Productive Capacity of Biodiversity: Crop Diversity and Permanent Grasslands in Northwestern France

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Abstract: Previous studies on the productive capacity of biodiversity emphasized that greater crop diversity increases crop yields. We examined the influence of two components of agricultural biodiversity – farm-level crop diversity and permanent grasslands – on the production of cereals and milk. We focused on productive interactions between these two biodiversity components, and between them and conventional inputs. Using a variety of estimators (seemingly unrelated regressions and general method of moments, with or without restrictions) and functional forms, we estimated systems of production functions using a sample of 3,960 mixed crop-livestock farms from 2002-2013 in France. The estimates highlight that increasing permanent grassland proportion increased cereal yields under certain conditions and confirmed that increasing crop diversity increases cereal and milk yields. Crop diversity and permanent grasslands can substitute each other and be a substitute for fertilizers and pesticides.

Keywords: Agriculture; Biodiversity; Ecosystem services; Pesticides; Productivity.

1. Introduction

Modern human activities have degraded biodiversity (MEA, 2005). Converting natural areas to agricultural land is considered the main driver of the decrease in biodiversity (Díaz et al., 2020). In addition, the decrease in the number of crops grown has amplified this issue (Kleijn et al., 2009). This trend has raised questions about the ability to combine intensive agriculture and biodiversity. Protecting biodiversity, however, is crucial because biodiversity contributes to ecosystem functioning, which ultimately influences the provision of many ecosystem services (ES) that are valued by societies, in particular by farmers (Hooper et al., 2005; MEA, 2005).

Supporting and regulating ES (e.g. nutrient cycles, biological control) have been increasingly recognized as inputs for agriculture (Zhang et al., 2007). Several economic studies have analyzed effects of these ES on the production of crop farms. To this end, they estimated production functions that used biodiversity indicators as inputs (e.g. Di Falco et al., 2010).[1] These biodiversity indicators, calculated as functions of proportions of agricultural land-use types, usually indicate the degree of habitat diversity within the studied agroecosystems. Even though the indicators reflect only a small portion of the full concept of biodiversity, they are correlated with species diversity and richness (Burel and Baudry, 2003) and can thus be considered as proxies of productive ES (i.e., ES with properties of agricultural inputs). For example, higher on-farm crop diversity is correlated with greater soil structure (Mäder et al., 2002), pollination (Kennedy et al., 2013) and biological control (Letourneau et al., 2011). Biodiversity indicators thus correspond to an observable but inherently imperfect description of an ecosystem, which supports a vector of several productive ES that can be provided to farms. We refer to the capacity of an ecosystem to provide productive ES based on its observable characteristics as the "biodiversity productive capacity".

Previous studies on the biodiversity productive capacity have emphasized that crop diversity increases mean agricultural yields and profits, while decreasing their variance (e.g. Di Falco and Chavas, 2006; Donfouet et al., 2017; Noack et al., 2019; van Rensburg and Mulugeta, 2016). This information is useful for policymakers because it highlights that high yields are compatible with diversified landscapes. These studies have focused, however, on a single biodiversity component, usually intraspecific or interspecific crop diversity,[2] considering crops as the main habitats within many agroecosystems and revealing how narrowly biodiversity is usually defined. However, crop-oriented agroecosystems usually have lower habitat heterogeneity than many others, which often include diverse alternative landscape elements, including semi-natural elements. These semi-natural elements are usually considered

[1] This method is often used in ecosystem services valuation studies (Perrings, 2010). Another method consists of stochastic frontier analysis, such as by Omer et al. (2007), Amsler et al. (2017) and Ang et al. (2018).

[2] Interspecific diversity refers to diversity among crop species, while intraspecific diversity refers to diversity among genetic varieties of the same crop.

as good-quality habitats for many species (Díaz et al., 2020). Semi-natural areas may also contribute to agricultural production via the flow of productive ES supported by the species they host. For example, Klemick (2011) found that upstream forest fallows have productive spillover effects on crops. Tilman et al. (2001) and Schaub et al. (2020) concluded that grassland diversity increases forage yields. Although these studies focused on semi-natural areas, they still considered only one biodiversity component, ignoring interactions between the diverse components of agroecosystems. Natural sciences suggest, however, that such interactions do exist. For example, several species involved in the biological control of crop pests dwell in semi-natural areas (Aviron et al., 2005).

The present study aimed to extend the knowledge of biodiversity productive capacity by (i) assessing the productivity of crop diversity and permanent grasslands (the latter being a well-known example of semi-natural areas) for cereals and milk and (ii) characterizing productive interactions between these two biodiversity components and between them and conventional variable inputs. Our study thus contributes to debates about the form of the functional relation between biodiversity and economic value (Paul et al., 2020). This knowledge is useful for policymakers since it may hinder implementation of certain policy measures to promote biodiversity conservation and/or decrease applications of polluting inputs.

Assuming that farmers maximize their very short-term profit, we estimated a primal model with two yield functions (cereals and milk) and two biodiversity habitats (crop interspecific diversity and permanent grasslands) on an unbalanced panel of farms from the French Farm Accountancy Data Network (FADN) from 2002-2013. To infer effects of permanent grasslands on cereal yields (or those of crop diversity on milk yields), we limited our sample to mixed crop-livestock farms that produced both milk and cereals. This type of farming is typical in northwestern France, which has the largest proportion of permanent grasslands in France's lowland regions (Desjeux et al., 2015).[3] The very short-term profit-maximizing framework uses the time-sequence of the farmers' decisions with, first, choices of land use in autumn and, second, choices of variable input applications during the growing season to assume that the farmers optimize only the variable inputs, taking the land use and related biodiversity indicators as givens. The system of yield equations was estimated using a variety of estimators from panel econometrics to account for (i) unobserved heterogeneity, (ii) autocorrelation between the two equations and (iii) potential endogeneity issues with variable input applications. We also tested several functional forms of the yield functions, which allowed us to specify the interactions sequentially. We found that (i) crop diversity is an input for cereals and milk, (ii) permanent grasslands are an input for cereals when crop diversity is low, (iii) crop diversity and permanent grasslands can substitute each other and (iv) can be substitutes for pesticides and mineral fertilizers.

Next, we present the case study region and the biodiversity indicators used. We then detail the empirical strategy (section 3), present the results (section 4) and discuss them (section 5).

2. Habitat diversity in northwestern France

2.1. Mixed crop-livestock farming in northwestern France

Due to its cool oceanic climate, agriculture in northwestern France has naturally developed towards animal production (Figure 1). Currently, its three regions – Bretagne, Basse-Normandie and Pays-de-la-Loire – together produce ca. 75% of pigs, 60% of eggs and 60% of milk in France, while still producing ca. 20% of cereals. Most farms have several crops and/or animal-production activities, which makes mixed crop-livestock farming the dominant type of

[3] Mountain regions in France have more permanent grasslands but less crop production.

farming in these regions. Mixed crop-livestock farming is concentrated mainly in western France (Chatellier and Gaigné, 2012).[4]

The interweaving of these activities has created diverse landscapes composed of a mixture of arable and semi-natural areas. In particular, dairy cattle production helps maintain permanent grasslands and a typical "bocage" landscape composed of hedgerows (Thenail, 2002). The diversity of land use provides a diversity of habitats for several species involved in agricultural production (e.g. carabid beetles), but this diversity induces complex spatial interdependencies in ecological processes. For example, Martel et al. (2019) found that hedgerow density increased the density of carabid beetles only in landscapes with low crop diversity. In addition, from 2007 (the beginning of the European Union's (EU's) Land Parcel Identification System in the Common Agricultural Policy (CAP)) to 2010, northwestern France experienced a rapid decrease in semi-natural areas and an increase in crop diversity on arable land (Desjeux et al., 2015). The region has conserved the highest density of permanent grasslands in lowland regions of France.

2.2. Biodiversity indicators

Given the characteristics of northwestern France, we selected two biodiversity components: crop diversity (noted B_{i1t} for farm *i* in year t) and permanent grasslands (noted B_{i2t} for farm *i* in year t). We measured them using two indicators based on land use. First, we measured B_{i1t} using the Shannon index (Baumgärtner, 2006), an indicator commonly used to measure crop diversity (Donfouet et al., 2017). It has the advantage of (i) correcting for both species richness and evenness of their proportional abundances, (ii) being insensitive to sample size and (iii) being well suited to measure habitat diversity (Mainwaring, 2001). Other indices (e.g. count

[4] We excluded southwestern France from our analysis since it has a notably smaller area of permanent grasslands than northwestern France does (especially due to its warmer climate).

index) do not usually correct for evenness (Baumgärtner, 2006). Specifically, the Shannon index is a measure of entropy based on proportions of land-use types. We calculated it using micro-scale data, in which a_{ijt} was the area of output *j* at the farm scale *i*. Since we assessed crop diversity instead of overall land-use diversity, we corrected the index for the area of permanent grassland a_{iJt}. Formally, we calculated B_{1t} as:

$$B_{i1t} = -\sum_{j=1}^{J-1} \frac{\frac{a_{ijt}}{A_{it}}}{1-\frac{a_{iJt}}{A_{it}}} \ln\left(\frac{\frac{a_{ijt}}{A_{it}}}{1-\frac{a_{iJt}}{A_{it}}}\right)$$

where A_{it} was the utilized agricultural area (UAA) of the farm *i* in year *t*. We calculated crop diversity using all crops defined in the FADN (41 annual crops including forages, i.e. maize and temporary grasslands, plus orchards, but without permanent grasslands, i.e. *J*–1=42). According to the Shannon index, B_{i1t} = 0 for a whole farm in monoculture and increases as crop diversity increases. Landscape ecologists have highlighted that biodiversity levels increase as B_{i1t} increases (Burel and Baudry, 2003). The productivity of B_{i1t} captures the productivity of ES such as the preservation of soil quality (Mäder et al., 2002) and biological control (Letourneau et al., 2011). Crop diversity's influence on soil structure explains how it may interact with fertilizer productivity, while its influence on biological control explains how it may interact with the application of pesticides.

We calculated the indicator for permanent grasslands (B_{i2t}) simply as the proportion of permanent grasslands in the UAA of farm *i* (i.e. $B_{i2t} = a_{iJt}/A_{it}$). Using land-use proportions directly as biodiversity indicators make sense when the land-use type considered differs significantly in quality from the other types (Burel and Baudry, 2003), which is likely true for permanent grasslands (Steffan-Dewenter et al., 2002). The literature highlights that B_{i2t} provides suitable habitat for pollinators (Steffan-Dewenter et al., 2002; Ricketts et al., 2008) or for insects involved in biological control (Martel et al., 2019). More generally, the proportion of permanent grasslands is also correlated with other permanent semi-natural landscape elements, such as hedgerows (Thenail, 2002), which may have positive effects on milk and crop yields, such as (i) providing wind breaks, (ii) providing habitats for insects involved in biological control, (iii) influencing hydrological flow, (iv) decreasing erosion and (v) contributing to microclimates (Baudry et al., 2000). Potential effects of permanent grasslands and other related landscape elements on hydrological flows, erosion and biological control also indicate that B_{i2t} may interact with productivities of fertilizers and pesticides.

3. Empirical strategy

In this section, we first present the econometric strategy used to estimate the productivity of crop diversity and permanent grasslands within a system of yield functions (for cereals and milk). Section 3.2. introduces the alternative functional forms that we use for the yield functions. Section 3.3. presents the descriptive statistics of the sample.

3.1. Econometric strategy

We have considered a population of farms **I** that produce milk and cereals, each farm identified by the subscript i ($i \in [1, \dots, I]$). Estimation consisted of a system of yield equations (vector $\boldsymbol{y_{it}}$ with the yield $y_{ijt} = Y_{ijt}/a_{ijt}$ for cereals (j=1) and milk (j=2), where Y_{ijt} is the production of output j on farm i in year t and a_{ijt} the corresponding area) that depends on (i) the two biodiversity indicators ($\boldsymbol{B_{it}}$, including B_{i1t} and B_{i2t}); (ii) conventional agricultural inputs, including variable inputs ($\boldsymbol{X_{it}}$, namely mineral fertilizers, pesticides, seeds and fuel in year t for milk and cereals; and cow feed, health and reproduction expenses for milk) and the quasi-fixed input levels ($\boldsymbol{Z_{it}}$, namely capital, labor and total UAA (A_{it}) in year t); and (iii) additional control variables ($\boldsymbol{C_{it}}$, including weather data and available organic fertilizer (manure) area in year *t*).[5] The two yield equations constituted the following system:

$$\begin{cases} y_{i1t} = f_1(\boldsymbol{B_{it}}, \boldsymbol{X_{it}}, \boldsymbol{Z_{it}}, \boldsymbol{C_{it}}) + \varepsilon_{i1t} \\ y_{i2t} = f_2(\boldsymbol{B_{it}}, \boldsymbol{X_{it}}, \boldsymbol{Z_{it}}, \boldsymbol{C_{it}}) + \varepsilon_{i2t} \end{cases} \quad (1)$$

where $f_1(\cdot)$ and $f_2(\cdot)$ are the estimated production functions for cereals and milk, respectively, and ε_{i1t} and ε_{i2t} are the respective error terms. The error terms captured the unspecified variability in yields, especially the unobserved heterogeneity in the farm population (e.g. farmers' skills and preferences, soil quality). Much of this heterogeneity was considered to be fixed over time, so the error terms were broken down into $\varepsilon_{ijt} = u_{ij} + v_{jt}$ for $j = \{1; 2\}$.[6] Introducing individual fixed effects u_{ij} allowed for control of fixed characteristics of farms that otherwise might have biased estimation of productivities of the biodiversity indicators (e.g. exogenous soil quality). We chose to estimate system (1) using panel econometric estimators, especially the *within* transformation (e.g. Baltagi, 2008), to remove u_{ij}. The v_{jt}, which are the white noise that remains, are assumed to be distributed symmetrically around zero.

We estimated system (1) using seemingly unrelated regressions (SUR). Indeed, since the farms considered were multi-output and thus likely to have jointness in production technologies, the error terms of the two equations were likely correlated (Zellner, 1962).[7] A well-known example of jointness is fertilization of cereals with organic fertilizers. Likewise, cereals can be consumed on-farm as a substitute for forage or purchased cow feed. More generally, any allocable (limiting) input that is marginally used more for one production is, by definition, used less for another. We called Model 1 the estimation of the *within* transformation of system (1) with SUR.

[5] Organic fertilizer (manure) is a crucial control variable since it is correlated with permanent grassland area. Excluding it from the estimation would have overestimated the productivity of permanent grasslands.
[6] A random individual effect could have been specified, but the Durbin-Wu-Hausman test indicated that an individual fixed effect was preferable.
[7] Moreover, the milk yield equation had two more regressors than that for cereals (cow feed and health expenses).

However, contrary to data from random experiments (e.g. Tilman et al., 2001; Schaub et al., 2020), the observed yields in our sample were not independent from the regressors. In particular, the data-generating process resulted from a *profit maximization* (or other optimization process). Formally, farmers modify input levels in response to input and output prices to the extent that the variable input uses depend on the yields the farmers target. This dependence can lead to endogeneity bias in the SUR estimation, which calls for an instrumental variable approach.

To choose the appropriate instruments, consider a risk-neutral farmer who maximizes her annual profit π_{it}. Given input price $\boldsymbol{w_t}$, she produces agricultural goods $\boldsymbol{Y_{it}}$ sold at price $\boldsymbol{p_t}$. We assumed that farmers maximize their profits in the very short term: $\boldsymbol{Z_{it}}$ and $\boldsymbol{B_{it}}$ are not adjusted and farmers optimize only the variable inputs $\boldsymbol{X_{it}}$ (Asunka and Shumway, 1996). This assumption differs from previous studies, which usually instrumented biodiversity indicators, implicitly assuming that farmers optimize $\boldsymbol{B_{it}}$, but did not instrument any other inputs (e.g. Di Falco and Chavas, 2008; Di Falco et al., 2010; Donfouet et al., 2017). There is, however, much evidence that farmers do optimize inputs, in particular variable inputs (e.g. McFadden, 1978). This implies that some explanatory variables are likely be correlated with the error terms. If uncorrected, this endogenous bias would spread to the other parameters estimated, including those measuring the productivity of biodiversity. Appendix 1 presents the decomposition of the profit maximization in a two-stage optimization process in which (i) farmers' land-use decisions $\boldsymbol{a_{it}}$ (and thus the related biodiversity indicators) are determined in the first stage based on (ii) the expected margins of the outputs, which depend on the productivity of the inputs (including $\boldsymbol{B_{it}}, \boldsymbol{X_{it}}$ and $\boldsymbol{Z_{it}}$) and the expected prices of outputs $E(\boldsymbol{p_t})$ and variable inputs $E(\boldsymbol{w_t})$. Following Carpentier and Letort (2012), we assumed that farmers have rational expectations of input prices ($E(\boldsymbol{w_{it}}) = \boldsymbol{w_{it}}$) but have naïve expectations of output prices ($E\left(p_{ijt}\right) = p_{ijt-1}$). However, because the first stage (land-use decisions) occurs ca. 3-6 months before the second stage (variable input applications),[8] expectations of variable input prices may differ between the two stages (due to new information), which may lead to differences between expected and realized gross margins. This difference in expected and realized margins justified the instrumentation of the variable input applications. Specifically, we estimated the *within* transformation of system (1) using the general method of moments (GMM) in Model 2, instrumenting variable input applications with observed output prices in year *t-1* and observed variable input prices in year *t*. We also used decoupled subsidies and milk quotas as additional instruments to capture heterogeneity in the farms' economic environment. Since farmers are price-takers, and milk quotas have never been tradable in France but are instead allocated administratively, our prices and policy instruments were exogenous from the farmer's viewpoint and should have been correlated with variable input applications (Appendix 1). We also instrumented total labor by including the labor of farm partners, which is fixed in the short term and can thus be considered exogenous. The GMM has the additional advantage of correcting for potential heteroscedasticity.

An additional problem arising in our data was that they contained only variable input purchases at the farm scale (and not for each output; e.g. Bareille and Letort, 2018). Specifying output-specific yield functions may thus have required additional technology assumptions about the allocation of the inputs among the outputs. For example, variable input applications can be considered to be rival among products because one unit of an input allocated to a given product cannot be applied to another. However, some of the input may also benefit other products if there is some jointness among the production processes. Therefore, we used two approaches to represent allocation of variable inputs between cereals and milk (see Appendix

[8] In France, the first stage (land-use decisions) usually occurs in autumn, while the second stage (variable input applications) usually occurs in spring.

2 for the theoretical relations that justify them). In the first approach, we considered variable inputs as allocable inputs and applied the corresponding rivalry property to derive optimal conditions of variable input allocation. These conditions led to a set of restrictions on the variable input productivities: the ratio of marginal productivities of cereals to milk must be equal for all variable inputs. We used this property for all shared variable inputs (mineral fertilizers, pesticides, seeds and fuel) to restrict parameters in Model 3 (SUR estimation) and Model 4 (GMM estimation). Thus, Models 3 and 4 corresponded to Models 1 and 2 with additional parameter restrictions, respectively. In the second approach, we simply modeled the variable inputs as non-allocable inputs (Baumol et al., 1988), which implied that variable inputs were the source of unspecified output complementarities and were available to all outputs at the farm level. This specification led to direct estimation of the *within* transformation of system (1), which consisted simply of Model 1 (SUR) and Model 2 (GMM). Choosing between the two approaches is an empirical issue.

Finally, for all four models, we made no assumptions about the allocation of $\boldsymbol{Z}_{it}$ and $\boldsymbol{B}_{it}$ among the outputs, since they were non-allocable inputs (Baumol et al., 1988), but considered some unspecified degree of non-rivalry among outputs. Agricultural economists often use this approach for $\boldsymbol{Z}_{it}$ (e.g. Carpentier and Letort, 2012). The possible non-rivalry of $\boldsymbol{B}_{it}$ among outputs seemed consistent, since ecological processes can have many spillover effects. Models 1 and 2 were compared to illustrate the usefulness of controlling for the endogeneity of variable input applications. Models 1 and 3 were compared to illustrate the utility of adding structure to the system to allocate the observed (farm-scale) variable input applications between cereals and milk. We expected Model 4 to be the best model since it controlled for both variable input endogeneity and allocation issues.

3.2. Alternative functional forms of the production functions

A variety of functional forms can be assumed for $f_1(\cdot)$ and $f_2(\cdot)$ in Models 1-4. We estimate the models using several forms, which we introduce below. We first used log-linear production functions, which other studies have used to estimate the productivity of crop diversity (e.g. Noack et al., 2019).[9] In addition, the log-linear function is usually considered the best functional form for mitigating heteroscedasticity and limiting unobserved heterogeneity biases (Wooldridge, 2015). Specifically, we estimated:

$$\begin{cases} \log(y_{i1t}) = \alpha_1 + \sum_{l=1}^{2} \beta_{l1} B_{ilt} + \sum_{k=1}^{4} \gamma_{k1} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m1} \frac{Z_{imt}}{A_{it}} + \rho_1 A_{it} + \sum_{n=1}^{4} \theta_{k1} C_{int} + u_{i1} + v_{1t} \\ \log(y_{i2t}) = \alpha_2 + \sum_{l=1}^{2} \beta_{l2} B_{ilt} + \sum_{k=1}^{6} \gamma_{k2} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m2} \frac{Z_{imt}}{A_{it}} + \rho_2 A_{it} + \sum_{n=1}^{4} \theta_{k2} C_{int} + u_{i2} + v_{2t} \end{cases} \quad (2)$$

The parameter set $(\alpha_1, \boldsymbol{\beta_{l1}}, \boldsymbol{\gamma_{k1}}, \boldsymbol{\delta_{m1}}, \rho_1, \boldsymbol{\theta_{k1}})$ was used to estimate effects of the independent variables on cereal yields. In it, $\boldsymbol{\beta_{l1}}$ represents the vector of productivity of crop diversity and permanent grassland for cereals (i.e. the productive capacity of the two biodiversity components). We considered four variable inputs for cereals: mineral fertilizer (*k*=1), pesticides (*k*=2), seeds (*k*=3) and fuel (*k*=4). The two fixed inputs *m* were available labor and farm capital. It had 11 control variables C_{int}: nine climatic variables and two variables for organic fertilization (manure production per ha from cattle or from other livestock).[10] We calculated the proxies for organic fertilization using an equation of the French Ministry of Agriculture, based on the number of animal units at the farm scale (CORPEN, 2006).

The parameter set $(\alpha_2, \boldsymbol{\beta_{l2}}, \boldsymbol{\gamma_{k2}}, \boldsymbol{\delta_{m2}}, \rho_2, \boldsymbol{\theta_{k2}})$ was used to estimate effects of the independent variables on milk yields. In it, $\boldsymbol{\beta_{l2}}$ represents the productive capacity of the two biodiversity components. We included the productivities of $\boldsymbol{B_{it}}$ and the four first variable inputs

[9] Most studies on the productivity of biodiversity have used log-log production functions (e.g., Di Falco and Zoupanidou, 2017). However, because approximately one-third of our observations had no permanent grassland, we could not estimate this function without transforming the data.

[10] The nine annual climatic variables are total rainfall, days of rain, total snowfall, days of snowfall, wind speed, humidity, and minimum, maximum and mean temperatures measured.

for milk because of their potential positive impacts on forage production (i.e. greater forage production should increase milk yields). To them, we added purchased feed (*k=5*) and health and reproduction expenses (*k=6*). Milk yields depended indirectly on the number of cows through the addition of the variable for cattle manure production per ha. Because we estimated the *within* transformation of system (2), the constants α_1 and α_2 captured the average technical progress.

Assuming that variable inputs were non-allocable inputs, Models 1 and 2 estimated system (2) directly using the SUR and GMM estimators, respectively. For Models 3 and 4, we added the following restrictions on variable input productivities between cereals and milk (see Appendix 3):

$\gamma_{11}/\gamma_{12} = \gamma_{21}/\gamma_{22}$ (Restriction 1)

$\gamma_{21}/\gamma_{22} = \gamma_{31}/\gamma_{32}$ (Restriction 2)

$\gamma_{31}/\gamma_{32} = \gamma_{41}/\gamma_{42}$ (Restriction 3)

We compared in Section 4.1 performances of the four models that estimated the *within* transformation of system (2) using the log-linear production functions. We also used the following log-quadratic production functions:

$$\begin{cases} \log(y_{i1t}) = \alpha_1 + \sum_{l=1}^{2} \beta_{l1} B_{ilt} + \sum_{l=1}^{2} \beta_{ll1} B_{ilt}^2 + \beta_{121} B_{i1t} B_{i2t} + \sum_{k=1}^{4} \gamma_{k1} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m1} \frac{Z_{imt}}{A_{it}} + \rho_1 A_{it} + \sum_{n=1}^{4} \theta_{k1} C_{int} + u_{i1} + v_{1t} \\ \log(y_{i2t}) = \alpha_2 + \sum_{l=1}^{2} \beta_{l2} B_{ilt} + \sum_{l=1}^{2} \beta_{ll2} B_{ilt}^2 + \beta_{122} B_{i1t} B_{i2t} + \sum_{k=1}^{6} \gamma_{k2} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m2} \frac{Z_{imt}}{A_{it}} + \rho_2 A_{it} + \sum_{n=1}^{4} \theta_{k2} C_{int} + u_{i2} + v_{2t} \end{cases} \quad (3)$$

where the additional $\boldsymbol{\beta}$ parameters represent the productivity of the two biodiversity components for milk and cereals at the second orders. In particular, β_{121} and β_{122} represent the cross-productivity of crop diversity with permanent grasslands. The log-quadratic production functions can capture interesting properties of the biodiversity productive capacity. Indeed, while previous studies found that crop diversity has a decreasing return to scale for cereal production (e.g. Di Falco and Chavas, 2006), they ignored its form for milk production. We also found no information about the form of the productivity of permanent grasslands for milk and cereals in the literature. More importantly, we ignored how the two biodiversity components interact, i.e., whether they are substitutes or complements foreach other (whether β_{121} and β_{122} are positive or negative). Studies from the natural sciences (e.g., Martel et al., 2019) suggest that landscapes with few semi-natural habitats require greater complexity of the crop mosaic to achieve a level of biological control similar to that in that landscapes with many semi-natural habitats. Assuming a positive effect of biological control on both milk and cereals, this observation would suggest that the two biodiversity components are substitute inputs. We aimed to verify this relation by estimating the *within* transformation of system (3) with Models 1, 2, 3 and 4.

As mentioned, several studies from the natural sciences suggest that biodiversity productive capacities may interact with applications of mineral fertilizers and/or pesticides (e.g. Letourneau et al., 2011). Some economic studies have already assessed these interactions. For example, Bareille and Letort (2018) found that higher crop diversity requires application of smaller amounts of fertilizers and pesticides to reach the same yields (i.e. that crop diversity leads to input-savings). To our knowledge, however, no study has assessed technical relations between biodiversity productive capacity and variable inputs when estimating production functions. We thus estimated the following system:

$$\begin{cases} \log(y_{i1t}) = \alpha_1 + \sum_{l=1}^{2} \beta_{l1} B_{ilt} + \sum_{k=1}^{4} \gamma_{k1} \frac{X_{ikt}}{A_{it}} + \sum_{l=1}^{2} \sum_{k=1}^{2} \beta_{lk1}^{\gamma} B_{ilt} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m1} \frac{Z_{imt}}{A_{it}} + \rho_1 A_{it} + \sum_{n=1}^{4} \theta_{k1} C_{int} + u_{i1} + v_{1t} \\ \log(y_{i2t}) = \alpha_2 + \sum_{l=1}^{2} \beta_{l2} B_{ilt} + \sum_{k=1}^{6} \gamma_{k2} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m2} \frac{Z_{imt}}{A_{it}} + \rho_2 A_{it} + \sum_{n=1}^{4} \theta_{k2} C_{int} + u_{i2} + v_{2t} \end{cases} \quad (4)$$

where the four additional $\boldsymbol{\beta}_1^{\gamma}$ parameters represent interactions between the two biodiversity components with mineral fertilizers and pesticides for cereals.[11] We were not aware of any studies that justified productive interactions of biodiversity components with seeds or fuel. To our knowledge, seeds and fuel should be insensitive to the productive ES supported by the two

[11] We attempted to add similar interactions for milk production, but performances of the models decreased considerably (e.g. several variable inputs had negative productivities for milk).

biodiversity components. Because of these new interactions in system (4), the three restrictions no longer held; thus, we estimated the *within* transformation of system (4) using only Models 1 and 2.

Finally, we estimated the most general model, which combined systems (3) and (4):

$$\begin{cases} \log(y_{i1t}) = \alpha_1 + \sum_{l=1}^{2} \beta_{l1} B_{ilt} + \sum_{l=1}^{2} \beta_{ll1} B_{ilt}^2 + \beta_{121} B_{i1t} B_{i2t} + \sum_{k=1}^{4} \gamma_{k1} \frac{X_{ikt}}{A_{it}} \\ \qquad + \sum_{l=1}^{2} \sum_{k=1}^{2} \beta_{lk1}^{\gamma} B_{ilt} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m1} \frac{Z_{imt}}{A_{it}} + \rho_1 A_{it} + \sum_{n=1}^{4} \theta_{k1} C_{int} + u_{i1} + v_{1t} \\ \log(y_{i2t}) = \alpha_2 + \sum_{l=1}^{2} \beta_{l2} B_{ilt} + \sum_{l=1}^{2} \beta_{ll2} B_{ilt}^2 + \beta_{122} B_{i1t} B_{i2t} + \sum_{k=1}^{6} \gamma_{k2} \frac{X_{ikt}}{A_{it}} + \sum_{m=1}^{2} \delta_{m2} \frac{Z_{imt}}{A_{it}} + \rho_2 A_{it} + \sum_{n=1}^{4} \theta_{k2} C_{int} + u_{i2} + v_{2t} \end{cases} \quad (5)$$

Given the interactions between the biodiversity components and variable inputs, the three restrictions did not hold. We thus estimated the *within* transformation of system (5) using only Models 1 and 2. The many interactions of the biodiversity components in system (5) were expected to highlight the main productive effects of crop diversity and permanent grasslands.

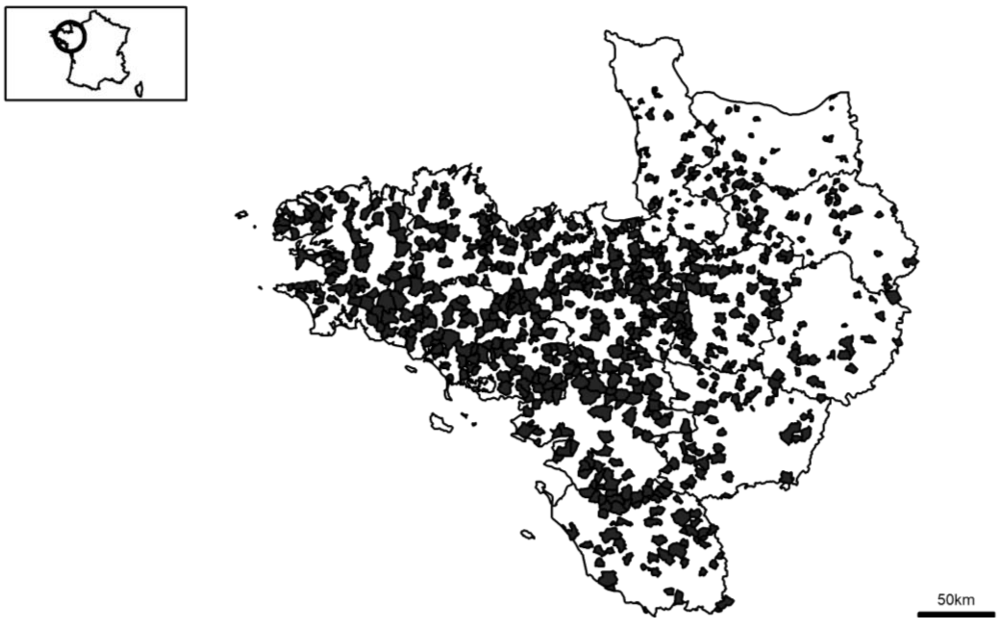

Figure 1. Location of municipalities in northwestern France that contained farms in the sample. Six municipalities are not displayed in order to maintain statistical anonymity.

3.3. Data description

Data came from the FADN for the three regions of northwestern France from 2002-2013. The FADN is a bookkeeping survey performed each year by the French Ministry of Agriculture with a rotating panel of farms. Each country in the EU must perform a similar survey to assess effects of past and future CAP reforms. We considered that the set of financial supports remained relatively homogenous during the sample period, since data from 2002 were used only for price expectations. Farms in the sample faced only the 2008 CAP reform, whose most notable changes were the removal of fallow obligations, gradual increase in milk quotas and further decoupling of CAP payments. We selected mixed crop-livestock farms that produced milk and cereals; they represented 76% of the FADN farms that produced milk in these regions. The rotating panel sample was composed of 3,960 observations, which corresponded to 999 different farms observed for a mean of 3.96 years. The observations were located in ca. 250 municipalities each year (out of the ca. 4,000 municipalities in these regions), illustrating their wide spatial distribution (Figure 1).

Since the FADN does not include prices of inputs, we calculated a quantity index for each input using each farm's purchases and mean regional prices for the three regions (base 100 in 2010). We deflated prices and subsidies by the national consumption price index. Cereals consisted of soft wheat, durum wheat, rye, spring barley, winter barley, escourgeon, oats, summer crop mix, grain maize, seed maize, rice, triticale, non-forage sorghum and other crops. We calculated cereal yields in constant euros using a Paasche index based on the mean price of each cereal in 2010. For milk, we used the prices that each farm had received. We also added annual climatic variables (data not shown).

Table 1 presents the descriptive statistics for the farms in the sample. Since the FADN excludes small farms, the average sampled farms had a UAA of 90 ha, which is somewhat larger than the French mean. The biodiversity indicators had wide ranges. For example, the maximum value of the crop diversity index was 11 times as large as the minimum value (0.206, which indicates a trend to monoculture). Permanent grasslands were also distributed extremely unequally: 30% of the observations had no permanent grasslands ($B_{i2t} = 0$). Consequently, we performed a sensitivity analysis in Section 4.3 in which B_{i2t} equaled the proportion of permanent grasslands in the UAA of (i) the municipality (LAU2 region),[12] (ii) district (LAU1 region) or (iii) province (NUTS3 region) of each farm *i*. Finally, milk and cereals were the most profitable products, providing a mean of 57% and 10% of total revenue, respectively. Some farms had other activities, especially pig production (11% of farms).

Table 1. Descriptive statistics of farms (N=3,960)

Variable	Mean	Median	Q1	Q3	Min	Max
Cereal yield (constant €/ha)	1064.14	1074.04	918.15	1217.05	58.65	2455.44
Milk yield (kg/ha)	6111.58	6171.39	4553.45	7852.81	276.81	20909.08
log(cereal yield)	6.942	6.979	6.822	7.105	4.071	7.806
log(milk yield)	8.718	8.727	8.423	8.968	5.623	9.947
Crop diversity (Shannon index)	1.246	1.207	1.021	1.496	0.206	2.287
Permanent grassland proportion	0.10	0.015	0	0.14	0	0.89
Utilized agricultural area (ha)	90.01	77.62	55.18	110.39	15.59	382.88
Main forage area (ha)	60.95	53.64	37.27	76.39	8.16	290.9
Fertilizer (quantity index)	9899.41	8028.13	4778.82	12821.82	0	87025.84
Pesticides (quantity index)	6402.45	4843.92	2754.69	7837.9	0	71907
Seeds (quantity index)	6866.18	5575.39	3567.07	8462.67	0	73701.09
Fuel (quantity index)	57.19	47.58	30.56	72.89	0	311.41
Cow feed (quantity index)	282.52	225.19	131.31	368.81	1.702	2803.41
Health and reproduction (quantity index)	54.2	42.77	25.9	74.32	0	407.17
Cattle manure (kg)	8871.66	7456.86	5093.1	10886.78	735.81	45234.26
Other livestock manure (kg)	2076.85	0	0	0	0	95850
Capital (1000€)	299.88	258.30	158.94	383.41	0	3822.41
Labor (annual worker unit/100)	218.19	200	150	272	100	1200

4. Results

4.1. Log-linear specifications

Table 2 presents the estimation of system (2) using Models 1-4. We find that crop diversity (B_{i1t}) increased both cereal and milk yields in the four models. Permanent grasslands (B_{i2t})

[12] LAUs (Local Administrative Units) are building blocks of the NUTS (Nomenclature of Territorial Units for Statistics) used by the European Union statistical system.

had no significant effect on cereal yields, which indicates that it had little or heterogeneous productive spillover effects on arable land. The productivity of B_{i1t} estimated by Models 1 and 3 (SUR estimates) was twice that estimated by Models 2 and 4 (GMM estimates), which suggested endogenous bias in Models 1 and 3 but also partly supported our assumption that farmers adjust variable input applications given the biodiversity levels. At least, it showed that the instrumentation of the variable inputs disentangled some correlations between them and B_{i1t}. However, Models 1 and 3 highlighted that B_{i2t} decreased milk yields.[13] Interestingly, the effect became null with Models 2 and 4 once we instrumented the variable input allocations. The lower estimated productivities of B_{i1t} and B_{i2t} in these models highlighted that variable inputs and biodiversity levels were correlated.

While productivities of the biodiversity components were our parameters of interest, the literature provided little information about their signs or amplitudes (at least for B_{i2t}). In contrast, much more is known about productivities of variable inputs, which are theoretically non-negative (e.g. Carpentier and Letort, 2012). We used this information to discriminate among the four models. Model 1 estimated that all productivities of variable inputs were positive or null, but as mentioned, the estimated productivities of the biodiversity components were likely overestimated due to endogenous biases in variable inputs. Correcting for this issue, Model 2 provides sensibly higher estimates for the productivities of variable inputs (and, thus, lower biodiversity productive capacities).[14] The single questionable issue was that the

[13] This result was not surprising: milk-producing farms with a larger proportion of permanent grasslands are usually considered the most extensive (Ryschawy et al., 2012).

[14] Equations of the variable input applications instrumented with prices and subsidies showed R^2 = 0.16-0.34 (results available upon request). Price ratios had significant effects and expected signs. In addition, we tested the assumption of short-term optimization by estimating the influence of the other exogenous variables on crop diversity. Ordinary-least-square estimation showed R^2 = 0.03 in the *within* form (results available upon request), which suggested little endogenous bias in crop diversity and tended to support the assumption of very short-term optimization.

productivity of pesticides for milk was negative,[15] perhaps because variable inputs should have been specified as allocable inputs instead of non-allocable inputs. Indeed, for Model 4, the three restrictions added to the productivities of variable inputs differed significantly from zero at the 5% level (i.e. they do act as binding constraints). Consequently, all productivities of variable inputs estimated by Model 4 were positive or null, which was consistent with theory. Most importantly, the different specifications for variable inputs did not influence estimates of biodiversity productive capacities (compare Models 2 and 4). Model 3 had similar characteristics but did not correct the endogeneity. Because Model 4 suggests productivities consistent with theory and accounts for endogeneity, we select it as the preferred model.

Finally, all fixed inputs had null productivity except UAA, which decreased milk yields: the total area captured the lower per-ha milk yields of extensive farms. The null productivity of other fixed inputs highlighted the difficulty in measuring them accurately. Increasing quantities of cattle manure decreased crop yields, but manure from other livestock had non-significant effects (at the 5% level). This result suggests inefficient management of cattle manure, perhaps because of legislative restrictions on application of organic fertilizers. Specifying alternative organic fertilizer proxies did not influence the significance or the sign of the productivity of B_{i1t} or the variable input productivities. Finally, all climatic variables influenced cereal yields significantly (data not shown). In contrast, only total snowfall and minimum, maximum and mean temperatures influenced milk yields. Omitting weather data led to negative productivities of certain variable inputs, highlighting that applications of variable inputs are influenced by the weather. The estimations of Models 1-4 without the individual fixed effects also led to negative

[15] Addition of an interaction variable between pesticide application and a trend highlighted that pesticide productivities were positive at the beginning of the period but negative at the end (Appendix 4). This result may have been due to a change in pesticide quality: farmers applied different types of pesticides during the period, and the pesticides that remained by the end may have been less effective. Since milk yields increased over the period, this may have been a temporal conjuncture confound.

productivities. The addition of weather variables and individual fixed effects thus decreased the unobserved heterogeneity, removing some endogenous biases.

Table 2. Estimates of system (2) with log-linear production functions (Models 1-4) (N=3,960).

	Model 1 (SUR)		**Model 2 (GMM)**		**Model 3 (SUR)**		**Model 4 (GMM)**	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators								
B_{i1t} (crop diversity)	0.108 ***	0.186 ***	0.052 *	0.120 ***	0.109 ***	0.186 ***	0.044 °	0.088 ***
	(0.018)	(0.014)	(0.023)	(0.029)	(0.018)	(0.014)	(0.023)	(0.026)
B_{i2t} (permanent grasslands)	0.054	-0.119 **	-0.007	-0.021	0.055	-0.119 **	0.012	-0.020
	(0.057)	(0.015)	(0.066)	(0.073)	(0.057)	(0.015)	(0.064)	(0.069)
Variable inputs								
Fertilizers	0.0002 **	0.0001	0.002 ***	0.0002	0.0001	0.0001	0.001 ***	0.0001 *
	(0.0001)	(0.0001)	(0.0003)	(0.0005)	(0.0001)	(0.0001)	(0.0003)	(0.00003)
Pesticides	0.0001	0.0004 ***	0.0001	-0.002 *	0.0001 *	0.0003 *	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.001)	(0.00005)	(0.0002)	(0.0002)	(0.0002)
Seeds	0.0001	0.0004 **	0.001 *	0.0005	0.0001	0.0004 **	0.001 *	0.001 *
	(0.0001)	(0.0001)	(0.0005)	(0.0008)	(0.0001)	(0.0001)	(0.0005)	(0.0004)
Fuel	0.016	0.017	0.114	0.575 ***	0.007	0.020	0.357 ***	0.300 ***
	(0.020)	(0.016)	(0.128)	(0.137)	(0.006)	(0.016)	(0.107)	(0.137)
Cow feed		0.048 ***		0.096 ***		0.049 ***		0.097 ***
		(0.002)		(0.013)		(0.002)		(0.010)
Health and reproduction		0.081 ***		0.214 *		0.081 ***		0.193 *
		(0.008)		(0.107)		(0.008)		(0.090)
Organic Fertilizer proxies								
Cattle manure/total area	0.039	0.167 ***	-0.061	-0.142 °	0.043	0.165 ***	-0.104 *	-0.109
	(0.030)	(0.025)	(0.043)	(0.077)	(0.030)	(0.025)	(0.041)	(0.069)
Other livestock manure/total area	-0.014	-0.017 °	-0.01	-0.025	-0.014	-0.017 °	-0,02	-0.022 °
	(0.011)	(0.009)	(0.012)	(0.016)	(0.012)	(0.009)	(0.013)	(0.013)
Other control variables								
Total area	0.0001	-0.0008 ***	0.0003	-0.0005	0.0001	-0.0008 ***	-0.0002	-0.0008 *
	(0.0002)	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Capital/total area	1E-04	0.001 ***	0.0004	-0.0007	0.0001	0.001 ***	-0.0001	-0.0005
	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Labor (annual worker unit)/total area	-0.614	2.079 ***	-2.933	1.877	-0.512	2.063 ***	-2.898	2.166
	(0.781)	(0.571)	(2.375)	(2.884)	(0.717)	(0.579)	(2.401)	(2.610)
Average technical progress	-0.007	-0.003	-0.006	0.002	-0.011 *	-0.003	-0.002	0.003
	(0.005)	(0.002)	(0.015)	(0.002)	(0.005)	(0.002)	(0.015)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Restrictions								
Restriction 1					-2.241 *		-2.203 *	
					(0.913)		(1.086)	
Restriction 2					0.391		-2.273 *	
					(2.021)		(1.090)	
Restriction 3					0.756		-2.545 *	
					(0.923)		(1.04)	

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively. SUR = seemingly unrelated regressions, GMM = general method of moments.

4.2. Models with alternative functions

Table 3 presents results of the estimation of Model 4 for system (3) when we added alternative interaction terms for the biodiversity indicators (Appendix 4 presents results of system (3) with Models 1-3). Table 3 includes two degraded forms of system (3) in which either the squared or cross terms of the biodiversity indicators were removed (noted system (3’) and system (3’’), respectively). Second-order parameters of the productivity of B_{i1t} were non-significant for milk once interaction terms were added (system (3)). Adding them even decreased the precision of the estimate of the first-order productivity of milk, except when the squared terms were removed (system (3’’) in Table 3). The results for cereals were more informative. In the most general form, B_{i1t} had a negative return to scale but did have positive productivity at the average point (system (3) in Table 3). The estimates of B_{i2t} and B_{i2t}^2 were both positive but non-significant. The drop in the interaction term between B_{i1t} and B_{i2t} suggested, however, that B_{i2t} had increasing return to scale (system (3’) in Table 3); in other words, the productivity of B_{i2t} for cereals was positive when permanent grassland proportions were high (specifically, when $B_{i2t} > 0.248$, representing ca. 15% of the sample).

Finally, the first-order productivity of B_{i2t} was positive for cereals once the squared terms were removed (system (3’’) in Table 3). More interestingly, the two biodiversity indicators interacted negatively with each other for cereal yields, suggesting that they were substitute inputs (systems (3) and (3’’)). B_{i2t} increased cereal yields only when its marginal productivity (0.261-0.217*B_{i1t} – system (3’’)) was positive (i.e. when B_{i1t} < 1.20). Based on the distribution of B_{i1t}, B_{i2t} increased cereal yields for 46% of the observations. Similarly, B_{i1t} increased cereal yields for 89% of the observations (when B_{i2t}< 0.35). At the average level of B_{i2t}, increasing B_{i1t} from an area equally distributed among three crops (B_{i1t}=1.099) to an area equally distributed among four crops (B_{i1t}=1.386) increased cereal yields by 2.3% and milk yields by 2.6%. In contrast, B_{i2t} did not influence cereal and milk yields at the average level of

B_{i1t}, but it did increase cereal yields at low levels of B_{i1t}. When B_{i1t}=1, an increase in B_{i2t} from 0.1 to 0.2 increased cereal yields by 0.4%, which is relatively small compared to the productivity of B_{i1t}.

Table 3. GMM estimates with log-quadratic production functions (Model 4) (N=3,960)

	Model 4 – System (3)		**Model 4 – System (3')**		**Model 4 – System (3'')**	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators						
B_{i1t}	0.467 ***	-0.043	0.330 ***	-0.030	0.077 **	0.096 **
	(0.104)	(0.103)	(0.094)	(0.100)	(0.026)	(0.028)
$(B_{i1t})^2$	-0.149 ***	0.052	-0.111 **	0.046		
	(0.036)	(0.038)	(0.034)	(0.038)		
B_{i2t}	0.111	0.051	-0.298 *	0.015	0.261 *	0.042
	(0.214)	(0.183)	(0.138)	(0.142)	(0.123)	(0.13)
$(B_{i2t})^2$	0.385	-0.075	0.602 **	-0.073		
	(0.246)	(0.224)	(0.227)	(0.222)		
$B_{i1t} * B_{i2t}$	-0.261 **	-0.040			-0.217 *	-0.069
	(0.103)	(0.108)			(0.093)	(0.11)
Variable inputs						
Fertilizers	0.001 ***	0.001 **	0.001 ***	0.001 **	0.001 ***	0.001 **
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Pesticides	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Seeds	0.0006	0.0006	0.001 °	0.001 *	0.001 °	0.001 *
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Fuel	0.348 **	0.293 **	0.37 **	0.311 **	0.34 **	0.276 **
	(0.108)	(0.102)	(0.108)	(0.102)	(0.108)	(0.09)
Cow feed		0.101 ***		0.097 ***		0.099 ***
		(0.010)		(0.010)		(0.010)
Health and reproduction		0.205 *		0.207 *		0.193 *
		(0.093)		(0.091)		(0.091)
Organic Fertilizer proxies						
Available cattle manure/total area	-0.097 *	-0.118 °	-0.112 **	-0.102	-0.094 *	-0.115 °
	(0.041)	(0.070)	(0.041)	(0.070)	(0.041)	(0.070)
Other available manure/total area	-0.013	-0.023 °	-0.018	-0.023	-0.016	-0.022
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Control variables						
Total area	0.0002	-0.0009 *	0.0002	-0.0008 °	-2.50E-4	-9.15E-4 *
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(2.65E-4)	(4.16E-4)
Capital/total area	-0.0001	-0.0006	-0.0001	-0.0006	-0.0001	-0.0006
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Labor (annual worker unit)/total area	-3.720	2.372	-2.907	2.149	-3.57	2.45
	(2.406)	(2.676)	(2.420)	(2.658)	(2.42)	(2.63)
Average technical progress	-0.006	0.003	-0.007	0.003	-0.002	0.002
	(0.015)	(0.002)	(0.015)	(0.002)	(0.015)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes
Restrictions						
Restriction 1	-2.227 *		-2.249 *		-2.109 *	
	(1.109)		(1.112)		(1.045)	
Restriction 2	-2.362 *		-2.406 *		-2.170 *	
	(1.097)		(1.117)		(1.044)	
Restriction 3	-2.419 *		-2.551 *		-2.310 *	
	(1.045)		(1.073)		(0.959)	

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

When we added interaction terms between variable inputs and biodiversity indicators for cereals, the parameters were less significant for Model 1 (SUR; Appendix 6) and Model 2 (Table 4) than for the previous models, but all of the interaction terms were significantly negative (except between fertilizers and B_{i2t} in system (5); Table 4).[16] This result suggested that the productive capacities of the two biodiversity components were substitute inputs for fertilizers and pesticides. Taking the estimated parameters from system (4), on average, a 10% increase in B_{i1t}decreased fertilizer and pesticide productivities for cereals by 3.6% and 3.3% respectively. Similarly, a 10% increase in B_{i2t}decreased fertilizer and pesticide productivities by 0.6% and 0.9%, respectively. The first-order productivities of the biodiversity indicators remained significant. At average points, productivities of B_{i1t} and B_{i2t} in systems (4) and (5) were consistent with those of systems (2) and (3), confirming that different specifications of variable input allocation did not influence the results. Like for system (2), the productivity of pesticide for milk was negative for systems (4) and (5), but as explained, we could not use the parameter restrictions; the only correction possible was to add an interaction term with a trend, as for system (2) (Appendix 4).

[16] Recall that systems (4) and (5) can be estimated only using Models 1 and 2 due to the interaction terms between the biodiversity indicators and variable inputs.

Table 4. GMM estimates of systems (4) and (5) (Model 2) (N=3,960)

	Model 2 – System (5)		**Model 2 – System (4)**	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators				
B_{i1t}	-0.056	0.105	0.929 ***	0.113 ***
	(0.039)	(0.102)	(0.248)	(0.025)
$(B_{i1t})^2$	0.577 **	0.002	2.804 ***	0.063
	(0.203)	(0.037)	(0.589)	(0.054)
B_{i2t}	2.090 *	0.164		
	(0.839)	(0.184)		
$(B_{i2t})^2$	-0.964	-0.254		
	(0.758)	(0.210)		
$B_{i1t} * B_{i2t}$	-0.314	0.025		
	(0.235)	(0.106)		
Variable inputs				
Fertilizers	0.007 **	0.0001	0.007 **	0.0001
	(0.002)	(0.0004)	(0.002)	(0.0004)
Fertilizers*B_{i1t}	-0.004 *		-0.004 *	
	(0.002)		(0.002)	
Fertilizers*B_{i2t}	-0.002		-0.011 ***	
	(0.003)		(0.003)	
Pesticides	0.023 ***	-0.002 *	0.013 **	-0.002 *
	(0.004)	(0.001)	(0.004)	(0.001)
Pesticides*B_{i1t}	-0.013 **		-0.006 *	
	(0.003)		(0.003)	
Pesticides*B_{i2t}	-0.022 *		-0.030 ***	
	(0.007)		(0.008)	
Seeds	0.001	0.002 **	0.001	0.002 **
	(0.001)	(0.0007)	(0.001)	(0.0007)
Fuel	0.009	0.443 ***	0.190	0.441 ***
	(0.156)	(0.128)	(0.157)	(0.128)
Cow feed		0.069 ***		0.068 ***
		(0.013)		(0.012)
Health and reproduction		0.261 **		0.236 **
		(0.087)		(0.084)
Organic Fertilizer proxies				
Available cattle manure/total area	-0.081	-0.066	0.037	-0.053
	(0.055)	(0.071)	(0.058)	(0.069)
Other available manure/total area	0.008	-0.018	0.019	-0.018
	(0.006)	(0.016)	(0.019)	(0.016)
Control variables				
Total area	0.0003	-0.0004	-0.0003	-0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Capital/total area	-0.0008	-0.0002	-0.0003	-0.0004
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Labor/total area	-0.607	0.469	-8.440	1.863
	(6.067)	(4.895)	(6.079)	(4.892)
Average technical progress	0.001	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

4.3. Sensitivity analysis for permanent grasslands

The choice of indicators depends greatly on the data available. Using the FADN database required us to rely on indicators calculated at the farm scale; however, landscape ecologists suggest that the scale at which these indicators are calculated matters (Burel and Baudry, 2003).

Although Donfouet et al. (2017) emphasized that the scale at which B_{i1t} was calculated had no significant influence on the assessment of the productivity of B_{i1t} in previous studies, we were not aware of such evidence B_{i2t}. We thus tested whether the scale at which the permanent grassland proportion was measured had an influence by estimating system (2) with alternative measures of B_{i2t}. Formally, we replaced B_{i2t} with the proportion of permanent grasslands in the UAA of the (i) municipality, (ii) district or (iii) province where the farmstead of i was located. This sensitivity analysis had the secondary advantage that B_{i2t} was always positive at these scales, which was not the case at the farm scale (Table 1). The disadvantage was that we had to decrease the number of observations from 3,960 to 2,344 since these alternative measures of B_{i2t} have been available only since 2007 in France (beginning of the Land Parcel Identification System).

Using Model 4 to estimate system (2) with B_{i2t} measured at alternative scales revealed that biodiversity productive capacity remained similar overall to that estimated at the farm scale (Table 5). Although the amplitudes differed, B_{i1t} still increased cereal and milk yields. The alternative measures of B_{i2t} did not influence estimates of the productivity of B_{i1t}. The lack of effect of B_{i2t} on cereal yields also remained, but the alternative measures of B_{i2t} influenced all milk yields negatively (and significantly). The proportion of permanent grasslands at the district level influenced the results the most. Estimating system (2) using all alternative measures of permanent grasslands at the same time, the alternative measures of permanent grasslands again had no effect on the productivity of B_{i1t} for cereals and milk (Appendix 7). We confirmed that the proportion of permanent grasslands at the district level drove the negative effect on farms' milk yields. Estimates of variable input productivities had lower quality (Table 5), however, than those of previous models due to the smaller sample size.

Table 5. GMM estimates of system (2) using biodiversity indicators for permanent grasslands measured at alternative scales (Model 4) (N=2,344)

	Farm		**Municipality**		**District**		**Province**	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators								
B_{i1t}	0.084 ***	0.137 ***	0.081 **	0.128 ***	0.083 **	0.115 ***	0.083 **	0.130 ***
	(0.025)	(0.028)	(0.025)	(0.029)	(0.025)	(0.029)	(0.025)	(0.027)
B_{i2t_farm}	-0.098	-0.051						
	(0.068)	(0.078)						
$B_{i2t\_municipality}$			-0.038	-0.681 **				
			(0.242)	(0.221)				
$B_{i2t\_district}$					-0.072	-1.450 ***		
					(0.236)	(0.383)		
$B_{i2t\_province}$							0.293	-0.689 °
							(0.452)	(0.383)
Variable inputs								
Fertilizer	0.0001	-0.0004	-0.001	0.0007	-0.001	0.001 **	-0.0001	0.0005
	(0.0001)	(0.0005)	(0.0001)	(0.0005)	(0.0001)	(0.0005)	(0.0007)	(0.00004)
Pesticides	0.0002	-0.001 °	0.0002	-0.002 *	0.0002	-0.001 °	0.0002	-0.002 *
	(0.0002)	(0.0007)	(0.0002)	(0.0008)	(0.0002)	(0.0008)	(0.0002)	(0.001)
Seeds	-0.0002	0.002 **	-0.0002	0.002 **	-0.0002	0.001 **	-0.0002	0.002 **
	(0.0003)	(0.0007)	(0.0003)	(0.0008)	(0.0003)	(0.0008)	(0.0002)	(0.0004)
Fuel	-0.005	0.041	0.0004	-0.004	0.001	-0.007	-0.002	0.023
	(0.007)	(0.027)	(0.013)	(0.144)	(0.004)	(0.030)	(0.004)	(0.027)
Cow feed		0.050 ***		0.048 ***		0.049 ***		0.048 ***
		(0.008)		(0.008)		(0.009)		(0.008)
Health and reproduction		0.090		0.179 *		0.214 *		0.136
		(0.095)		(0.097)		(0.098)		(0.089)
Organic Fertilizer proxies								
Cattle manure/total area	0.039	0.086	0.022	0.108	0.019	0.087	0.027	0.096
	(0.045)	(0.075)	(0.044)	(0.075)	(0.011)	(0.067)	(0.044)	(0.065)
Other livestock manure/total area	0.017	-0.008	0.015	0.003	0.013	-0.007	0.013	0.0001
	(0.012)	(0.010)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.010)
Control variables								
Total area	-0.0003	-0.0007 °	-0.0004	-0.0004	-0.0004	-0.0005	-0.0003	-0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
Capital/total area	-0.0001	0.001 *	-0.0003	0 °	-0.0004	0.001 °	-0.0004	0.001 *
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Labor/total area	-6.431 °	2.536	-5.838 °	0.759	-5.110 °	0.87	-5.324 °	2.226
	(3.294)	(3.559)	(3.220)	(3.469)	(3.092)	(3.490)	(3.135)	(3.365)
Average technical progress	-0.018	0.0001	-0.020	0.0004	-0.018	0.0001	-0.018	0.001
	(0.016)	(0.003)	(0.017)	(0.003)	(0.016)	(0.003)	(0.017)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Restrictions								
Restriction 1	-0.074		0.509		0.447		0.563	
	(0.094)		(1.864)		(2.480)		(1.299)	
Restriction 2	1.149		1.617		1.910		2.297	
	(3.606)		(2.486)		(2.245)		(3.162)	
Restriction 3	0.006		-0.079 **		0.072		0.011 *	
	(1.315)		(0.026)		(0.249)		(0.756)	

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

5. Discussion and concluding remarks

The literature on the productivity of biodiversity has paid great attention to the productivity of crop diversity for crops. Estimating a system of yield equations consistent with the assumption of farmers' very short-term optimization, our study extends current knowledge about biodiversity productive capacity to (i) two biodiversity components (crop diversity and permanent grasslands), (ii) two products (milk and cereals) and (iii) interactions with conventional variable inputs (fertilizers and pesticides). We estimated a variety of functional forms of the production functions, which provide additional information about biodiversity productive capacities (Paul et al., 2020).

First, we confirmed that crop diversity is an input for cereal production. In particular, we agree with Donfouet et al. (2017) that crop diversity is a productive input in regions with wet climates. In line with Di Falco and Chavas (2006), we found that crop diversity has a decreasing return to scale for cereals. We also found that crop diversity is an input for milk production. We interpret it as the increasing of forage yields, which means that forages are sensitive to the productive ES that crop diversity supports. It may also suggest that dairy cows benefit from more varied feed. While van Rensburg and Mulugeta (2016) found a positive effect of habitat diversity on livestock farm profits, we are the first (to our knowledge) to identify that crop diversity increases production of products besides crops. The positive effect of crop diversity on milk yield is consistent, however, with the recent increase in crop diversity in the studied regions (Desjeux et al., 2015).

In contrast, we found no significant positive effects of permanent grassland proportion on either cereals or milk when using log-linear production functions. However, when using log-quadratic production functions, permanent grassland proportion increased cereal yields when crop diversity was low, highlighting some productive spillover effects of semi-natural areas on arable lands. The existence of these productive spillovers has been suggested by agronomic and ecological studies (Baudry et al., 2000; Steffan-Dewenter et al., 2002; Ricketts et al., 2008). Klemick (2011) also highlighted similar spillovers from forest fallows in Brazil. The negative interaction between crop diversity and permanent grassland proportion also implies that both biodiversity components are substitute inputs for cereal production. This result could confirm recent results in landscape ecology; for example, Martel et al. (2019) observed that landscapes with few natural areas need more complex crop mosaics to achieve the same level of biological control that landscapes with higher density of natural habitats have. We conclude that farmers have no incentives to increase both components of biodiversity productive capacity simultaneously. This conclusion is consistent with Desjeux et al. (2015), who observed a trade-off between crop diversity and permanent grasslands in most French regions.

Bareille and Letort (2018) stressed that crop diversity leads to variable input savings. In the present study, we also emphasized that both biodiversity productive capacities interact with variable inputs within the production function. Crop diversity is a substitute for pesticides, with an elasticity of pesticide productivity relative to crop diversity of 0.33%. This extends results of Di Falco and Chavas (2006), who found that crop diversity and pesticides are substitute inputs for risk management. Crop diversity is also a substitute for fertilizer, with an elasticity of fertilizer productivity relative to crop diversity of 0.36%. This is consistent with Kim et al. (2000) and Di Falco and Zoupanidou (2017), who highlighted that soil quality and fertilizers are substitutes in the short term in the United States and Italy, respectively. Because crop diversity increases soil quality, our results confirm their previous findings. In addition, we also found that permanent grasslands are substitutes for pesticides and fertilizers in the short term (elasticities of 0.09% and 0.06%, respectively). This result could confirm the positive effects of permanent grasslands and associated elements on biological control (Baudry et al., 2000). Crop diversity appears to interact more with variable inputs than permanent grasslands do, confirming its greater influence on agricultural production. However, unlike crop diversity, permanent grasslands have a marginally greater influence on crop protection than on crop fertilization, which is consistent with ecological studies (Martel et al., 2019).

Our results are robust to several panel econometric methods and functional forms. Among the models estimated, we highlighted the need to instrument variable input applications: not doing so overestimates the productivity of the biodiversity components. We also showed that adding parameter restrictions on variable input productivities provided estimates consistent with theory, although they had little influence on the biodiversity productivities estimated. Our results should be considered, however, as consistent in the short term, locally and in intensive agricultural regions.[17] Our results are also valid if farmers do optimize in the very short term and if we modeled the correct sequence of decisions (i.e. farmers optimize variable input application based on previous land-use decisions and related biodiversity levels). We are relatively confident about this assumption since linear regressions of the biodiversity indicators on the other exogenous variables (including variable inputs) had low explanatory power. We thus consider our biodiversity indicators as "predetermined" and exogenous. The instrumentation of the Shannon index with time-lagged values by Di Falco and Chavas (2008), for example, illustrates the quasi-fixity of crop diversity. However, assuming "predetermined" biodiversity in the longer term is probably incorrect. In the longer term, biodiversity productive capacities should be considered as quasi-fixed inputs and instrumented, or a structural model should be built that explicitly considers biodiversity dynamics, especially to capture the long-term benefits of biodiversity (Di Falco and Chavas, 2008; Bareille and Letort, 2018). Finally, the biodiversity indicators we used may be correlated with other economic confounders such as soil quality or levels of fixed inputs. These issues are common to all economic studies on biodiversity productive capacity. Although we attempted to capture these effects using individual fixed effects and considering the quasi-fixed input levels (and additional control variables), some results may have been biased due to remaining confounders.

[17] The relation between variable inputs and biodiversity productive capacity may differ in developing regions, where variable inputs are limiting inputs.

5.1. Implications for environmental policies

Policymakers often aim to improve environmental quality and biodiversity levels due to their positive effects on social welfare. Our results can help policymakers because they emphasize incentives encountered by profit-maximizing farmers who manage biodiversity. Our results highlight that the two biodiversity components increase cereal and milk yields, suggesting no conflict between biodiversity and high yields. However, the estimated second-order effects of the biodiversity indicators reveal the difficulty in designing optimal sets of policy instruments that target crop diversity and permanent grasslands at the same time. Policy instruments that provide incentives to increase crop diversity also encourage a decrease in permanent grasslands and vice-versa. For example, a subsidy to conserve or increase permanent grasslands should lead to a decrease in crop diversity. This substitution is amplified because crops and permanent grasslands compete for UAA, which is a limited resource for farmers. Thus, cross-compliance requirements introduced in the 2014 CAP reform may lead to counterintuitive land-use dynamics. For example, crop-oriented regions (with high initial levels of crop diversity) receive incentives to enhance ecological focus areas and permanent grasslands, which in turn leads to a decrease in the marginal productivity of crop diversity: assuming profit-maximizing farmers, cross-compliance requirements should lead to a decrease in crop diversity.

Finally, we want to emphasize optimistic implications of the substitution between variable inputs and biodiversity productive capacity (in the short term and in intensive agricultural regions). This substitution implies that any policy instruments that discourage use of variable inputs (e.g. a tax on fertilizers or pesticides) would provide incentives to farmers to increase biodiversity levels. Similarly, biodiversity subsidies should encourage farmers to decrease application of fertilizers and pesticides. Environmental policies could thus reach several objectives simultaneously.

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Appendices

Appendix 1: very short-term optimization

We considered a risk-neutral farmer who maximizes her annual profit π_{it} by adjusting her applications of variable inputs ($\boldsymbol{X_{it}}$) according to her quasi-fixed input levels ($\boldsymbol{Z_{it}}$) and levels of biodiversity productive capacity ($\boldsymbol{B_{it}}$). We wrote the general farmer's program as follows:

$$\pi_{it} = \max_{\boldsymbol{X}_{it}}\{E(\boldsymbol{p}_{it})'\boldsymbol{Y}_{it} - E(\boldsymbol{w}_{it})'\boldsymbol{X}_{it} + S_{it}; (\boldsymbol{Y}_{it}, \boldsymbol{X}_{it}, \boldsymbol{Z}_{it}, \boldsymbol{B}_{it}, A_{it}) \in \mathrm{T}\} \tag{A.1}$$

where $E(\boldsymbol{p}_{it})$ and $E(\boldsymbol{w}_{it})$ are the farmer's expected prices, S sums the area-based subsidies received by the farm[18], and T is the production feasible plan of the multi-output farm. Program (A.1) defined the multi-output multi-input profit function that represents T if T is bounded compact and quasi-convex in ($\boldsymbol{X}_{it}$,$\boldsymbol{Y}_{it}$) for each $\boldsymbol{Z}_{it}$, $\boldsymbol{B}_{it}$ and A_{it} (McFadden, 1978).

Program (A.1) represented the farmer's annual production decisions, which we divided into a two-stage optimization process that isolated the estimated yield functions. The first stage occurs at the beginning of the agricultural year, when the farmer sows her land based on decoupled area subsidies s_{ijt} (with $S_{it} = \sum_j s_{ijt}a_{ijt}$) and expected margins per ha $E(\omega_{ijt})$, with her land-use decisions being composed of *J* components a_{ijt}. $E(\omega_{ijt})$ depends on the farmer's price expectations during this stage (usually in October in France). Unlike prices, s_{ijt} is known and depends only on the type of land use (arable or grasslands).[19] The second stage (i.e. very short-term optimization) occurs during the agricultural year when the farmer optimizes gross margins of each area based on variable input application given her land use, which is assumed to be fixed (Asunka and Shumway, 1996). Following Carpentier and Letort (2012) and Bareille and Letort (2018), we assumed that farmers know input prices ($E(\boldsymbol{w_{it}}) = \boldsymbol{w_{it}}$) but have naïve expectations of output prices ($E(p_{ijt}) = p_{ijt-1}$). However, because the first stage (land-use decisions) occurs ca. 3-6 months before the second stage (variable input applications),[20] expectations of variable input prices may differ between the two stages (due to new information), which may lead to differences between expected and realized margins. This difference justified the very short-term optimization. Specifically, we broke down (A.1) into a first-stage optimization (A.2) followed by a second-stage optimization (A.3):

[18] In subsequent model development, area-based subsidies of the European Union's Common Agricultural Policy were not considered in the empirical estimation since they were decoupled from yields before the beginning of our panel.

[19] Since area-based subsidies were decoupled from yields, they influence land allocation among products but not yields.

[20] In France, the first stage usually occurs in autumn, while the second stage usually occurs in spring.

$$\pi_{it} = \max_{a_{i1t};\ldots;a_{iJt}} \left\{\sum_{j=1}^{J} a_{ijt} \left[E\left(\omega_{ijt}\left(p_{ijt-1}, E(\boldsymbol{w_{it}}), \boldsymbol{Z_{it}}\right)\right) + s_{ijt}\right]; \sum_{j=1}^{J} a_{ijt} = A_{it}\right\} \quad \text{(A.2)}$$

$$E\left(\omega_{ijt}\left(p_{ijt-1}, \boldsymbol{w_{it}}, \boldsymbol{Z_{it}}\right)\right) = \max_{\boldsymbol{x_{ijt}}}\{p_{ijt-1} \cdot y_{ijt} - \boldsymbol{w_{it}}'\boldsymbol{x}_{ijt};\ y_{ijt} \leq f_j(\boldsymbol{x}_{ijt}; \boldsymbol{B_{it}}, \boldsymbol{Z_{it}}, \boldsymbol{Y_{-ijt}})\} \quad \text{(A.3)}$$

where the vector $\boldsymbol{x_{ijt}}$ contains the variable input applied per ha of product *j* such that $\sum_j a_{ijt}\, \boldsymbol{x_{ijt}}$ are the components of $\boldsymbol{X}$. We assumed that T is defined completely by the *J* output-specific frontiers $f_j(\cdot)$ such that $Y_{ijt} \leq a_{ijt} f_j(\cdot)$ where Y_{ijt} is output production at the farm level and $\boldsymbol{Y_{-ijt}}$ represents the vector of the outputs besides *j*. The output-specific frontiers thus consider technological jointness at the farm level (e.g. organic fertilization, on-farm cereal consumption). Function $f_j(\cdot)$ is nonnegative, nondecreasing, linearly homogenous and concave in $\boldsymbol{x}_{ijt}$. Note that $f_j(\cdot)$ does not depend on a_{ijt} explicitly (i.e. we assumed that marginal short-run returns to area are constant in output area). [21] In the econometric strategy, we focused only on the second stage (A.3), in which variable inputs are determined based on the exogenous land-use decisions and related biodiversity indicators.

[21] Carpentier and Letort (2012), for example, also made this assumption. We estimated the production functions assuming non-constant return to area, but the estimated parameters were non-significant.

Appendix 2. Allocation of variable inputs between outputs

We considered the case in which variable inputs are allocable inputs (which corresponds to $\boldsymbol{x}_{ijt}$ in relations (A.3)). Without loss of generality, we considered two outputs (*j=1* for cereals and *j=2* for milk) and solved the second stage (A.3) for x_{ijkt} (x_{ijkt} being the k$^{\text{th}}$ element of $\boldsymbol{x}_{ijt}$). With $Y_2 = a_2 y_2$ and the area devoted to milk production $a_2 > 0$ (which corresponds to the total forage area[22] and is exogenous in the second stage), we obtained the following first-order conditions:

$$\frac{\partial f_2(\boldsymbol{x}_{i2t};\boldsymbol{B}_{it},\boldsymbol{Z}_{it},Y_{i1t})}{\partial x_{i2kt}} = \frac{w_{kt}}{p_{2t-1} + \frac{a_{i1t}}{a_{i2t}} p_{1t-1} \frac{\partial y_{i1t}}{\partial y_{i2t}}}$$

where $\partial y_{i1t}/\partial y_{i2t}$ represents additional cereal yields due to the increase of one unit of milk yield (which is null when there is no jointness). Farmers apply x_{i2kt} on a_{i2t} until the sum of the expected marginal productivity of x_{i2kt} on y_{i2t} and its indirect marginal productivities on y_{i1t} equals w_{kt}. Like the common short-term maximization conditions, the previous relation highlights that an increase in the expected price of one output leads to increased input use (because $f_j(\cdot)$ is concave in $\boldsymbol{x}_{ijt}$). Because the above relation is valid for each input and output, we obtained:

$$\frac{\partial f_1(\cdot)}{\partial x_{i11t}} \Big/ \frac{\partial f_2(\cdot)}{\partial x_{i21t}} = \cdots = \frac{\partial f_1(\cdot)}{\partial x_{i1Jt}} \Big/ \frac{\partial f_2(\cdot)}{\partial x_{i2Jt}} = \frac{p_{2t-1}+p_{1t-1}\frac{a_{i1t}\partial y_{i1t}}{a_{i2t}\partial y_{i2t}}}{p_{1t-1}+p_{2t-1}\frac{a_{i2t}\partial y_{i2t}}{a_{i1t}\partial y_{i1t}}} \qquad \text{(A.4)}$$

The ratios of marginal input productivities of cereals for milk are equal if variable inputs are actually allocable inputs. We used relation (A.4) for the shared variable inputs (fertilizers, pesticides, seeds and fuel) as parameter restrictions in Model 3 (SUR) and Model 4 (GMM).

In the second case, we modeled the variable inputs as non-allocable inputs (Baumol et al., 1988). We broke down program (A.1) into programs (A.5) (land-use decisions) and (A.6). (variable input application). Unlike in program (A.3.), the farmer cannot optimize each margin separately in the second stage. We obtained:

$$\pi_{it} = \max_{a_{i1t};\ldots;a_{iJt}} \left\{ \sum_{j=1}^{J} a_{ijt} \left[E\left(\omega_{ijt}\left(p_{ijt-1}, E(\boldsymbol{w}_{it}), \boldsymbol{Z}_{it}\right)\right) + s_{ijt} \right]; \sum_{j=1}^{J} a_{ijt} = A_{it} \right\} \qquad \text{(A.5)}$$

$$E\left(\omega_{ijt}\left(p_{ijt-1}, \boldsymbol{w}_{it}, \boldsymbol{Z}_{it}\right)\right) = \max_{\boldsymbol{x}_{it}} \left\{ p_{ijt-1} \cdot y_{ijt} - \boldsymbol{w}_{it}{}' \boldsymbol{x}_{it};\ y_{ijt} \leq g_j(\boldsymbol{x}_{it}; \boldsymbol{B}_{it}, \boldsymbol{Z}_{it}, \boldsymbol{Y}_{-ijt}) \right\} \qquad \text{(A.6)}$$

where $\boldsymbol{x}_{it}$ is the vector of variable input applied per ha at the farm level such that $\boldsymbol{X}_{it} = A\boldsymbol{x}_{it}$. $E(y_k)$ and $E(\boldsymbol{x})$ defined in (A.5) are the solutions of (A.6) in which $\boldsymbol{w}$ is imperfectly known. The vector of yields $\boldsymbol{y}_{it}$ is composed of J

[22] Total forage area equals the sum of the areas of maize silage, temporary grassland and permanent grassland. Note that a_{i2t} and B_{i2t} differ: B_{i2t} provides information only about permanent grasslands. The areas of maize silage and temporary grasslands are ecosystem components captured by B_{i1t}.

yields y_{ijt}. The function $g_j(\boldsymbol{x}_{it}; \boldsymbol{B}_{it}, \boldsymbol{Z}_{it}, \boldsymbol{Y}_{-ijt})$ is the yield function of y_{ijt}, which differs from function $f_j(\cdot)$ by the form of the modelling of the variable inputs. We assumed that T is defined completely by the K output-specific frontiers $g_j(\cdot)$ such that $Y_{ijt} \leq a_j g_j(\cdot)$. Like function $f_j(\cdot)$, $g_j(\cdot)$ is nonnegative, nondecreasing, linearly homogenous and concave in $\boldsymbol{x}_{it}$.

The variable input in program (A.6) was optimized in the very short term for all products at the same time (here, only milk and cereals), which led to the following:

$$a_{i1t}p_{1t-1}\left(\frac{\partial g_1(\boldsymbol{x}_{it}; \boldsymbol{B}_{it}, \boldsymbol{Z}_{it}, Y_{i2t})}{\partial x_{i2kt}} + \frac{\partial y_{1it}}{\partial y_{12t}}\frac{\partial g_2(\boldsymbol{x}_{it}; \boldsymbol{B}_{it}, \boldsymbol{Z}_{it}, Y_{i21})}{\partial x_{i2kt}}\right) + a_{i2t}p_{2t-1}\frac{\partial g_2(\boldsymbol{x}_{it}; \boldsymbol{B}_{it}, \boldsymbol{Z}_{it}, Y_{i21})}{\partial x_{i2kt}} = w_{kt}$$

The sum of the direct and indirect marginal productivities of $\boldsymbol{x}_{it}$ equals $\boldsymbol{w}$, which prevented deriving parameter restrictions between outputs and inputs as was done in Models 3 and 4. Modeling variable inputs as non-allocable inputs led to direct estimation of the *within* transformation of system (2), with instrumentation (Model 2) or without instrumentation (Model 1) of the variable input applications.

Appendix 3. Verification of parameter restrictions for a log-linear production function and unobserved variable input application

We considered system (2) when the variable inputs were assumed to be private (Appendix 2). We verified the parameter restriction (A.4) when the production functions had a log-linear form (and assuming $\partial y_{i1t}/\partial y_{i2t} = \partial y_{i2t}/\partial y_{i1t} = 0$, as in system (2)). We calculated marginal productivities of $x_{ikt} = X_{ikt}/A_{it}$ ($k \in [1;4]$) for cereals and milk. Noting that $X_{ikt} = a_{i1t}x_{i1kt} + a_{i2t}x_{i2kt}$, we obtained respectively:

$$\begin{cases} \dfrac{\partial \log(y_{i1t})}{\partial x_{ikt}} = \gamma_{k1}\dfrac{a_{i1t}}{A_{it}} \\ \dfrac{\partial \log(y_{i2t})}{\partial x_{ikt}} = \gamma_{k2}\dfrac{a_{i2t}}{A_{it}} \end{cases}$$

Which is equivalent to:

$$\begin{cases} \dfrac{\partial y_{i1t}}{\partial x_{ikt}} = \gamma_{k1}\dfrac{a_{i1t}}{A_{it}}y_{i1t} \\ \dfrac{\partial y_{i2t}}{\partial x_{ikt}} = \gamma_{k2}\dfrac{a_{i2t}}{A_{it}}y_{i2t} \end{cases}$$

Thus, we obtained $\forall k \in [1;4]$:

$$\frac{\frac{\partial y_{i1t}}{\partial x_{ikt}}}{\frac{\partial y_{i2t}}{\partial x_{ikt}}} = \frac{\gamma_{k1}a_{i1t}y_{i1t}}{\gamma_{k2}a_{i2t}y_{i2t}}$$

Because $a_{i1t}y_{i1t}$ and $a_{i2t}y_{i2t}$ do not depend on x_{ikt}, we had the three valid restrictions, which held if we added Y_{i2t} to the cereal yield function explicitly or vice-versa (see program (A.4), Appendix 2).

Appendix 4. Alternative estimates of Model 2

Table A4.1. Estimates of Model 2 without or with an additional interaction term for pesticides (N=3,960)

	Without interaction term		**With interaction term**	
	log(y_cereals)	**log(y_milk)**	**log(y_cereals)**	**log(y_milk)**
Biodiversity indicators				
B_{i1t}	0.081 **	0.117 ***	0.075 **	0.090 **
	(0.026)	(0.030)	(0.027)	(0.034)
B_{i2t}	0.234 °	-0.049	0.225 °	-0.101
	(0.126)	(0.134)	(0.126)	(0.139)
B_{i1t}* B_{i2t}	-0.207 *	0.002	-0.195 *	0.012
	(0.094)	(0.116)	(0.094)	(0.121)
Variable inputs				
Fertilizer	0.002 ***	0.0001	0.002 ***	0.0005
	(0.001)	(0.0005)	(0.001)	(0.0005)
Pesticides	0.0003	-0.002 **	0.0003	0.005 °
	(0.0004)	(0.001)	(0.0004)	(0.003)
Pesticides*trend				-0.001 *
				(0.0004)
Seeds	0.001 °	0.001	0.001 °	0.001
	(0.001)	(0.0008)	(0.001)	(0.0008)
Fuel	0.118	0.539	0.136	0.518
	(0.131)	(0.139)	(0.131)	(0.143)
Cow feed		0.101 ***		0.101 ***
		(0.014)		(0.014)
Health and reproduction		0.189 °		0.171
		(0.113)		(0.121)
Organic Fertilizer proxies				
Cattle manure/total area	-0.045	-0.167 *	-0.050	-0.192 *
	(0.048)	(0.079)	(0.048)	(0.080)
Other livestock manure/ total area	-0.006	-0.032	-0.006	-0.040 °
	(0.013)	(0.019)	(0.014)	(0.021)
Fixed inputs				
Total area	3.70E-04	-0.0005	3.80E-4	-0.0007
	(3.21E-4)	(0.0005)	(3.21E-4)	(0.0005)
Capital/total area	0.001	-0.0009	0.001	-0.001 °
	(0.001)	(0.0005)	(0.001)	(0.0006)
Labor/total area	-4.186	4.556	-4.304	7.503
	(3.950)	(4.739)	(3.952)	(4.953)
Technical progress	-0.016	0.002	-0.018	0.004
	(0.026)	(0.002)	(0.026)	(0.003)

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

Appendix 5. Additional estimates of log-quadratic production functions

Table A5.1. Estimates of log-quadratic production functions (system (3)) with Models 1-3 (N=3,960)

	Model 1 (SUR)		**Model 2 (GMM)**		**Model 3 (SUR)**	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators						
B1	0.496 ***	0.035	0.497 ***	0.013	0.502 ***	0.035
	(0.085)	(0.069)	(0.104)	(0.109)	(0.085)	(0.069)
B1²	-0.141 ***	0.061 *	-0.158 ***	0.039	-0.143 ***	0.053 **
	(0.032)	(0.026)	(0.036)	(0.041)	(0.032)	(0.015)
B2	0.168	0.054	0.108	0.064	0.175	0.054
	(0.188)	(0.152)	(0.216)	(0.197)	(0.188)	(0.152)
B2²	0.283	-0.197	0.393	-0.184	0.267	-0.194
	(0.209)	(0.169)	(0.246)	(0.263)	(0.209)	(0.169)
B1*B2	-0.258 *	-0.059	-0.270 **	0.008	-0.255 *	-0.060
	(0.101)	(0.080)	(0.103)	(0.114)	(0.101)	(0.081)
Variable inputs						
Fertilizers	0.0003 **	0.0001	0.002 ***	0.0003	0.0003	0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0005)	(0.0003)	(0.0001)
Pesticides	0.0001	0.0004 **	0.0001	-0.002 *	0.0001 °	0.0004 **
	(0.0001)	(0.0001)	(0.0002)	(0.001)	(0.00005)	(0.0001)
Seeds	0.0001	0.0004 **	0.001	0.0005	0.0001	0.0004 **
	(0.0001)	(0.0001)	(0.0006)	(0.0008)	(0.0001)	(0.0001)
Fuel	0.014	0.018	0.129	0.558 ***	0.006	0.020
	(0.020)	(0.016)	(0.127)	(0.138)	(0.006)	(0.016)
Cow feed		0.049 ***		0.096 ***		0.049 ***
		(0.002)		(0.013)		(0.002)
Health and reproduction		0.081 ***		0.224 *		0.081 ***
		(0.008)		(0.133)		(0.008)
Organic Fertilizer proxies						
Available cattle manure/total area	0.035	0.170 ***	-0.055	-0.144 °	0.039	0.168 ***
	(0.030)	(0.025)	(0,043)	(0.077)	(0.029)	(0.025)
Other available manure/total area	-0.012	-0.019 *	-0.004	-0.026	-0.011	-0.019 *
	(0,012)	(0,009)	(0,011)	(0,016)	(0,011)	(0,009)
Control variables						
Total area	0.0001	-0.0009 ***	-0.0003	-0.0005	1.09E-5	-0.0009 ***
	(0.0002)	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0002)
Capital/total area	0,0001	0.001 ***	0.0003	-0.0008	1E-04	0.001 ***
	(0,0003)	(0.0003)	(0,0004)	(0.0005)	(0,0004)	(0.0003)
Labor/total area	-0.668	2.081 ***	-3.918	1.967	-0.567	2.067 ***
	(0.716)	(0.579)	(2.377)	(2.920)	(0.715)	(0.579)
Average technical progress	-0.008	-0.003	-0.008	0.002	-0.011 *	-0.003
	(0.005)	(0.002)	(0.015)	(0.002)	(0.005)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes
Restrictions						
Restriction 1					-2.202 *	
					(0.888)	
Restriction 2					0.408	
					(2.095)	
Restriction 3					0.721	
					(0.953)	

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

Appendix 6. Seemingly unrelated regression estimates of systems (4) and (5)

Table A6.1. SUR estimates of log-quadratic production functions with Model 1 (N=3,960)

	System (5)		System (4)	
	log(y_crops)	log(y_milk)	log(y_crops)	log(y_milk)
Biodiversity indicators				
B_{i1t}	0.464 ***	0.034	0.185 ***	0.186 ***
	(0.088)	(0.069)	(0.035)	(0,014)
$(B_{i1t})^2$	-0.112 **	0.061 *	0.030	-0.119 **
	(0.037)	(0.026)	(0.091)	(0.015)
B_{i2t}	0.001	0.054		
	(0.222)	(0.151)		
$(B_{i2t})^2$	0.304 *	-0.197		
	(0.102)	(0.169)		
$B_{i1t} * B_{i2t}$	-0.304 **	-0.059		
	(0.110)	(0.081)		
Variable inputs				
Fertilizer	0.0004	0.0001	0.0004	0.0001
	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Fertilizer*B_{i1t}	-0.0001		-0.0002	
	(0.0002)		(0.0002)	
Fertilizer*B_{i2t}	0.0001		-0.0001	
	(0.0006)		(0.0006)	
Pesticides	0.0015 *	0.0004 **	0.002 ***	0.0004 ***
	(0.0006)	(0.0002)	(0.0005)	(0.0001)
Pesticides*B_{i1t}	-0.0005		-0.0009 *	
	(0.0004)		(0.0003)	
Pesticides*B_{i2t}	0.002 *		0.0006	
	(0.001)		(0.001)	
Seeds	-0.0001	0.0004 **	-0.0001	0.0004 **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fuel	0.008	0.018	0.010	0.017
	(0.020)	(0.016)	(0.020)	(0.016)
Cow feed		0.049 ***		0.048 ***
		(0.001)		(0.002)
Health and reproduction		0.081 ***		0.081 ***
		(0.008)		(0.008)
Organic Fertilizer proxies				
Cattle manure/total area	0.044	0.169 ***	0.045	0.167 ***
	(0.030)	(0.025)	(0.030)	(0.025)
Other livestock manure/total area	-0.011	-0.019 *	-0.012	-0.017 °
	(0.012)	(0.009)	(0.011)	(0,009)
Control variables				
Total area	0.0001	-0.0009 ***	0.0001	-0.0008 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Capital/total area	0.0001	0.001 ***	-0.0001	0.001 ***
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Labor/total area	-0.304	2.081 ***	-0.783	2.079 ***
	(0.715)	(0.579)	(0.716)	(0.571)
Average technical progress	-0.002	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effect	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.

Appendix 7. Estimates of system (2) with all alternative measures of permanent grassland proportion (farm, municipality, district and province scales)

Table A7.1. Estimates of system (2) with all indicators for permanent grasslands and Model 4 (N=2,344)

	Model 4 (GMM)	
	log(y_crops)	log(y_milk)
Biodiversity indicators		
B_{i1t}	0.085 ***	0.126 ***
	(0.025)	(0.028)
B_{i2t_farm}	-0.101	0.003
	(0.066)	(0.080)
$B_{i2t\_municipality}$	-0.008	0.530
	(0.461)	(0.404)
$B_{i2t\_district}$	-0.100	-1.676 *
	(0.396)	(0.720)
$B_{i2t\_province}$	0.351	0.226
	(0.486)	(0.583)
Variable inputs		
Fertilizer	-0.0001	0.0006
	(0.0001)	(0.0004)
Pesticides	0.0002	-0.002 *
	(0.0002)	(0.0008)
Seeds	-0.0002	0.002 **
	(0.0003)	(0.0007)
Fuel	-0.002	0.017
	(0.003)	(0.027)
Cow feed		0.048 ***
		(0.008)
Health and reproduction		0.150 °
		(0.088)
Organic Fertilizer proxies		
Available cattle manure/total area	0.024	0.082
	(0.045)	(0.067)
Other available manure/total area	0.015	-0.001
	(0.012)	(0.010)
Control variables		
Total area	-0.0004	-0.0005
	(0.0004)	(0.0004)
Capital/total area	-0.0003	0.001 *
	(0.0005)	(0.0004)
Labor/total area	-5.358 °	2.482
	(3.226)	(3.553)
Average technical progress	-0.018	0.0005
	(0.017)	(0.003)
Individual fixed effect	Yes	Yes
Weather variables	Yes	Yes
Restrictions		
Restriction 1	0.562	
	(1.478)	
Restriction 2	2.257	
	(3.201)	
Restriction 3	0.005	
	(0.587)	

Standard errors are in parentheses; ***, **, * and ° denote p-values of 0.1%, 1%, 5% and 10%, respectively.