finger, R., Sok, J., Ahovi, E., Akter, S., Bremmer, J., Dachbrodt-Saaydeh, S., et al., 2024. Towards sustainable crop protection in agriculture: a framework for research and policy. Agric. Syst. 219, 104037. https://doi.org/10.1016/j.agsy.2024.104037.

Flach, B., Lieberz, S., Bolla, S., 2019. Biofuels Annual EU Biofuels Annual 2019. USDA.

Folke, C., Carpenter, S.R., Walker, B., Scheffer, M., Chapin, T., Rockström, J., 2010. Resilience thinking: integrating resilience, adaptability and transformability. Ecol. Soc. 15.

Frank, E.G., 2024. The economic impacts of ecosystem disruptions: costs from substituting biological pest control. Science 385, eadg0344. https://doi.org/10.1126/science.adg0344.

Hardaker, J.B., Lien, G., Anderson, J.R., Huirne, R.B.M., 2015. Coping with risk in agriculture. In: Applied Decision Analysis, 3rd edition. CABI.

Hartell, J., Ibarra, H., Skees, J., Syroka, J., 2006. Risk Management in Agriculture for Natural Hasards.

Holland, J.M., Douma, J.C., Crowley, L., James, L., Kor, L., Stevenson, D.R.W., et al., 2017. Semi-natural habitats support biological control, pollination and soil conservation in Europe. Rev. Agron. Sustain. Dev. 37, 31. https://doi.org/10.1007/s13593-017-0434-x.

Horowitz, J.K., Lichtenberg, E., 1993. Insurance, moral Hazard, and chemical use in agriculture. Am. J. Agric. Econ. 75, 926–935. https://doi.org/10.2307/1243980.

Klebl, F., Feindt, P.H., Piorr, A., 2023. Farmers' behavioural determinants of on-farm biodiversity management in Europe: a systematic review. Agric. Hum. Values. https://doi.org/10.1007/s10460-023-10505-8.

Kleijn, D., Bommarco, R., Fijen, T.P.M., Garibaldi, L.A., Potts, S.G., van der Putten, W.H., 2019. Ecological intensification: bridging the gap between science and practice. Trends Ecol. Evol. 34, 154–166. https://doi.org/10.1016/j.tree.2018.11.002.

Koellner, T., Schmitz, O.J., 2006. Biodiversity, ecosystem function, and investment risk. BioScience 56, 977–985. https://doi.org/10.1641/0006-3568(2006)56[977:BEFAIR]2.0.CO;2.

Landis, D.A., Wratten, S.D., Gurr, G.M., 2000. Habitat management to conserve natural enemies of arthropod pests in agriculture. Annu. Rev. Entomol. 45, 175–201. https://doi.org/10.1146/annurev.ento.45.1.175.

Logar, I., van den Bergh, J.C.J.M., 2013. Methods to assess costs of drought damages and policies for drought mitigation and adaptation: review and recommendations. Water Resour. Manag. 27, 1707–1720. https://doi.org/10.1007/s11269-012-0119-9.

Maas, B., Fabian, Y., Kross, S.M., Richter, A., 2021. Divergent farmer and scientist perceptions of agricultural biodiversity, ecosystem services and decision-making. Biol. Conserv. 256, 109065. https://doi.org/10.1016/j.biocon.2021.109065.

Markowitz, H.M., 1991. Foundations of portfolio theory. J. Financ. 46, 469–477. https://doi.org/10.2307/2328831.

McLaughlin, A., Mineau, P., 1995. The impact of agricultural practices on biodiversity. Agric. Ecosyst. Environ. 55, 201–212. https://doi.org/10.1016/0167-8809(95)00609-V.

Meuwissen, M.P.M., Mey, Y.De., van Asseldonk, M., 2018. Prospects for agricultural insurance in Europe. Agric. Finan. Rev. 78, 174–182. https://doi.org/10.1108/AFR-04-2018-093.

Milazzo, F., Francksen, R.M., Zavattaro, L., Abdalla, M., Hejduk, S., Enri, S.R., et al., 2023. The role of grassland for erosion and flood mitigation in Europe: a meta-analysis. Agric. Ecosyst. Environ. 348, 108443. https://doi.org/10.1016/j.agee.2023.108443.

Möhring, N., Bozzola, M., Hirsch, S., Finger, R., 2020a. Are pesticides risk decreasing? The relevance of pesticide indicator choice in empirical analysis. Agric. Econ. 51, 429–444. https://doi.org/10.1111/agec.12563.

Möhring, N., Dalhaus, T., Enjolras, G., Finger, R., 2020b. Crop insurance and pesticide use in European agriculture. Agric. Syst. 184, 102902. https://doi.org/10.1016/j.agsy.2020.102902.

Montgomery, I., Caruso, T., Reid, N., 2020. Hedgerows as ecosystems: service delivery, management, and restoration. Annu. Rev. Ecol. Evol. Syst. 51, 81–102.

Mustafa, Z., Vitali, G., Huffaker, R., Canavari, M., 2024. A systematic review on price volatility in agriculture. J. Econ. Surv. 38, 268–294. https://doi.org/10.1111/joes.12549.

Naeem, S., Thompson, L.J., Lawler, S.P., Lawton, J.H., Woodfin, R.M., 1994. Declining biodiversity can affect the functioning of ecosystems. Nature 368, 734–737.

Paavola, J., Primmer, E., 2019. Governing the provision of insurance value from ecosystems. Ecol. Econ. 164, 106346. https://doi.org/10.1016/j.ecolecon.2019.06.001.

Pannell, D.J., 1991. Pests and pesticides, risk and risk aversion. Agric. Econ. 5, 361–383. https://doi.org/10.1016/0169-5150(91)90028-J.

Paul, C., Hanley, N., Meyer, S.T., Fürst, C., Weisser, W.W., Knoke, T., 2020. On the functional relationship between biodiversity and economic value. Sci. Adv. 6, eaax7712. https://doi.org/10.1126/sciadv.aax7712.

Peled, Y., Zemah Shamir, S., Israel, A., Shechter, M., Ofir, E., Gal, G., 2020. Incorporating insurance value into ecosystem services assessments: mitigation of ecosystem users' welfare uncertainty through biological control. Ecosyst. Serv. 46, 101192. https://doi.org/10.1016/j.ecoser.2020.101192.

Perrot, T., Rusch, A., Coux, C., Gaba, S., Bretagnolle, V., 2021. Proportion of grassland at landscape scale drives natural Pest control Services in Agricultural Landscapes. Front. Ecol. Evol. 9, 227. https://doi.org/10.3389/fevo.2021.607023.

Perrot, T., Bretagnolle, V., Gaba, S., 2022. Environmentally friendly landscape management improves oilseed rape yields by increasing pollinators and reducing pests. J. Appl. Ecol. 59, 1825–1836. https://doi.org/10.1111/1365-2664.14190.

Perrot, T., Rusch, A., Gaba, S., Bretagnolle, V., 2023. Both long-term grasslands and crop diversity are needed to limit pest and weed infestations in agricultural landscapes. Proc. Natl. Acad. Sci. 120, 49. https://doi.org/10.1073/pnas.2300861120.

Primmer, E., Paavola, J., 2021. Insurance value of ecosystems: an introduction. Ecol. Econ. 184, 107001. https://doi.org/10.1016/j.ecolecon.2021.107001.

Pywell, R.F., Heard, M.S., Woodcock, B.A., Hinsley, S., Ridding, L., Nowakowski, M., et al., 2015. Wildlife-friendly farming increases crop yield: evidence for ecological intensification. Proc. R. Soc. B 282, 20151740. https://doi.org/10.1098/rspb.2015.1740.

Quaas, M., Baumgärtner, S., 2008. Natural vs. financial insurance in the management of public-good ecosystems. Ecol. Econ. 65, 397–406. https://doi.org/10.1016/j.ecolecon.2007.07.004.

R Core Team, 2018. R: A language and environment for statistical computing.

Renard, D., Mahaut, L., Noack, F., 2023. Crop diversity buffers the impact of droughts and high temperatures on food production. Environ. Res. Lett. 18, 045002. https://doi.org/10.1088/1748-9326/acc2d6.

Rommel, J., Sagebiel, J., Baaken, M.C., Barreiro-Hurlé, J., Bougherara, D., Cembalo, L., Zagórska, K., 2023. Farmers' risk preferences in 11 European farming systems: A multi-country replication of Bocquého et al., 2014. Applied Economic Perspectives and Policy 45 (3), 1374–1399.

Saha, A., Shumway, C.R., Havenner, A., 1997. The economics and econometrics of damage control. Am. J. Agric. Econ. 79, 773–785. https://doi.org/10.2307/1244419.

Sánchez, I.A., Lassaletta, L., McCollin, D., Bunce, R.G.H., 2010. The effect of hedgerow loss on microclimate in the Mediterranean region: an investigation in Central Spain. Agrofor. Syst. 78, 13–25. https://doi.org/10.1007/s10457-009-9224-z.

Sánchez-Bayo, F., Wyckhuys, K.A.G., 2019. Worldwide decline of the entomofauna: a review of its drivers. Biol. Conserv. 232, 8–27. https://doi.org/10.1016/j.biocon.2019.01.020.

Schaak, H., Bommarco, R., Hansson, H., Kuns, B., Nilsson, P., 2023. Long-term trends in functional crop diversity across Swedish farms. Agric. Ecosyst. Environ. 343, 108269. https://doi.org/10.1016/j.agee.2022.108269.

Schaub, S., Buchmann, N., Lüscher, A., Finger, R., 2020. Economic benefits from plant species diversity in intensively managed grasslands. Ecol. Econ. 168, 106488. https://doi.org/10.1016/j.ecolecon.2019.106488.

Singh, S.J., Haberl, H., Chertow, M., Mirtl, M., Schmid, M., 2013. Long Term Socio-Ecological Research: Studies in Society-Nature Interactions across Spatial and Temporal Scales. Springer, Dordrecht.

Smith, V.H., Goodwin, B.K., 1996. Crop insurance, moral Hazard, and agricultural chemical use. Am. J. Agric. Econ. 78, 428–438. https://doi.org/10.2307/1243714.

Staley, J.T., Wolton, R., Norton, L.R., 2023. Improving and expanding hedgerows—recommendations for a semi-natural habitat in agricultural landscapes. Ecol. Sol. Evid. 4, e12209. https://doi.org/10.1002/2688-8319.12209.

Tscharntke, T., Karp, D.S., Chaplin-Kramer, R., Batáry, P., DeClerck, F., Gratton, C., et al., 2016. When natural habitat fails to enhance biological pest control – five hypotheses. Biol. Conserv. 204, 449–458. https://doi.org/10.1016/j.biocon.2016.10.001.

Tudi, M., Daniel Ruan, H., Wang, L., Lyu, J., Sadler, R., Connell, D., et al., 2021. Agriculture development, pesticide application and its impact on the environment. Int. J. Environ. Res. Public Health 18, 1112. https://doi.org/10.3390/ijerph18031112.

USDA, 2023. Oilseeds: World markets and trade. In: USDA Foreign Agricultural Service. https://www.fas.usda.gov/data/oilseeds-world-markets-and-trade. (Accessed 3 February 2023).

Wagner, T.L., Wu, H.-I., Sharpe, P.J.H., Coulson, R.N., 1984. Modeling distributions of insect development time: a literature review and application of the Weibull function. Ann. Entomol. Soc. Am. 77, 475–483. https://doi.org/10.1093/aesa/77.5.475.

Woodcock, B.A., Garratt, M.P.D., Powney, G.D., Shaw, R.F., Osborne, J.L., Soroka, J., et al., 2019. Meta-analysis reveals that pollinator functional diversity and abundance enhance crop pollination and yield. Nat. Commun. 10, 1481. https://doi.org/10.1038/s41467-019-09393-6.

Zheng, X., Koopmann, B., Ulber, B., von Tiedemann, A., 2020. A global survey on diseases and pests in oilseed rape—current challenges and innovative strategies of control. Front. Agronomy 2.

Zweifel, P., Eisen, R., 2012. Insurance Economics. Springer, Heidelberg.