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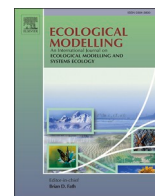
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Estimating landscape intensity through farming practices: An integrative and flexible approach to modelling farming intensity from field to landscape.

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ABSTRACT

Context: Landscape intensity is a major driver of biodiversity and ecosystem functioning in agricultural landscapes, and is often used to inform environmental quality. It is commonly described by land cover alone, as farming practices are assumed to be correlated with crop types. Despite their potential impact on field quality, distribution of farming practices at landscape scale is poorly understood, due to the lack of methods for summarizing the numerous farming practices at field and landscape levels.

Objectives: The main objective was to develop a modelling approach that synthesizes the intensity of farming practices at field and landscape levels. Additionally, we sought to assess the importance of considering farming practices in addition to land cover when studying landscape quality.

Methods: Using survey data collected in two contrasting French agricultural areas, we selected and summarized PCA components using an equation adapted from Herzog et al. (2006; DOI: 10.1016/j.eja.2005.07.006) to compute practice intensity indices integrating levels of fertilization, pesticides, tillage, mowing/harvesting, or of all practices. We compared the distribution of these indices between crops, landscapes, and study areas. Finally, we compared landscape patch richness as an indicator of their (dis)similarities on the basis of land cover, intensity, and the two superimposed, comparing the use of 2 to 20 intensity classes.

Results and conclusion: We found significant differences between land cover intensities, which were not consistent depending on the level of practice considered. Furthermore, for similar crops, we found significant differences between areas. This shows that land cover may not be a good indicator of practice intensity at field level. Moreover, landscape structure described by patch richness differs significantly according to the classification systems studied, and depends on the number of intensity classes considered, which we likened to the sensitivity of a response variable. Thus, landscape intensity based on land cover does not effectively describe that caused by agricultural practices either.

Significance: The method we developed allows studying farming practice intensity at the landscape scale, using any number of numerical descriptors of the intensity of farming practices, to be used flexibly, depending on the objectives and hypotheses of the researchers and the finesse of the practice data available. It also demonstrates its value insofar as land cover proves insufficient to describe the distribution of farming practices between fields and, consequently, the resulting landscape quality. Our method can be used to study a wide range of phenomena linked to landscape intensity, and to reconsider previous assumptions based solely on land cover.

1. Introduction

Agricultural intensity is the main driver of biodiversity and ecosystem services in agricultural landscapes (Estrada-Carmona et al.,

2022; Tschamtko et al., 2021). In general, agricultural intensity is defined as the ratio of inputs and outputs within a farming system, i.e., yields per land area and per unit of inputs, or as the sum of different categories of input costs and the farm's total usable agricultural area, i.

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e., the fraction of arable land that is harvested (Ruiz-Martinez et al., 2015). A more restrictive view of agricultural intensity is, however, commonly taken at the landscape scale, where it is often only linked — implicitly or explicitly — to land cover patterns. Among the most frequent hypotheses of linkage are the size of fields, the diversity of crop rotations and the quantity of semi-natural elements (Herzog et al., 2006; Kuemmerle et al., 2013). Despite the fact that this view of agricultural intensity obscures the importance that farming management practices can play in defining the degree of landscape intensity (Armengot et al., 2011; Marrec et al., 2022), to date a very small number of studies have been interested in characterizing the effect of practices as such on biodiversity and associated ecosystem services at landscape scale (see Brusse et al., 2024). And therefore, few studies have defined agricultural intensity in terms of the negative impact of all — or a set of — farming operations on biodiversity and environmental quality, as we do in the present study.

Despite numerous examples of the impact of the intensity of individual farming practices on biodiversity and other environmental parameters, there is indeed a lack of landscape metrics that would make it possible to synthesize and study intensity linked to practices at this scale. The most common method, which focuses on the land cover-based structure of the landscape as a descriptor of the suitability of fields and their surroundings (Diehl et al., 2013; Elliott et al., 2018; Jeanneret et al., 2021), presumably suggests that the land cover reflects the average intensity of associated practices. However, it can be highly simplistic in the case of management variability between fields of similar land cover type. Another, increasingly common, approach is to describe farming management from a farming system perspective — mainly organic vs. non-organic farming (Petit et al., 2020). However, the contrast between organic and non-organic farming is not always obvious due to the variety of farming practices implemented in each of the two systems, which can even sometimes overlap (Gosme et al., 2012; Puech et al., 2014). In addition, the impact of organic farming can at times be confounded with that of landscape structural heterogeneity (Tschardt et al., 2021). Indeed, the proportion of organic farming often positively correlates with greater land cover diversity, smaller fields, and a greater proportion of semi-natural habitats (Gabriel et al., 2009; Levin, 2007).

A more complex method for describing agricultural intensity in the landscape is to use management information for individual fields (Brusse et al., 2024). As the full set of data on farming practices carried out on each field is rarely available at landscape scale, most studies focus on specific farming practices (e.g., crop rotation, intercropping, nitrogen fertilization, tillage, etc.) (Aguilera et al., 2021; Garratt et al., 2011; Kurhak et al., 2023; Le Féon et al., 2013; Tamburini et al., 2016; Wang et al., 2021) and less frequently a wider set of practices (Büchi et al., 2019). Two main approaches to synthesize farming practices have been investigated in the literature. The first one is the additive aggregation of a very small number of uncorrelated operations to characterize each category of practices and their relative effects based on an *a priori* selection. The most commonly used method is the one of Herzog et al. (2006), adapted from Legendre and Legendre (1998):

$$I = \sum_{i=1}^n \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \times \frac{1}{n} \quad (1)$$

where I is the overall intensity index based on i farming practice categories, y_i the observed value for the variable i in the considered field, y_{\min} and y_{\max} the minimum and maximum observed values among all fields, and n the number of variables (here, all farming practice indices). Another index used by Shriar (2000) associated weights to each practice in order to mitigate the effect of each on intensity relatively to the others. While these methods are useful to summarize uncorrelated practice metrics in one index, they overestimate intensity when inputting correlated aspects of farming practices such as operation frequency, product diversity, or applied quantity.

To avoid a preliminary — and often subjective — selection of variables, a second approach based on Principal Component Analysis (PCA) has been investigated (Armengot et al., 2011; Büchi et al., 2019). This approach allows taking into account the correlation between the variables it incorporates, and thus to combine as many variables as desired. In addition, it offers researchers the flexibility needed to construct intensity indices for competing hypotheses on the relationship between landscape intensity and biological/ecological/environmental patterns and processes of interest, involving potentially very different combinations of variables. Yet, each component must be investigated independently as they represent different aspects of the imputed practices' variability.

Nevertheless, none of these methods allows us to synthesize the farming practices of the fields into a single index that would integrate numerous variables associated with several aspects of farming practices, which would be useful for calculating meaningful landscape metrics. In this study, we combined these two approaches to develop an index that incorporates the multiple aspects of farming practices (i.e., the PCA components) at field and landscape levels into a single index. We illustrate its use on two distinct datasets collected in two contrasting agricultural areas in France, where surveys were carried out among 151 farmers to inform farming practices in 541 fields within 50 landscapes. First, we describe an adaptation of the model proposed by Herzog et al. (2006) that allows us to compute intensity at the field and landscape levels based on PCA components integrating numerous — and potentially correlated — practice variables. We illustrate the flexibility of this approach by considering and comparing the intensity due to four practice categories (pesticide use, fertilization, tillage, and mowing) and the overall intensity. Second, to acknowledge the interest of integrating practices in addition to land cover when quantifying landscape intensity, we compare landscape intensity maps computed as a product of either land cover, farming intensity, or both, following an approach to good modelling practices (Jakeman et al., 2024). As so, we carry out a sensitivity analysis to assess the extent to which the resulting patch richness varies according to the number of landscape intensity classes to give an insight of the impact of scaling on our model output as a tool for decision making. Finally, we discuss the strengths and limitations of our approach, and argue that it allows synthesizing farming practice intensity at both field and landscape levels and integrating any number of practices, whatever the biological and environmental object of study.

2. Materials and methods

2.1. Study area

The study took place in two contrasted French agricultural areas: the Northern France area (hereafter, NF; 45°01'N – 0°43'E to 50°55'N – 4°54'E) and the Moselle area (hereafter MS; 48°38'N – 6°29'E to 48°55'N – 7°01'E; Fig. 1). In both areas, we considered landscapes as independent, as they do not overlap and do not share farmers. The surveyed NF landscapes are mainly dedicated to cash crop production, with winter wheat (41 ± 12 %; mean ± standard deviation) and sugar beet (17 ± 8 %) being the main crops, while grassland accounts for 6 ± 9 % of the surface. The average field size is 7 ± 6.7 hectares. In contrast, the MS area is dominated by livestock production, with 66 ± 33 % of the landscape's surveyed area occupied by meadows and pastures. The main crops are winter wheat (13 ± 21 %), oilseed rape (5 ± 15 %), and barley (4 ± 10 %). The average field size is 7.6 ± 8.3 hectares.

2.2. Surveys of farming operations

Surveys were carried out among 94 farmers in 32 landscapes in NF and 57 farmers in 18 landscapes in MS areas, for a total of 343 and 198 fields, respectively (Table 1). The surveys were carried out in two separate projects, in landscapes surrounding the central fields sampled for biodiversity data (data not used in this article), resulting in

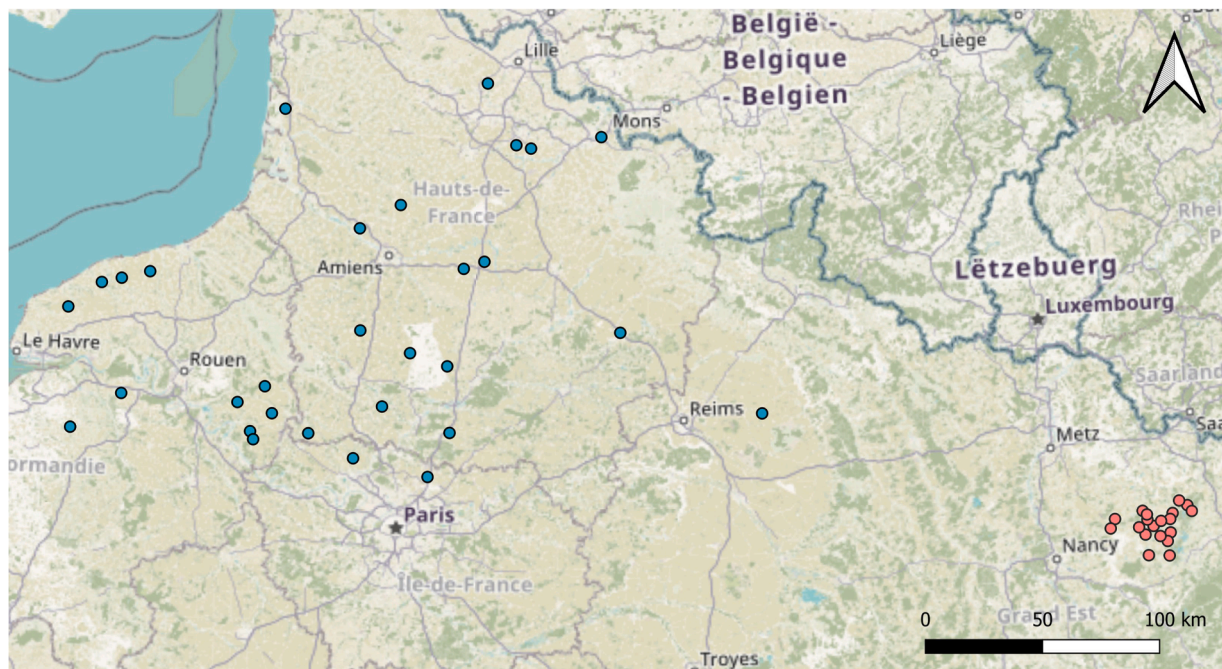


Fig. 1. Map of surveyed landscapes in the NF (blue) and MS (orange) agricultural areas.

Table 1

Number of fields surveyed in the two agricultural areas per land cover type.

Land cover type	Northern France (NF) area (2019 and 2020)	Moselle (MS) area (2021)
Wheat (<i>Triticum aestivum</i>)	377	22
Barley (<i>Hordeum vulgare</i>)	63	10
Oilseed rape (<i>Brassica napus</i>)	67	9
Sugar Beet (<i>Beta vulgaris</i>)	120	0
Flax (<i>Linum usitatissimum</i>)	55	0
Maize (<i>Zea mays</i>)	26	11
Potato (<i>Solanum tuberosum</i>)	70	0
Grassland	101	135
Other crops	68	11

differences in the total area considered for each landscape. In NF, the fields targeted for survey included the central field and all fields in a 500 m radius doughnut-shaped buffer zone starting at the margins of the central field. In MS, the targeted fields intersected a circular buffer zone of 500 m radius centered on the centroid of the central field. The surface of surveyed landscapes was on average 144 ± 61 hectares and ranged from 79 to 341 hectares. Farmers were interviewed by telephone or directly at the farm to find out about farming practices implemented on their arable land and grassland (used as meadows and pastures) fields in 2019 and 2020 cropping periods (i.e., a cropping period started from soil preparation for sowing to harvesting) for NF, and 2021 cropping period for MS using the exact same questionnaire. On average, 66.0 ± 20.6 % of the utilized agricultural area (UAA) of selected landscapes was informed in NF and 91.4 ± 9.9 % in MS. The surveys focused on farming operations which fall into four categories of practices: (1) pesticide use, including insecticide, herbicide, and fungicide applications; (2) nitrogen, phosphorus, and potassium fertilization; (3) tillage intensity; and (4) grassland mowing and crop harvesting intensity. For each operation, the date and main characteristics (e.g., products, tools, quantities) were recorded.

2.3. Field level intensity

Step 1 – Computation of farming practices' intensity variables

On the basis of the survey responses, we summarized the information per type of operations carried out on each field by calculating four types of variable relating to the intensity of farming practices (Table 2, step 1 in Fig. 2): (1) the number of individual operations (e.g., the number of insecticide applications) illustrating the weight of each farming practice in the field management; (2) the diversity (e.g., the number of different active molecules of applied insecticides) illustrating the diversity of products and so, the effect range; (3) the quantity (e.g., the treatment frequency index) illustrating the pressure generated by each practice; and (4) the average time interval between two operations in days (if only one operation has been performed, the value of 365 has been assigned as one per year) illustrating the frequency of implementation for each practice. For the types of operations associated with pesticide use, fertilization, and tillage, variables were averaged for each individual operation (diversity and quantity) and summed up for all operations carried out during the cropping period (number of operations, diversity, quantity, and mean time interval/mineral rate). For instance, when considering nitrogen (N) fertilization, we computed:

- the average number of fertilizer products applied per operation (diversity);
- the total number of fertilizer products applied during the cropping period (diversity);
- the average amount in $\text{kg}\cdot\text{ha}^{-1}$ applied per operation (quantity);
- the total amount in $\text{kg}\cdot\text{ha}^{-1}$ applied during the cropping period (quantity);
- the rate of mineral nitrogen applied.

For the types of operations associated with mowing and harvesting, only frequency was computed. In order to be able to compare the intensity levels of the two areas studied, information on grassland grazing has not been taken into account, as it is very incomplete in the NF dataset.

Intensity variables were computed so that higher values reflected a higher level of intensity of farming practices (in other words, the higher the value, the higher the level of intensity, for all variables). For

Table 2

Synthesis of the studied farming practices (grouped by practice category and overall) and their related intensity variables. The quantity refers to the treatment frequency index for pesticides (applied dose/registered dose), the amount of nitrogen, potassium, and phosphorus for fertilizers (kg.ha⁻¹) and the maximum depth for tillage (cm). Frequency is the occurrence of the practice over a cropping period. The diversity refers to the number of different active molecules for pesticides, of different products for fertilizers, and of different tools for tillage. See Table A1.1 in Supplementary Material for extended definitions of variables.

Practice category	Overall				
	Pesticide use	Fertilization	Tillage	Mowing/Harvesting	
Related practice	<ul style="list-style-type: none"> - Herbicide - Insecticide - Fungicide 	<ul style="list-style-type: none"> - Nitrogen - Potassium - Phosphorus 	-	-	
Related variables	by cropping period	<ul style="list-style-type: none"> - number of operations - diversity - quantity 	<ul style="list-style-type: none"> - number of operations - diversity - quantity 	<ul style="list-style-type: none"> - number of operations - diversity - quantity 	number of events (=1 for crops)
	by operation	<ul style="list-style-type: none"> - mean diversity - mean quantity 	<ul style="list-style-type: none"> - mean diversity - mean quantity 	<ul style="list-style-type: none"> - mean diversity - mean quantity 	-
	other	<ul style="list-style-type: none"> - average time interval between operations 	<ul style="list-style-type: none"> - mineral fertilization rate 	<ul style="list-style-type: none"> - average time interval between operations 	-

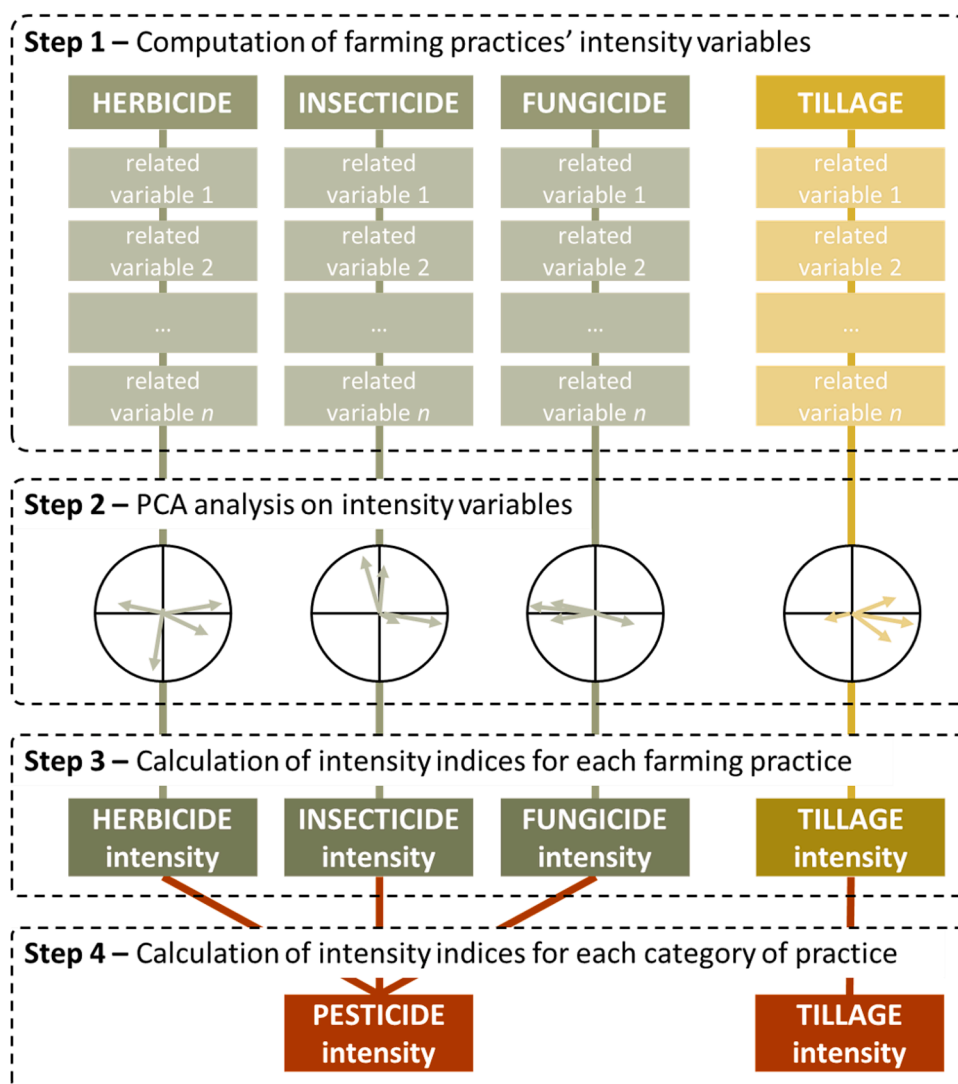


Fig. 2. Overview of the intensity estimation process at field level, using pesticide use and tillage-related intensity as an illustrative example. Variables 1 to n are the variables related to each practice described in Table 2.

instance, shorter intervals between pesticide applications are assumed to be more intensive, so we calculated the inverse of the time interval, making the shorter intervals the higher values. All analyses were performed using the R language (R Core Team, 2022).

Step 2 – PCA analysis on intensity variables

We used Principal Component Analyses (PCA), run independently for each practice, to synthesize the information linked to intensity variables related to the given practice (see Table 2 and step 2 in Fig. 2). This approach allows reducing the dimensionality of each practice while integrating potentially correlated variables (Armengot et al., 2011).

Fields from both agricultural areas were included in the same PCA so that they could be compared. Indeed, the PCA coordinates of the fields (and therefore their intensity) are relative to each other. Because variables included in a same PCA are on different scales, we standardized the variables by dividing them by one standard deviation and mean-centering them. For each PCA, principal components (PCs) were selected according to Kaiser's criterion ($\lambda > 1$, where λ is their eigenvalue; Kaiser, 1960). We extracted the coordinates of each field along each of these selected dimensions. These fields' coordinates were used as synthetic intensity variables summarizing each farming practice in the following calculations.

Step 3 – Calculation of intensity indices for each farming practice at the field level

For each field surveyed, we calculated an intensity index for each farming practice independently, which cumulates the relative intensity of each selected PC for the considered farming practice (step 3 in Fig. 2). On the basis of the index developed by Herzog et al. (2006), we modified Eq. (1) to consider selected PCs as synthetic intensity variables. Since, by definition, each of these synthetic variables (PCs) explains inter-field variability in different magnitudes, we have weighted the equation according to the cumulative eigenvalues of the selected PCs rather than by the number of variables included, as is the case in Eq. (1):

$$I = \sum_{i=1}^n \frac{y_i - y_{min}}{y_{max} - y_{min}} \times \frac{1}{\sum_{j=1}^n \lambda_j} \quad (2)$$

where y_j is the coordinate of the field along the PC j , λ_j , the eigenvalue of the PC j , y_{min} and y_{max} the minimum and maximum observed values among all fields for the considered PC, and n the number of PCs for which λ_j is above 1. Weighting by the cumulated eigenvalues of selected PCs is necessary to compare intensity indices between practices and allow mixing them in integrative indices (step 4 below).

Step 4 – Calculation of intensity indices for each category of practice at the field level

For each field, we finally calculated the intensity index of five groupings of practice categories: pesticide use, fertilization level, tillage intensity, mowing intensity, and all combined. Using Eq. (1), we considered intensity indices of each corresponding practice computed at step 3 as variables. We computed intensity with a practice level approach, however a PCA can be performed directly on practice categories or overall to associate practices that have been identified to be correlated or to have a similar effect on a given subject of study. The advantage of the practice level approach is that it allows us to distinguish between fields with different levels of intensity, whereas the overall approach associates only one intensity value with each field. In addition, it estimates practice intensity on temporal, quantitative and diversity aspects while getting rid of correlations between the corresponding variables. We chose to compute the intensity of grouped practices with Eq. (1) instead of (2) so each practice would contribute equally to the intensity.

Step 5 – Statistical analyses at the field level

Using fields per cropping period as individual observations, we investigated whether the distributions of intensity indices were significantly associated with crop types, for each grouping of practice categories. To do this, we performed Kruskal-Wallis tests by ranks, as the conditions were not met for parametric tests. In case of significant association with crop type (p -value < 0.05), we computed pairwise Fisher's LSD (least-significant difference) tests to determine which crops differed from each other.

2.4. Landscape level intensity

To test the value of taking practices into account at landscape level, we calculated a patch richness index for each landscape, based on three types of patch classification schemes: (1) intensity (IT), (2) land cover (LC), and (3) the two superimposed (LCIT). We have chosen patch

richness to characterize classification schemes, as this metric is linked to many other aspects of landscape conformation such as patch number, aggregation, or edge density.

As patch richness is a raster-based index, it requires pixels to be assigned to classes, as by maintaining continuous values, the slightest difference in value would distinguish each patch from the others in an exaggerated and unreasonable manner. We therefore had to group the fields into classes of intensity value. However, landscape metrics are greatly impacted by the number of patch categories (Huang et al., 2006), and choosing the right number of classes is not trivial, and should be determined by the expected sensitivity of the response variable to intensity, as well as the variability of that intensity. In addition, we expect the relative difference between classifications based on land cover, intensity, or both, to depend on the number of intensity classes used, since this number of classes defines the difference in the number of landscape categories. Consequently, for classification schemes involving farming intensity, we calculated patch richness indices for intensity classes of equal size ranging from 2 to 20, to cover a wide range around the number of land cover classes, which is 9 for NF and 5 for MS.

Patch richness was computed for each classification scheme in both study areas and for each grouping of practices using the function `lsm_lpr()` from the package *landscapemetrics* (Hesselbarth et al., 2019). We rasterized the land cover data for cropland and grassland from the French Land Parcel Identification System (<https://geoservices.ign.fr/rpg>) at a resolution of 20×20 m, maintaining the original crop classes. We then compared the patch richness values of studied landscapes based on the different classifications (LC, IT, or LCIT) using a pairwise Wilcoxon-Mann-Whitney test. To illustrate the differences, we computed the average patch richness deviation between schemes depending on the number of intensity classes.

Finally, we compared landscape intensity between NF and MS to see if the agricultural areas differ in terms of intensity of practices in addition to land cover. Landscape-level intensity indices were estimated as the area-weighted mean of field intensity. The two regions were then compared using non-parametric tests for each intensity category (Kruskal-Wallis and Wilcoxon-Mann-Whitney tests). The surface that could be surveyed was considered to be representative of the total surface of the UAA of each landscape, and we therefore extrapolated the landscape intensity value to the entire area occupied by UAA.

3. Results

3.1. Field level intensity

The relative intensity index for each crop varies considerably for each practice category, except grassland, which remains the least intensive land cover type in both regions (Fig. 3; see Tables A2.1-A2.4 in Supplementary Material for statistical details). Significant and complex overlaps exist between annual crop types, partly due to important variability between fields of similar type. When we look at overall intensity (Fig. 3A), we see that in NF, sugar beet (0.71 ± 0.13 ; mean \pm standard deviation) and potato (0.70 ± 0.13) are significantly the most intensive annual crops, followed by flax (0.61 ± 0.12), and that wheat (0.54 ± 0.12), maize (0.55 ± 0.09), and barley (0.55 ± 0.11) are the least intensive annual crops (Fig. 3A). No significant differences are found between annual crops in MS, even if maize (0.49 ± 0.12) tends to be the most intensive annual crop, and oilseed rape (0.33 ± 0.23) the least intensive one (Fig. 3A).

Regarding fertilization intensity (Fig. 3B), we observe similar contrasts and relative positions of annual crop types in NF except for wheat (0.36 ± 0.19) and barley (0.39 ± 0.18) that are less intensive than maize (0.46 ± 0.19). Also, the variability within each crop type (0.20 ± 0.01) is much higher than for overall intensity (0.12 ± 0.02 ; Fig. 3B). In MS, wheat (0.20 ± 0.14) and oilseed rape (0.25 ± 0.178) are the least intensive and maize (0.43 ± 0.18) the most intensive (Fig. 3B).

Concerning the intensity due to pesticide use (Fig. 3C), sugar beet

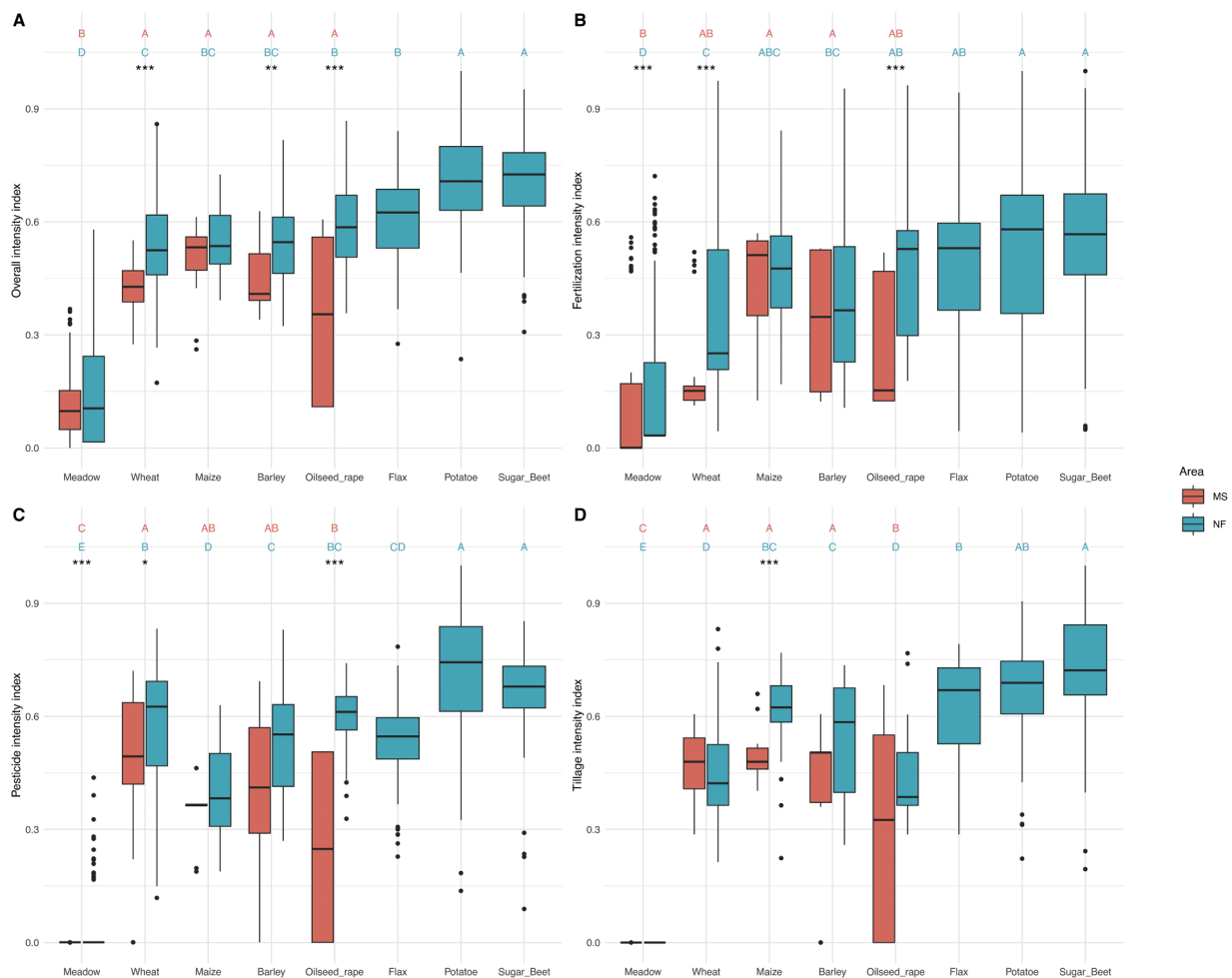


Fig. 3. Overall (A), fertilization (B), pesticide use (C), and tillage (D) normalized intensity depending on land cover type for Moselle (MS; in red and on the left) and Northern France (NF; in blue and on the right). Letters indicate significant differences between land covers for each agricultural area independently (Kruskal-Wallis Bonferonni adjusted with post-hoc LSD Fisher test, $\alpha = 0.05$); in red and at the top for MS and in blue and at the bottom for NF. Asterisks indicate significant differences between the two areas for each land cover independently (Wilcoxon-Mann-Whitney test, $\alpha = 0.05$; *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$).

(0.66 ± 0.13) and potato (0.71 ± 0.18) remain the most intensive crops in NF, followed by oilseed rape (0.59 ± 0.09) and wheat (0.59 ± 0.14), and maize (0.40 ± 0.13) is the least intensive crop, followed by flax (0.53 ± 0.13) and barley (0.54 ± 0.13 ; Fig. 3C). In MS, wheat (0.49 ± 0.17) is the most intensive crop, followed by barley (0.39 ± 0.24) and maize (0.35 ± 0.09), and oilseed rape (0.25 ± 0.25) is the least intensive crop (Fig. 3C).

Tillage intensity (Fig. 3D) is significantly the lowest for wheat (0.45 ± 0.11) and oilseed rape (0.43 ± 0.11) and the highest for sugar beet (0.72 ± 0.14), followed by potato (0.66 ± 0.15), in NF (Fig. 3D). In MS, tillage intensity is the lowest in oilseed rape (0.43 ± 0.11) and there are no statistical differences between other crops (Fig. 3D). Variability is quite high in MS, particularly for oilseed rape (0.31 ± 0.31) and barley (0.42 ± 0.17), for which the number of fields surveyed is rather low ($n = 9$ and 10 , respectively).

For common land covers, differences between agricultural areas (MS and NF) also depend on the index of intensity selected (Fig. 3). Meadow management differs between the two areas for fertilization (0.18 ± 0.22 for NF; 0.13 ± 0.18 for MS), pesticide use (0.04 ± 0.09 for NF; 0.00 ± 0.00 for MS), and mowing intensity, but not for overall (0.16 ± 0.17 for NF; 0.12 ± 0.10 for MS) and tillage intensity (0.00 ± 0.00 for NF; 0.00 ± 0.00 for MS). Overall and fertilization intensities are quite variable between fields in both regions, contrary to tillage (null for all fields) and pesticide use (null for the majority of fields except a few fields in NF that could be considered outliers). Mowing intensity in MS was significantly

higher than in NF (Wilcoxon-Mann-Whitney, $p = 0.004$) with a mean of 0.31 ± 0.39 and 0.29 ± 0.18 for MS and NF, respectively. Even if most grasslands in NF were less intensive than in MS on average, some highly intensive fields in NF rise the average of this study area (see Fig. A3.1 in Supplementary Material).

Wheat and oilseed rape are more intensive for overall, fertilization, and pesticide intensity in NF than in MS. For tillage intensity, maize is more intensive in NF than in MS. Intensity of barley is different between areas only for overall intensity.

3.2. Landscape scale intensity

IT (i.e., intensity-based) patch richness increases with the number of classes for all intensity categories in NF (Fig. 4) but only for overall intensity in MS (Fig. 5). In NF, average intensity patch richness significantly differs from LC (i.e., land cover-based) patch richness except when the number of intensity classes approaches the number of LC categories: non-significant from 9 to 12 classes for overall intensity; for 8, 9, 10 and 12 classes for fertilization; from 10 to 16 classes for pesticide use and from 10 to 18 classes for tillage.

Patch richness resulting from the combination of land cover and intensity (LCIT) is always significantly higher than that resulting from land cover or patch richness, and increases as the number of classes increases (pairwise Wilcoxon-Mann-Whitney test, $\alpha = 0.05$). Patch richness deviation between LCIT and LC in NF ranges from 1.17 to 5.48

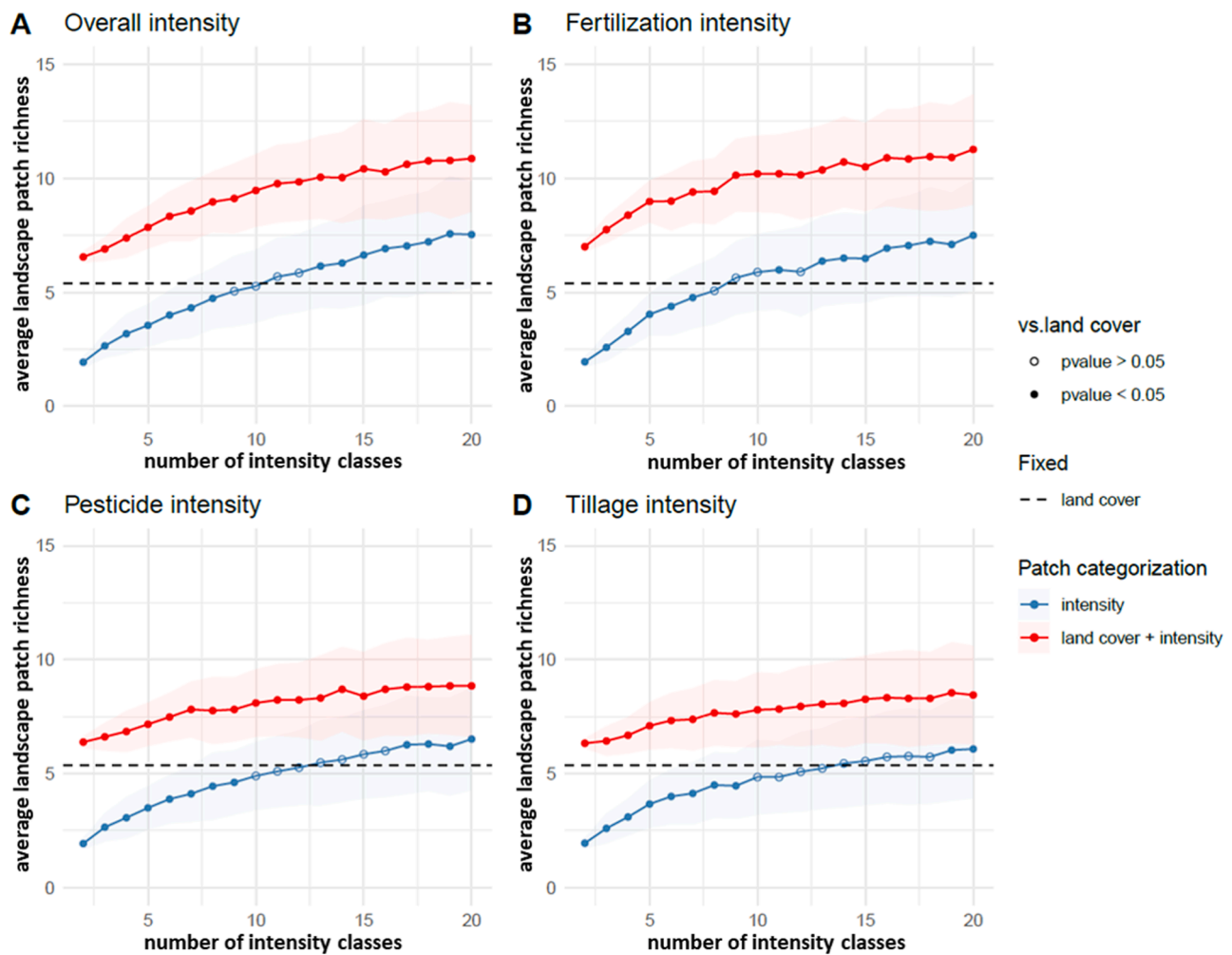


Fig. 4. NF's overall (A), fertilization (B), pesticide use (C), and tillage (D) average patch richness for three patch classification schemes: land cover (LC; black dashed line), intensity (IT; blue line), and intensity and land cover superimposed (LCIT; red line). Ribbons represent standard deviation. Full points represent the number of intensity classes for which land cover diversity significantly differed from the corresponding patch classification schemes and hollow points those for which it did not (pairwise Wilcoxon-Mann-Whitney test, $\alpha = 0.05$).

for overall intensity, 1.62 to 5.88 for fertilization, 1.00 to 3.47 for pesticide use, and 0.95 to 3.17 for tillage. In MS, LC and IT did not differ except for overall intensity for 2 and 11 to 20 classes and fertilization for 6, 12, 16 and 17 classes. Patch richness deviation between LCIT and LC ranges from 0.06 to 1.33 for overall intensity, 0.33 to 1.05 for fertilization, 0.06 to 0.11 for pesticide use, and 0.00 to 0.83 for tillage.

The map presented in Fig. 6 illustrates the three classification schemes applied to the studied landscapes, and how land cover and intensity can differ and create new patches when associated. Areas that are not surveyed are either non-cultivated or non-grassland fields, or fields that could not be surveyed. For the represented NF landscape, there are 10 continuous patches when considering land cover only, 13 patches when considering intensity due to practices (three classes), and 19 patches when considering the two superimposed. Concerning patch richness, there are seven different land covers, three intensity levels, and nine different types of patches when superimposed. The MS landscape has three patches when considering land cover, one when considering the intensity due to practices, and three when considering the two superimposed. Patch richness in MS is two for land cover, one for intensity, and two for both superimposed.

3.3. Agricultural areas comparison

NF intensity is significantly higher than MS for every landscape scale

intensity index except for mowing, for which MS is the most intensive (Fig. 7). The deviation between the two areas is higher for pesticide use followed by tillage, overall intensity, fertilization, and mowing. As this index is relative, when the proportion of intensive landscapes increases in one area, it decreases in the other. The variability in landscape intensity is higher in MS than in NF likely due to the lower number of surveyed landscapes and crop types as illustrated in Fig. 3.

4. Discussion

We have combined both existing approaches to develop a flexible index for estimating the intensity of farming management at field and landscape scale, considering five groupings of practice categories to illustrate it (i.e., overall intensity, and intensity due to either fertilization, pesticide use, tillage, and harvesting/mowing). The results showed that heterogeneity linked to intensity at field and landscape scale differs from that linked to land cover. In addition, the relationship between intensity and land-cover type depends on the agricultural area. Consequently, field intensity cannot be directly assimilated to land cover, but depends on the groupings of farming practices and the agricultural areas considered. We came to similar conclusions at landscape level, given that landscape intensity differs between areas and for each component of farming practices. Finally, we showed significant differences between the classification scheme based on land cover and land cover combined

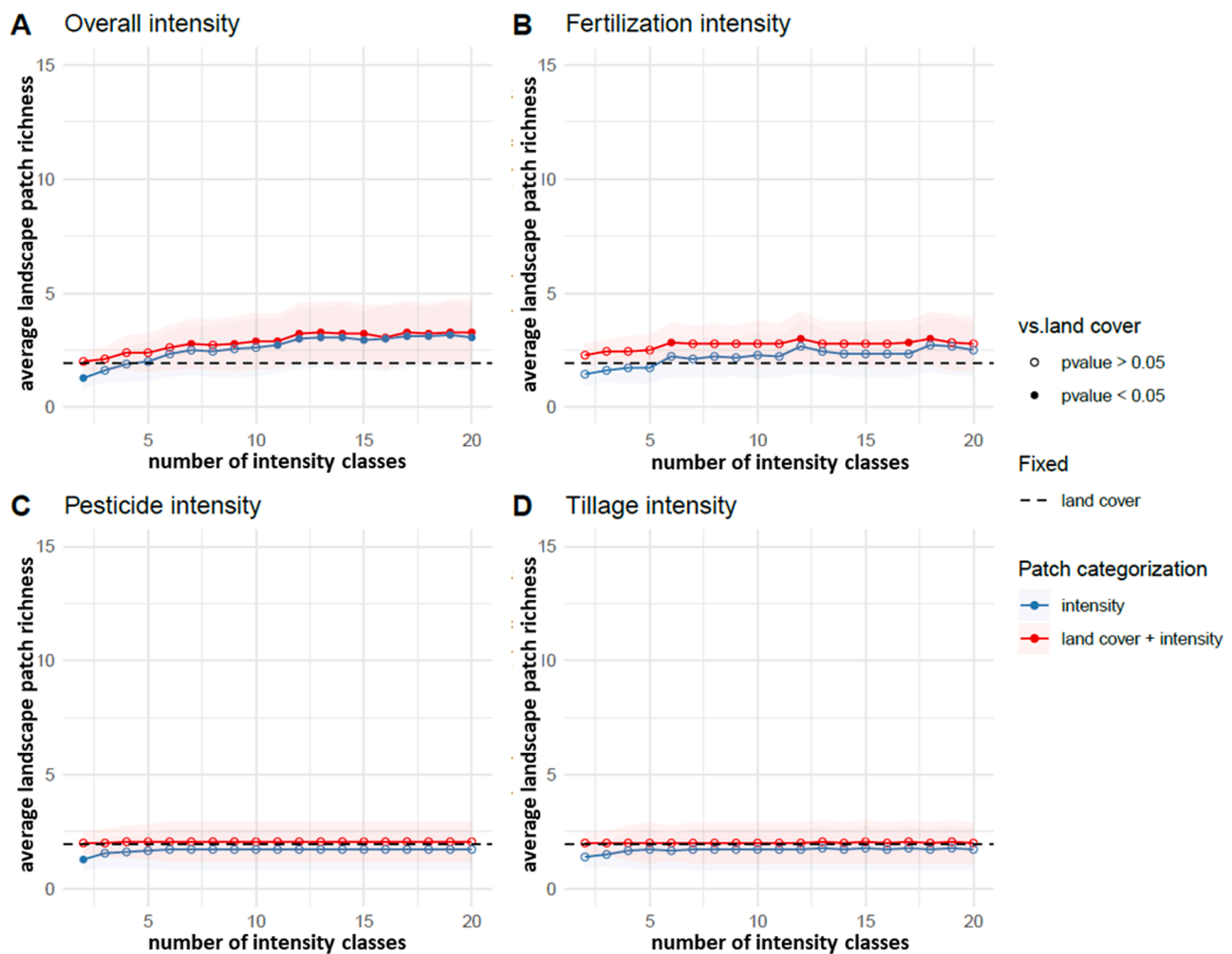


Fig. 5. MS's overall (A), fertilization (B), pesticide use (C), and tillage (D) average patch richness for three patch classification schemes: land cover (LC; black dashed line), intensity (IT; blue line), and intensity and land cover superimposed (LCIT; red line). Ribbons represent standard deviation. Full points represent the number of intensity classes for which land cover diversity significantly differed from the corresponding patch classification schemes and hollow points those for which it did not (pairwise Wilcoxon-Mann-Whitney test, $\alpha = 0.05$).

with intensity. This was made possible by the large amount of practice data obtained, thanks to farmers' interest in our survey. Our results suggest that the added value generated by the information contained in these data is paramount in describing the functional suitability of fields and landscapes more accurately than considering land cover alone.

Landscape structure can be defined by a "visible" mosaic of land covers and a "hidden" heterogeneity of farming practices associated to intensity (Marrec et al., 2022; Vasseur et al., 2013). To highlight the relationship between these two components, we compared the landscape structure resulting from the use of three landscape classification schemes: land cover (LC), intensity (IT), and the two superimposed (LCIT) as illustrated in Fig. 6. We found that patch richness at landscape level diverged considerably depending on the classification scheme considered, particularly in NF. For any number of classes, classification based on LCIT always led to a greater patch richness than those based on LC and IT in NF (Fig. 4). As LCIT superimposes information on land cover and practices, this result is directly linked to the fact that, for each type of land cover, the intensity of practices varies widely. This is in line with our results and those of previous studies at field level (Gosme et al., 2012; Kurhak et al., 2023; Puech et al., 2014): for both agricultural areas, we showed that intra-crop variability in farming practices is high for all crops and overlaps considerably between crop types (Fig. 3). Nevertheless, patch richness based on IT and LCIT classifications only poorly deviated from the one based on LC alone in MS. This result is due

to the fact that utilized agriculture area in MS is strongly dominated by grasslands, while NF is more diversified and dominated by annual crops. Therefore, in most MS landscapes, intensity levels were predominantly distributed within grasslands or otherwise in only one or two crops. However, as grasslands have a very low level of intensity compared to the annual crops studied (Fig. 2), the divergence between classifications based on LC and IT is almost zero. Consequently, the most structuring effect in MS is linked to the grasslands vs. crops dichotomy. Yet while most studies have shown that grasslands are less intensive based on the consideration of individual practices (Landis et al., 2000), by taking multiple practices into account we have verified that this pattern is true for overall, fertilization, pesticide use, and tillage intensity, but not for mowing/harvesting intensity for which grasslands are more intensive. Even if some grasslands in our dataset had similar levels of pesticide and fertilization intensity than annual crops. As such, in MS, the intensity of fertilization in grasslands significantly overlapped with that of wheat and oilseed rape (Fig. 3B), which could be explained by a desire on the part of farmers to increase the productivity of their grasslands and increase the surface area on which they can spread the excess manure produced in this area dominated by cattle farming.

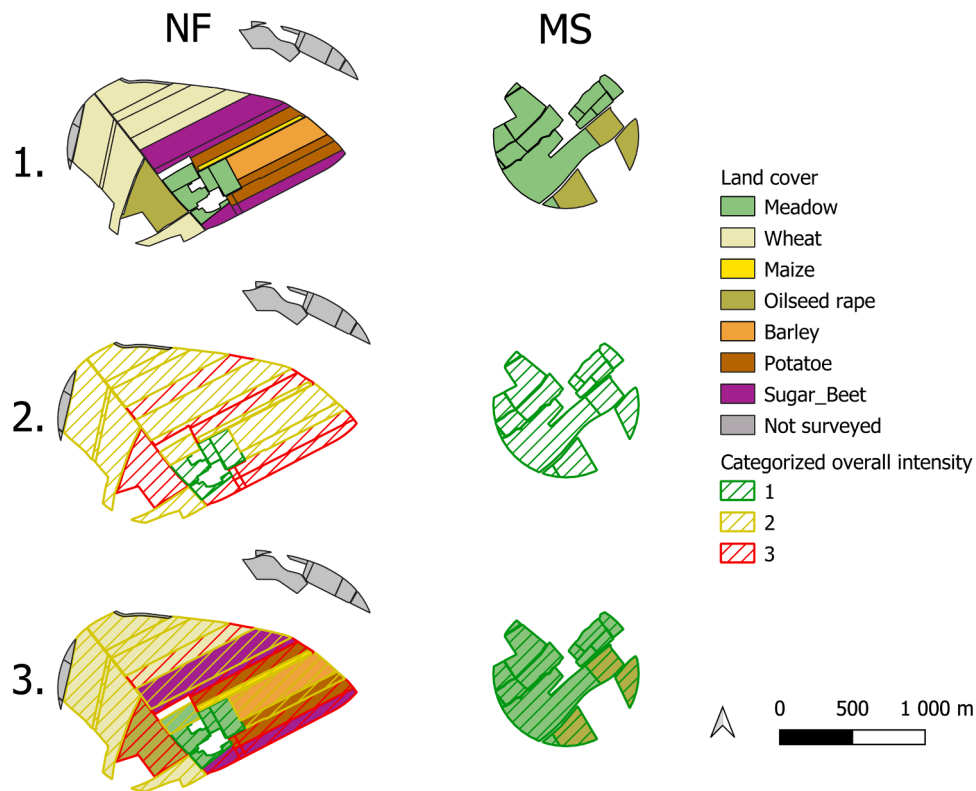


Fig. 6. Maps showing the fields represented using classification schemes based on land cover (1; LC), categorized overall intensity (2; IT), and the two superimposed (3; LCIT) for two landscapes from Northern France (NF) and Moselle (MS). Here, overall intensity is categorized into three regular classes of levels of intensity (low, medium, and high).

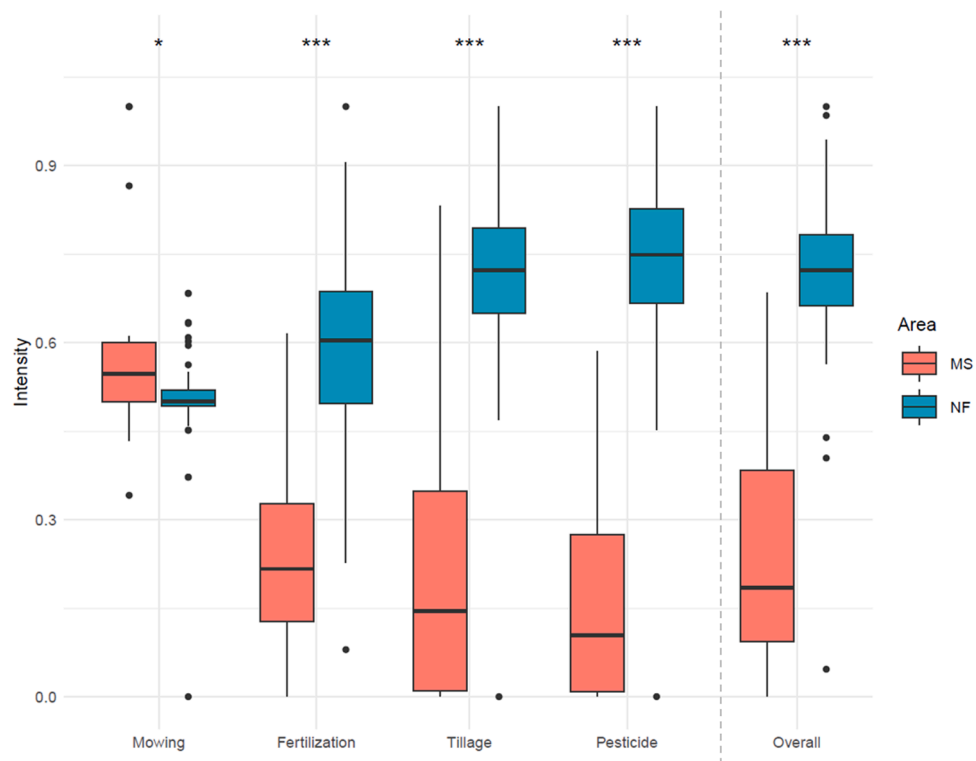


Fig. 7. Intensity indices at landscape level for Moselle (MS) and Northern France (NF). Asterisks indicate significant differences between the two areas (Wilcoxon-Mann-Whitney test, $\alpha = 0.05$; *: p-value < 0.05, **: p-value < 0.01, ***: p-value < 0.001). Intensity at landscape level is the average intensity of the corresponding fields weighted by their surface.

4.1. Interests of landscape characterization by intensity in addition and association with landcover

For both agricultural areas, but especially for NF, we observed that the divergence in patch richness between the sole consideration of land cover (LC) and the addition of agricultural practices (LCIT) increased as the number of classes increased. As LC classes are changeless, the patch richness based on LCIT increases at the same rate as the deviation between LC and IT. Mechanically, the greater the variability of intensity classes there are, the greater the number of classes created in the LCIT classification, which increases the diversity of landscape patches. Even if this trend is true for all groupings of practices, we can add nuance by saying that the variability and intensity of practices within and between crops vary depending on the grouping (Fig. 3), thus modifying the degree of divergence between LC and IT/ LCIT. For instance, in NF, maize was less intensive than wheat for pesticide use but more intensive for soil tillage. Therefore, land cover could not be similarly associated with intensity, resulting in a different landscape structure in each case.

Since the resulting structure of the landscape is dependent on both the number of IT classes and the nature of the practices considered, it seems more than important to apply an approach based on hypotheses when the response of a biological, ecological, or environmental variable is the object of study. In addition, these results indicate that the more sensitive the response variable is assumed to be to practices (including locally), the more critical it becomes to consider these practices in addition to land cover. The definition of the number of classes should therefore be based on the expected sensitivity of the response variable to farming practices. Thus, it is very likely that the abundance of a species highly sensitive to agricultural activities will vary in the face of small changes in intensity, and thus respond to smaller classes. In such real case studies, tools such as scaling functions could be used to optimize selecting an appropriate number of classes (Huang et al., 2006). In the same logic, land cover classes should be defined regarding their relationship with the response variable. This could be done by estimating or assuming a positive or negative effect of each land cover class, but also based on functional traits, depending on the objectives and the nature of the object of study. In this methodological paper, we illustrate the use of the approach only considering the average landscape patch richness — along a gradient of class number (Fig. 4 and 5) —, as it has been shown to be linked to most landscape metrics (Huang et al., 2006). Nevertheless, LC and IT classifications can also differ in other structural (compositional and configuration) aspects and their combination could be used to determine suitable hotspots or intensity barriers.

4.2. Similarities and differences between two contrasted territories

The average landscape intensity is lower in MS than NF for each intensity group, except mowing/harvesting (Fig. 7). This can be explained by the fact that MS crops are as much or less intensive as NF crops, depending on the considered intensity grouping (Fig. 3). In addition, the higher proportion of grasslands in MS (45 % vs. 5 % in NF), which are less intensive than other land covers except for mowing/harvesting, drives MS landscape intensity down. Also, NF has a higher proportion of annual crops such as wheat and sugar beet, which tend to be more intensive (Fig. 3). This result illustrates that landscape intensity is greatly affected by the nature and diversity of the production systems chosen by all farmers in that landscape. This is in line with several previous studies, such as the one by Shriar (2005), that has shown that the intensity of farming systems in Petèn (Guatemala) varies at farm and regional scales depending on farmers' needs, willingness, and capabilities to intensify their practices. Also, the farm production system and the landscape context in which it is embedded can greatly influence the probability of implementing agro-ecological measures, and thus "intensify" farming practices (Paulus et al., 2022).

At the field level, our results reveal that the land covers considered do not present the same levels of relative intensity according to the

groupings of practices and agricultural areas considered. This implies that the ordering of crops in one territory cannot be directly transposed to other territories, which is a fundamental prerequisite when we assume that land cover describes crop intensity. It is therefore necessary to determine which practices can be used to discriminate between fields in a given territory, before formulating hypotheses on the most favorable or unfavorable land cover for the response variable under consideration. Above all, it is essential to identify which practices are discriminating in the study region under consideration, and avoid selecting one or more practices in particular that have been identified as discriminating in other studies and agricultural and regional contexts. For instance, our results show that oilseed rape, which is often studied in terms of pollinator dependency and yield, is much more pesticide-intensive in NF than in MS. If this difference lies within the sensitivity range of pollinator species, this could lead to a positive effect in MS and a reduced or even negative effect in NF. This could explain the regional differences observed in the literature and the unintended effect of pest management practices on pollination dependency in oilseed rape reviewed by Ouvrard and Jacquemard (2019).

Through the use of PCAs, our approach has the advantage of facilitating the consideration of variability between agricultural areas by allowing several variables to be combined to characterize practices, without a priori selection. In addition, analysis of PCA alone enables us to identify, for each grouping of practices, those that are the most discriminating for the agricultural area under consideration. In future work, this may make it possible to better target the practices to be surveyed/quantified, and reduce the data collection effort. However, since the intensity of each field is relative to that of the other fields studied, if several agricultural areas are to be considered, the PCA steps must be carried out by assembling the entire dataset. Also, the resulting intensity index can be challenging to interpret, which can involve additional analysis when studying specific practices effects (Büchi et al., 2019).

4.3. Implications and applications of our approach

Given the differences in landscape structure induced by land cover and intensity, there is a risk to improperly describe field suitability distribution by considering only land cover. In the current agricultural context, which relies heavily on intensive farming practices, it is more likely to overestimate the number of suitable fields, as the positive effect attributed to certain crops could be cancelled out by a high intensity level of some fields of these crops. While this effect has been studied for specific relationships, for instance for oilseed rape and solitary bees (Le Féon et al., 2013) or weed species diversity and cereal fields management (Armengot et al., 2011), our method could be used to mitigate this bias for every crop in the landscape and thus to describe agricultural landscapes more accurately than it is possible with land cover maps. Previous assumption on the suitability of fields depending on land cover only should be reconsidered before investing in unsuitable landscapes as the effect of practice intensity could negate the benefits of semi-natural environment preservation (Marrec et al., 2022). Nevertheless, the procedure we used in this study is based on obtaining data on farming practices by means of surveys carried out directly with farmers. Although this strategy is the most accurate for collecting data on all farming practices, it cannot be used to scale up and consider larger spatial areas. The widespread use of freely accessible agricultural databases or the use of indices derived from satellite remote sensing as proxies for practices are serious avenues for this scaling-up and the generalization of their use (e.g., Bégué et al., 2018; Karmakar et al., 2023; Zhang et al., 2024).

One of the primary benefits of our method is its ability to investigate the impact of farming management intensity on a diverse range of research subjects and spatial scales (from field to landscape). For instance, biodiversity is a relevant example. Despite several studies exploring the effects of organic and conventional farming or farming

practices on biodiversity (Lichtenberg et al., 2017; Rusch et al., 2010), most of them did not account for the intensity of farming management. Similarly, our approach can investigate the impact of farming management intensity on environmental quality, with a specific focus on crucial components such as water and soil quality. Our method facilitates an objective analysis of how varying degrees of farming management intensity can potentially affect the quality of these essential environmental elements. For example, our approach may aid in examining the potential impact of high-intensity farming practices on water quality in relation to nutrient run-off (Dupas et al., 2015) and their influence on soil health and productivity (Guerra and Pinto-Correia, 2016). Additionally, our method can be utilized to investigate the impact of farming management intensity on various socio-economic factors, such as farmers' profits, working practices, and attitudes (Cong et al., 2014; Vuillot et al., 2016). For example, researching the impact of farming management intensity on farmers' income and its influence on the wider economic context of the agricultural industry could provide valuable insights.

Our method is versatile and can be applied across various spatial scales, from field to landscape. This adaptability provides opportunities for different applications in the farming management field. For instance, while our primary aim was to estimate the intensity of agricultural management at the landscape scale, this method can prove useful to those monitoring a set of fields who are solely concerned with the local effects of farming management. Furthermore, the approach can be adapted to all farming practice datasets, regardless of whether they encompass multiple practices or solely focus on a single practice, such as insecticide treatments. This adaptability makes it an ideal tool for any study interested in the notion of agricultural management intensity. Finally, it is important to note that while our work was conducted in an agricultural setting, our method is transferable to other environments. As an index of management intensity, it can be applied in any environment managed by humans, including forests, aquatic environments, and more. With regard to forests, our method could be used to assess the impact of forest management practices on biodiversity. It could help to identify areas where intensive management has led to a loss of biodiversity and to propose mitigation strategies. In aquatic environments, our method could be used to assess the impact of human activities such as fishing or aquaculture on marine ecosystems. It could help identifying areas where these activities have a negative impact on marine biodiversity and propose strategies to minimize this impact. In short, our method offers a flexible and adaptable approach for assessing the impact of human activities on biodiversity in a variety of environments. This opens many potential applications in environmental management and biodiversity conservation.

5. Conclusion

In view of our results and the recognized impact of farming practices on biodiversity and environmental quality, land cover cannot generally be considered sufficient to describe the quality and intensity of fields and landscapes, especially when multiple contrasting agricultural territories are taken into account — within and between which the intensity of the same crops can be highly variable. The method for estimating the intensity of agricultural practices developed in this article could help to solve this problem, as it allows multiple combinations of metrics associating farming practices and land cover to be easily integrated into models. By integrating the limitations of several other approaches, we can better represent and understand the match between field “quality” and the response of the study model under consideration. The next step will be to test our method against response data in an environment with contrasting practices, thereby testing the effect of intensity as well as the effectiveness and limitations of our method.

CRedit authorship contribution statement

Simon Maudet: Writing – review & editing, Writing – original draft,

Visualization, Validation, Methodology, Formal analysis, Data curation. **Théo Brusse:** Writing – review & editing, Validation, Methodology, Investigation, Data curation. **Benoit Poss:** Writing – review & editing, Investigation, Formal analysis, Data curation. **Gaël Caro:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Ronan Marrec:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Ronan Marrec reports financial support was provided by French National Establishment for Agricultural and Marine Produce. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.ecolmodel.2024.110975](https://doi.org/10.1016/j.ecolmodel.2024.110975).

Data availability

Farming practices data available on request. In compliance with the European Union's General Data Protection Regulation (GDPR), field localization will not be shared in order to preserve farmers anonymity.

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