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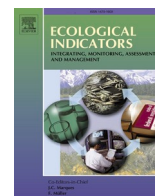
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Review

Which soil microbial indicators should be included in routine laboratory tests to support the transition to sustainable management of arable farming systems? A meta-analysis

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ABSTRACT

Our research aims to address the gap in understanding the sensitivity of multipurpose active pools of soil organic matter (SOM) and microbiological indicators, in addition to the usual physico-chemical measurements, to assess the effects of the shift from conventional to sustainable management practices under various pedoclimatic conditions. We conducted a meta-analysis (166 articles) on the sensitivity of these indicators on six practices: exogenous organic matter input (EOM), crop residue retention (RR), cover crop introduction (CC), crop rotation/diversification (CR), tillage reduction (TR), and conversion from conventional to innovative or organic systems (IOS). Random effects models considering the natural log of the response ratio were applied.

Our study showed that climatic factors did not significantly influence indicator responses, while clay content, organic matter, pH, trial durations, and sampling depth significantly modulate the response of soil indicators. In detail, our results emphasized that both physico-chemical (soil organic carbon (SOC) and total nitrogen (STN) contents) and microbiological indicators (e.g., microbial biomass carbon (MBC), total phospholipids fatty acids (PLFA), and B-glucosidase (B-GLU)) were sensitive to EOM, RR, CC, and TR. For instance, CC significantly increased SOC (+7%) and STN (+8%), as well as MBC (+14%), total PLFA (+19%), and B-GLU (+11%). On the other hand, CR and IOS practices did not impact SOC and STN, contrary to some microbiological indicators. For these two practices, MBC increased between 7 and 34% and PLFA between 8 and 24%. Moreover, B-GLU raised by +58% with IOS practice. This suggests that the microbiological indicators may be more responsive to specific agricultural practices, such as CR and IOS, even if the changes they induce are not immediately related to carbon inputs. SOC and STN provide information on the changes in the organic status of soil under carbon input practices and TR, though they are less sensitive to crop diversification and innovative farming in short-term studies, highlighting the time needed for sustainable management practices to modify soil health. Microbiological indicators (MBC and PLFA) and enzyme activities (FDA, B-GLU, and URE) showed greater sensitivity to a large range of agricultural practices, regardless of the age of agricultural practice, suggesting their potential use as more responsive, early, and versatile indicators in evaluating soil health.

1. Introduction

The ongoing increase in the world population has significant implications for land use and soil quality, which refer to the capacity of soil to function and provide ecosystem services (Aznar-Sánchez et al., 2019; Gerland et al., 2014; Kopitke et al., 2019). Indeed, to meet growing food

demand, the intensification of agriculture may contribute to soil quality degradation over time (Li et al., 2023). Common consequences include soil erosion, nutrient depletion, compaction, and loss of organic matter (Auerswald et al., 2003; Aziz et al., 2013; Fuentes et al., 2009; Kouselou et al., 2018; Marinari et al., 2006; Page et al., 2020). To promote sustainable land use, the transition to agroecological practices is

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encouraged by different public policies (Place et al., 2022). Agroecology, an approach emphasizing the integration of ecological principles into agriculture, promotes sustainable farming systems through long and diversified crop rotations, intercropping, cover crop introduction, soil disturbance reduction, and the use of alternative fertilizers and natural pest management methods (Duru et al., 2015; Kerr et al., 2023; Kremen et al., 2012; Wezel et al., 2014). The agroecological approach has been shown to enhance the chemical properties and structure of soils by increasing their organic carbon and nitrogen contents and aggregate stability (Alvarez and Steinbach, 2009; Testani et al., 2023; Virginia et al., 2018; Wezel et al., 2020). This approach also impacts soil functioning through an increase in soil microbial abundances and activities (Araújo et al., 2009; McDaniel and Grandy, 2016; Onwona-Kwakye et al., 2020; Williams et al., 2023; Wolińska et al., 2022). By impacting both soil physico-chemical and biological components, sustainable management practices aim to enhance soil fertility and health (Altieri, 2018). Awareness of these positive effects is accompanied by a need for routine monitoring of changes in soil properties following an agroecological transition (Karlen et al., 2003). Routine tests currently rely predominantly on the analysis of physical and chemical soil components (Franzuebbers, 2020; McDaniel et al., 2020). Recent research has focused on enhancing these tests by incorporating the analysis of active pools of soil organic matter (SOM) and soil microbial communities (Hurisso et al., 2018; Krüger et al., 2018). This integration will enable comprehensive bio-physico-chemical soil characterizations, offering crucial additional information about changes in soil microbial communities and soil functioning (Bhaduri et al., 2022; Labouyrie et al., 2023; Paz-Ferreiro and Fu, 2016; Schloter et al., 2018). Microbiological indicators could include the measurement of microbial abundances through analysis of carbon (C), nitrogen (N) and phosphorus (P) contents in microbial biomass or PLFA, as well as microbial activities involved in C, N, P, and sulfur (S) biogeochemical cycles (Cui et al., 2022; Fanin et al., 2022; Li et al., 2018; Riah-Anglet et al., 2021).

To be considered relevant indicators for monitoring soil properties after agricultural management changes, soil analytical variables must (i) involve limited time constraints for sampling and sending to the lab, (ii) be scientifically reliable, technically mature and not require high technical expertise (Griffiths et al., 2016), (iii) avoid time-consuming lab analysis (Griffiths et al., 2016), (iv) incur reasonable costs for routine soil analysis (Bagnall et al., 2023; Griffiths et al., 2016), (v) be analyzed using a standardized or normatively available protocol to ensure consistent and comparable results, (vi) provide informative insights into soil processes and functions, and (vii) be sensitive to agricultural changes. Currently, routine analysis of physico-chemical indicators offers advantages such as lower time constraints for sampling and sending to the lab, reduced technical requirements, shorter duration, and lower cost compared to analyzing certain active SOM pools or microbiological indicators (Perrin et al., 2023).

In addition to these technical advantages, active SOM pools and microbiological indicators play a crucial role in providing information about changes in soil processes and functions in response to agricultural transition. Studies have focused on the relationship between biophysico-chemical indicators and soil functions, such as soil nutrient recycling and C transformation through organic matter (OM) cycling using conceptual frameworks, but our understanding of these connections remains incomplete (Bünemann et al., 2018; Lenka et al., 2022; Schulte et al., 2015). The sensitivity of certain active SOM pools and microbiological indicators to agricultural changes has been extensively studied in the literature (Kibblewhite et al., 2008; Vogel et al., 2018). To assess the potential value of including these indicators in routine tests based on this criterion, it is essential to compile all available literature and compare a range of indicators regarding their sensitivity to agroecological practices. If some meta-analyses have examined the effects of individual practices (e.g., cover crop, tillage, or biochar application) on some microbiological indicators such as MBC and N or on enzymatic activities (Kim et al., 2020; Li et al., 2018; Pokharel et al., 2020; Zuber

and Villamil, 2016), there is a lack of studies on the responses of a large panel of active SOM pools and microbiological indicators to a wide range of sustainable management practices, which are essential for identifying multipurpose soil indicators suitable for various agricultural contexts. To address this gap, the objectives of this work were:

- (i) To identify co-variables related to pedoclimatic context, soil sampling strategy, or time since change in agricultural management practices, which modulate the responses of soil indicators following the shift from conventional to sustainable management practices.
- (ii) To identify relevant indicators among a set of active pools of SOM and microbiological indicators, complementing routine physico-chemical tests based on their sensitivity to agricultural management practices changes within diverse pedoclimatic conditions.

2. Material and methods

2.1. Literature search strategy

Primary research gathered for this study evaluated the effects of exogenous organic matter input (EOM), crop residue retention (RR), cover crop introduction (CC), crop rotation/ diversification (CR), tillage reduction (TR), and conversion to innovative or organic systems (IOS) practices on soil microbial communities and C and N dynamics. Our work focused on a set of active pools of SOM and microbiological indicators identified as suitable candidates for soil routine analyses in previous research (Bloem et al., 2005; Thoumazeau et al., 2019). In each study, these indicators were examined using a fixed-depth sampling strategy. Despite potential biases due to differences in soil bulk density between soil treatments (Rovira et al., 2022), this methodological choice was made considering the potential use of these indicators in routine soil tests. The literature was collected, synthesized, and compiled from peer-reviewed journals from 2004 to 2022. Platforms for searching scientific literature and scholarly articles “Science Direct,” “Wiley,” “Springer,” and “Google Scholar” were used as search engines. To select relevant publications, the following search strings were used: (exogen organic matter OR manure OR slurry OR green waste OR organic fertilization OR compost OR organic amendment OR cover crop OR intermediate crop OR inter crop OR catch crop OR tillage OR plough* OR plow* OR no-till* OR direct seeding OR direct sowing OR shallow tillage OR non-inversion tillage OR diversified rotation OR crop diversity OR temporal crop diversification OR plant diversity OR organic systems OR organic farming OR conventional systems OR agroecological systems OR conservation agriculture OR cropping system OR agricultural system OR plant residues OR straw OR straw incorporation OR residues incorporation OR straw retention OR residues retention OR straw return) AND (soil quality OR soil microb* OR soil health OR soil properties OR soil microbial abundance OR soil fungal abundance OR soil bacterial abundance OR soil enzymatic activities).

Publications included in the review process had to fulfill the following criteria:

- (1) Articles should provide results exclusively from field experiments to identify indicators relevant for soil state assessment,
- (2) Articles should focus on major crops, including cereals, oilseed crops, root and tuber crops with high starch or inulin content, leguminous crops, sugar crops, and other crops classified as grass crops according to the Indicative Crop Classification of the FAO,
- (3) Multiple sampling depths were examined (minimum sampling depth: 0 to 2 cm and maximum sampling depth: from 0 to 30 cm); however, the maximum depth considered is 0 to 30 cm, considering that the potential storage of SOC associated with sustainable management practices mainly occurred in this layer,
- (4) Each article had to present quantitative data (either in tables or in graphical forms) regarding both physical–chemical and microbiological soil indicators. This data needed to be related to a set of variables

presented in Table 1,

(5) Data should be provided for a reference treatment (control) and for one or several treatment(s) with the implementation of one of the six studied agricultural practices, and

(6) Each study had to include information about field trial design, including the number of replicates per treatment, and trial length (from 1 to 59 years).

After considering the above criteria, 166 relevant articles were identified according to the procedure. These references are listed in Appendix A.

2.2. Data extraction and homogenization

Mean and standard deviation values of soil indicators were extracted from each paper and field treatment. When the standard deviation data was not given, it was estimated as 10 % of the mean value (Allam et al., 2021). When only the standard error was given, the standard deviation was calculated according to equation (1):

$$SD = SE * \sqrt{n} \quad (1)$$

with SD: standard deviation, SE: standard error, and n: observation size. Metadata was extracted from each selected article. This metadata included trial location (latitude, longitude, site elevation (m)), climate conditions (mean annual precipitation (MAP) (mm) and mean annual temperature (MAT) (°C)), experimental design (block number), pedological features (clay, silt, sand, carbonate and organic matter contents, and pH), trial length (duration between the beginning of the experiment and soil sampling time (years)), sampling strategy (minimum and maximum sampling depths), and agronomic data. The agronomic metadata included the type and the length of the crop rotations, type of EOM, N-P-K mineral fertilization, diversity of cover crops, soil tillage (depth, tools), residue management, and type of cropping systems. To homogenize the database, soil pH values measured in KCl and CaCl₂ were converted to H₂O pH using equations (2) and (3), respectively (He et al., 2021; Sadowski, 2019):

$$pH(H_2O) = 1.65 + 0.86 \times pH(CaCl_2) \quad (2)$$

$$pH(H_2O) = 1.53466 + 0.88787 \times pH(KCl) \quad (3)$$

Table 1

Overview of soil indicators studied in the meta-analysis and their description.

Soil indicators	Abbreviations	Descriptions	References
Reference physico-chemical indicators			
Soil Organic Carbon	SOC	Organic soil content	O'Rourke et al., 2015
Soil Total N	STN	N total soil content	Mazzoncini et al., 2011
Active pools of SOM			
Permanganate Oxidizable Carbon	POXC	Labile C soil content	Culman et al., 2012; Weil et al., 2003
Biologically Mineralizable Nitrogen	BMN	Mineralizable N	Keeney and Bremner, 1966
Potentially Mineralizable Nitrogen	PMN		Gianello and Bremner, 1986
Microbial abundance indicators			
Microbial biomass carbon	MBC	Abundance of total soil microorganisms	Vance et al., 1987
Total Phospholipid fatty acid	Total PLFA		Zhang et al., 2019b
Microbial molecular biomass	Total DNA		Gangneux et al., 2011
Bacterial 16S rDNA genes copy number	16S rDNA	Abundance of total soil bacteria	Rezgui et al., 2020
Total bacterial PLFA	B. PLFA		Bååth and Anderson, 2003
Fungal 18S rDNA genes copy number	18S rDNA	Abundance of total soil fungi	Rezgui et al., 2020
Total fungal PLFA	F. PLFA		Bååth and Anderson, 2003
Ergosterol	Ergo		Montgomery et al., 2000; Gong et al., 2001
Glomalin	Glomalin	A soil glycoprotein	Wang et al., 2014
Microbial activities indicators			
Fluorescein diacetate hydrolase	FDA	Global enzymatic activity	Adam et al., 2001
Leucine aminopeptidase	LAP	N-Cycling Enzyme Activities	Clivot et al., 2020
Arylamidase	ARYLN		Acosta-Martínez et al., 2000; Cheviron et al., 2022
Protease	PROT		Greenfield et al., 2021
Urease	URE		de Santiago-Martín et al., 2013; Cheviron et al., 2022
N-acetylglucosaminidase	NAG		Trap et al., 2012; Cheviron et al., 2022
Beta-glucosidase	B-GLU	C-Cycling Enzyme Activity	Trap et al., 2012; Cheviron et al., 2022

From the location of each experimental site (Fig. 1), the corresponding climate class was defined based on the Köppen-Geiger classification (Peel et al., 2007). The soil texture group was determined using the USDA classification system (Ditzler et al., 2017)

2.3. Pairwise comparisons

To compare the values of indicators between the reference treatment (control) and a treatment based on sustainable management practices, pairwise comparisons were made per article within the same experimental site. For all studied practices, a total of 1566 pairwise comparisons were carried out. Due to the varying numbers of selected articles for each agricultural practice (73 articles related to RT, 48 to EOM, 32 to CC, 29 to CR, 24 to RR, and 22 to IOS), the number of pairwise comparisons varied accordingly. Among the total number of pairwise comparisons, 534 were related to RT, 291 to EOM, 260 to CC, 263 to CR, 154 to RR, and 64 to IOS.

These comparisons are based on data from all articles related to a practice, regardless of climate zone, soil texture, and soil sampling depth. The number of these comparisons per climate zone and textural class are presented in Table S1, those per sampling depth in Table S2, and those per type of agronomic treatment in Table S3. For instance, among the total number of 154 pairwise comparisons of RR practice, 81 were done in an arid climate, 38 in a warm, temperate climate, and 35 in a cold, snow-forest climate; 50 comparisons were done on fine-textured group soils, 48 on medium-textured group soils, and 32 on coarse-textured group soils (Table S1). Among the total number of pairwise comparisons for this practice, 51 comparisons were done on 0–20 cm (Table S2). Regarding the type of agronomic treatment, 70 comparisons studied treatments with residues returning (surface) related to a control treatment with residue exportation (Table S3).

2.4. Data treatment & statistical analyses

All subsequent data treatment and statistical analyses were performed using R studio (version 1.3.1093). The response ratio of a soil indicator in response to each agricultural practice was investigated per pairwise comparison. This corresponds to the ratio of the mean variable value in the sustainable management treatment to its mean value in the control treatment. Data was normalized by calculating the natural log of

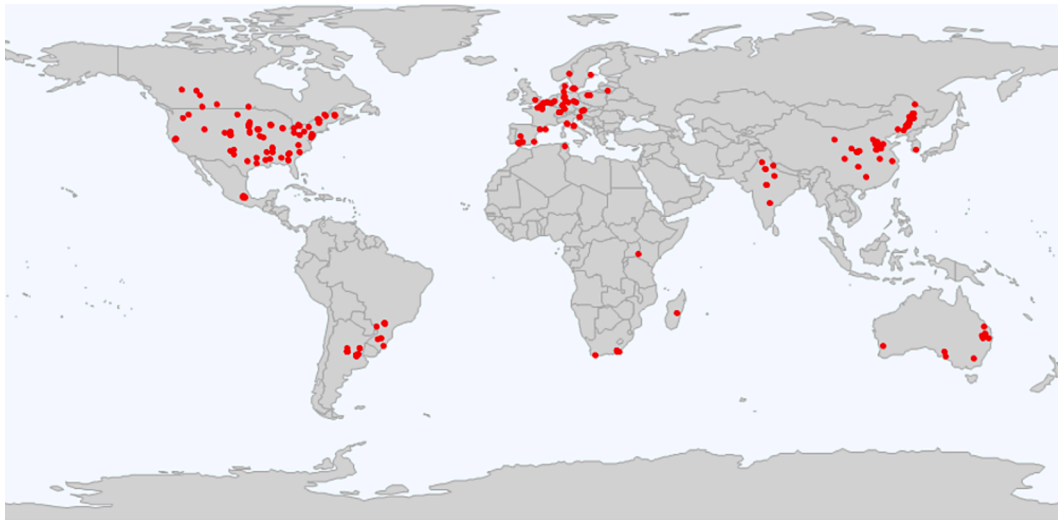


Fig. 1. Worldwide distribution of field studies (represented by red dots) reported in the articles selected for the meta-analysis. The map was generated using the `getMap` function of `rworldmap` R package.

the response ratio (LRR) according to equation (4). The associated variance was also computed (Kim et al., 2020; Puissant et al., 2021).

$$\text{LRR} = \ln\left(\frac{\bar{X}_p}{\bar{X}_c}\right) \quad (4)$$

$$\text{Var}(\text{RR}) = \frac{(SD_p)^2}{n_p \cdot \bar{X}_p^2} + \frac{(SD_c)^2}{n_c \cdot \bar{X}_c^2} \quad (5)$$

with \bar{X} : the mean value, SD: the standard deviation, and n : the observation size for the control (c) and the tested practice treatments.

The LRR values were transformed according to equation (6), to be expressed in percentage of change:

$$\text{Percentage of change (\%)} = (e^{\text{LRR}} - 1) * 100\% \quad (6)$$

To study the effect of agricultural practices on a soil indicator using the results of LRRs and associated variances, random effects models were applied using the `rma.uni` function from the `metafor` R package (Allam et al., 2021; Viechtbauer, 2010). These overall models compute the mean true effect and its associated 95 % confidence interval (CI 95) regardless of pedoclimatic context. The effect of a practice was considered significant if the Z statistic gave a p-value lower than 0.05 (Lori et al., 2017). In this case, the confidence interval (CI) does not include zero. The sign of the mean true effect indicated whether the practice had a positive or negative impact on the soil indicators. Results of mean effects and associated CI 95 were represented in forest plots. The possible publication bias for each agricultural practice and soil indicator was investigated visually using the `funnel` function to create funnel plots (Kim et al., 2020; Viechtbauer, 2010). To study the model's robustness, Rosenberg's fail-safe number was computed. This number indicates the number of studies with a non-significant effect size that would need to be included in the meta-analysis to overturn the result (Puissant et al., 2021; Rosenberg, 2005). The higher this number, the more robust the model. A model can be considered robust if Rosenberg's fail-safe number is higher than $5 * n + 10$, with n : the number of observations (Zhao et al., 2022). In total, 101 overall models were studied in this meta-analysis.

To check whether the effects of agricultural practices on soil indicators depend on factors related to site location elevation, climate conditions (MAT and MAP), soil characteristics, trial length, or soil sampling strategy, these factors were considered potential co-variables (moderators) (Bárcena et al., 2014; Puissant et al., 2021). Regarding the OM soil content co-variable, it was decided to assimilate the moderating variable "OM content of the control" to the initial OM of the

soil before the transition from conventional to sustainable management practice. Indicator responses to agricultural practice were considered significantly sensitive to a moderator if the p-value of the meta-regression was less than 0.05 and the corresponding data had been processed in at least 10 articles (Fu et al., 2008). To determine whether each of these factors significantly modulates the response of indicators to practices, the p-values of meta-regressions between these potential moderators and variables LRR values were investigated.

3. Results

3.1. Moderators' impact on soil analytical indicators in response to agricultural management practice change

Metadata for site characteristics, soil and climate, trial length, and soil sampling strategy are provided as potential moderators of analytical indicators responses. The breakdown of the metadata categories is presented below:

1. Elevation and Climatic Metadata:
 - o Experimental Site Elevation: Ranges from 18 to 2240 m.
 - o Mean Annual Precipitation (MAP): Ranges from 89 to 1774 mm.
 - o Mean Annual Temperature (MAT): Ranges from 1.5 to 28 °C.
2. Soil Metadata:
 - o Clay Content: Ranges from 1.1 to 71 %.
 - o Soil pH: Ranges from 4 to 8.9.
 - o Organic Matter (OM) Content of the Control: Ranges from 0.24 to 5.72 %.
3. Trial Length and Sampling Strategy Metadata:
 - o Trial Length: Ranges from 1 to 59 years.
 - o Minimum Sampling Depth: Ranges from 0 to 20 cm.
 - o Maximum Sampling Depth: Ranges from 2 to 30 cm.

The wide ranges in elevation, climate, soil characteristics, trial length, and sampling depths indicate a diverse set of conditions, suggesting that our study covers a broad spectrum of agropedoclimatic contexts. This metadata provides a comprehensive overview of the impacts of environmental and soil conditions factors considered in our study (Table 2). In this table, significant regressions are indicated by symbols ▲ and ▼, which correspond to positive and negative relations, respectively. The number of articles/observations is indicated for significant meta-regressions based on data from at least 10 papers. When only one number is indicated, the article number studying the relation

Table 2

Meta-regressions between potential moderators (site characteristics, soil and climate, trial length and soil sampling strategy) and soil indicator responses to all agricultural practices.

Soil variables	Moderators								
	Site & Climate			Soil			Trial length & sampling strategy		
	Elevation	MAP	MAT	Soil clay content	Soil pH	Soil OM content of the control	Trial length	Min. sampling depth	Max. sampling depth
SOC	NS	NS	NS	NS	NS	▼*** 105/824	NS	▼*** 119/1061	NS
STN	▲* 30/384	▲*** 57/491	▲*** 47/333	▼*** 32/301	▼* 46/383	NS	▲* 66/690	▼*** 70/707	▼*** 70/707
POXC	NS	▼** 6	NS	NS	NS	NS	NS	NS	NS
BMN	NS	▲*** 3	NS	NS	NS	▼*** 5	▼* 6	NS	▼*** 6
PMN	NS	NS	NS	NS	NS	NS	NS	▼*** 2	▼*** 2
MBC	NS	▲* 75/675	▼*** 57/462	▼* 48/393	NS	NS	NS	▼*** 89/768	NS
Total PLFA	NS	NS	NS	NS	NS	NS	NS	▼*** 36/309	▼** 36/309
Total DNA	▼* 2	▼** 5	▲*** 5	▲* 3	NS	NS	NS	▼* 6	NS
16S rDNA	NS	NS	NS	NS	NS	NS	▲* 13/57	▼** 14/60	NS
B. PLFA	NS	NS	NS	NS	NS	▼** 20/149	NS	▼*** 31/233	▼* 31/233
18S rDNA	NS	NS	NS	NS	NS	NS	NS	NS	NS
F. PLFA	NS	NS	NS	▼* 18/110	▼* 15/84	▲*** 24/161	NS	NS	NS
Ergo	▲*** 4	NS	NS	▲*** 4	NS	▲** 4	▼*** 5	▼* 6	NS
Glomalin	▼*** 2	NS	NS	NS	NS	NS	NS	NS	NS

Soil indicators	Moderators								
	Site & Climate			Soil			Trial length & sampling strategy		
	Elevation	MAP	MAT	Soil clay content	Soil pH	Soil OM content of the control	Trial length	Min. sampling depth	Max. sampling depth
FDA	NS	NS	NS	NS	▲*** 2	▼* 9	▲* 10/141	▼** 11/145	NS
LAP	NS	NS	NS	NS	▲* 4	NS	NS	▲*** 8	NS
ARYLN	NS	▲* 2	NS	NS	NS	NS	NS	NS	NS
PROT	NS	NS	NS	NS	NS	▲*** 8	NS	NS	NS
URE	NS	NS	▼*** 12/79	▲* 6	NS	NS	NS	NS	NS
NAG	NS	NS	NS	NS	NS	▼* 4	NS	▼* 5	NS
B-GLU	▲** 10/193	NS	NS	▼* 10/154	▼** 22/287	NS	NS	▼*** 35/426	▼** 35/426

MAT: mean annual temperature; MAP: mean annual precipitation.

SOC: Soil Organic Carbon; STN: Soil Total N; POXC: Permanganate Oxidizable Carbon; BMN: Biologically Mineralizable Nitrogen; PMN: Potentially Mineralizable Nitrogen; MBC: Microbial biomass carbon; Total PLFA: Total Phospholipid fatty acid; Total DNA: Microbial molecular biomass; 16S rDNA: Bacterial 16S rDNA genes copy number; B. PLFA: Total bacterial PLFA; 18S rDNA: Fungal 18S rDNA genes copy number; F. PLFA: Total fungal PLFA; Ergo: Ergosterol; Glomalin: Glomalin; FDA: Fluorescein diacetate hydrolase; LAP: Leucine aminopeptidase; ARYLN: Arylamidase; PROT: Protease; URE: Urease; NAG: N-acetylglucosaminidase; B-GLU: Beta-glucosidase.

30/384: Pairwise comparisons number / Articles number.

▲, ▼: increase or decrease values=, respectively.

Notes: Significance level: *: p-value < 0.05, **: p-value < 0.01, ***: p-value < 0.001.

was lower than 10 (not interpreted). NS and white boxes correspond to non-significant regressions and non-studied relations, respectively.

The data analysis did not reveal a predominant effect of site and climate moderators on the response of soil indicators. Indeed, elevation and MAP were identified as significant moderators in the response of 2 indicators out of 24 (STN and B-GLU for site elevation and STN and MBC for MAP) (Table 2). MAT was also found to be a significant moderator for three indicators' responses out of 24 (STN, MBC, and URE) (Table 2). These findings indicate that although site and climate moderators do not consistently affect all variables, some indicators (such as STN, B-GLU, MBC, and URE) are influenced by specific moderators (elevation, MAP, and MAT). The analysis shows that the impact of site and climate moderators differs among various soil analytical indicators, with specific indicators demonstrating significant responses to particular moderators. Detailed results are provided in Table 2.

Soil pH and soil clay content were found to be significant moderators for STN, F. PLFA, B-GLU and STN, MBC, F. PLFA, and B-GLU responses, respectively. These co-variables negatively influenced the indicator responses, showing lower responses to agroecological practices for higher values of each co-variable. Negative relations have also been found between the OM content of the control treatment and SOC and B. PLFA responses (Table 2).

Trial length was identified as a significant moderator for STN, 16rDNA, and FDA responses, suggesting that longer lengths between agricultural management practice changes and soil sampling were associated with higher responses in these variables (Table 2). Regarding soil sampling strategy, minimum and maximum sampling depths significantly modulated the response of eight soil variables (SOC, STN, MBC, Total PLFA, 16S rDNA, B. PLFA, FDA, and B-GLU) and four soil variables (STN, Total PLFA, B. PLFA, and B-GLU), respectively (Table 2), suggesting the importance of sampling depth in soil monitoring.

These results highlight the importance of soil properties (pH, clay, and OM contents), trial length, and soil sampling strategy in influencing the responses of various soil analytical variables to sustainable management practices.

3.2. Response of soil indicators to agricultural practices

In theory, each agricultural practice and soil indicator combination should be represented by a separate model, resulting in a maximum of 21 models per practice corresponding to the 21 indicators studied. Each model represents the sensitivity of a bioindicator to a specific agricultural practice. However, the actual number of models varies among practices due to variations in missing data across practices (e.g., no data

available for the arylamidase (ARYLN) indicator in the EOM practice). Consequently, some practices may have fewer models; for instance, the EOM practice might have 20 out of the 21 models, resulting in varying model numbers across different practices.

Among 101 models run for all practices, 67 showed significant effect sizes. The majority of the models (61 out of 67) with significant effect sizes were considered robust according to Rosenberg’s fail-safe criterion (Fig. 2). This suggests a high level of confidence in the reliability and stability of the observed effects across the various models and practices studied. Additional details are available in Table S4.

In our paper, the data treatment was done per practice because the collected literature focused on the effects of each practice on soil indicators. However, we studied practices with potential common effects on soils. Indeed, indicators’ responses to practices can depend on C inputs in soils (EOM, CC, and RR practices), crop diversification (CC and CR practices), and tillage reduction (TR practice). Given that conversion from conventional to sustainable management systems can involve several of these practices, responses of analytical indicators to IOS were discussed separately. Indicators’ sensitivities to practices are presented based on this practice’s typology.

3.2.1. Exogenous organic matter input (EOM)

The effects of EOM practice were studied using data from 48 papers, and the analysis included 20 soil variables. Significant effect sizes were observed for 16 out of the 20 models studied. Among these 16 models, 15 were considered robust according to Rosenberg’s fail-safe criterion (the glomalin model was non-robust) (Table S4).

All robust models showed positive LRR values, highlighting the global increment in soil variables because of the EOM practice. SOC and STN increased by 27 % and 25 %, respectively. Microbial biomass abundances (MBC, PLFA, and total DNA) increased by 39 %, 30 %, and 36 %, respectively. Bacterial abundance (16S rRNA gene) increased by 38 %, while fungal biomass (PLFA) increased by 62 %. Soil enzyme activities including FDA showed an increase of 61 %, while LAP, B-GLU, and PROT showed increases of 21 %, 30 %, and 46 %, respectively (Fig. 2A).

The EOM practice had positive and robust effects on various soil indicators, including SOC, N, microbial biomass, bacterial and fungal abundances, and enzyme activities. The detailed percentage increases provide a quantitative understanding of the impact of the EOM practice on soil health and functioning.

3.2.2. Crop residues retention (RR)

The study of the effects of the RR practice involved data from 24 articles, and the analysis included 15 soil indicators. The effect size was significant for 12 of the 15 models studied. All of these significant models were considered robust according to Rosenberg’s fail-safe criterion (Table S4).

The positive response ratio for all significant robust models demonstrated a global increment of soil indicators in response to RR compared to residue removal. SOC and STN increased by 11 and 12 %, respectively. Total microbial biomass increased by 23 % for MBC and 26 % for total PLFA, and bacterial and fungal PLFA abundances by 29 % and 43 %, respectively. Microbial activities were also positively impacted by

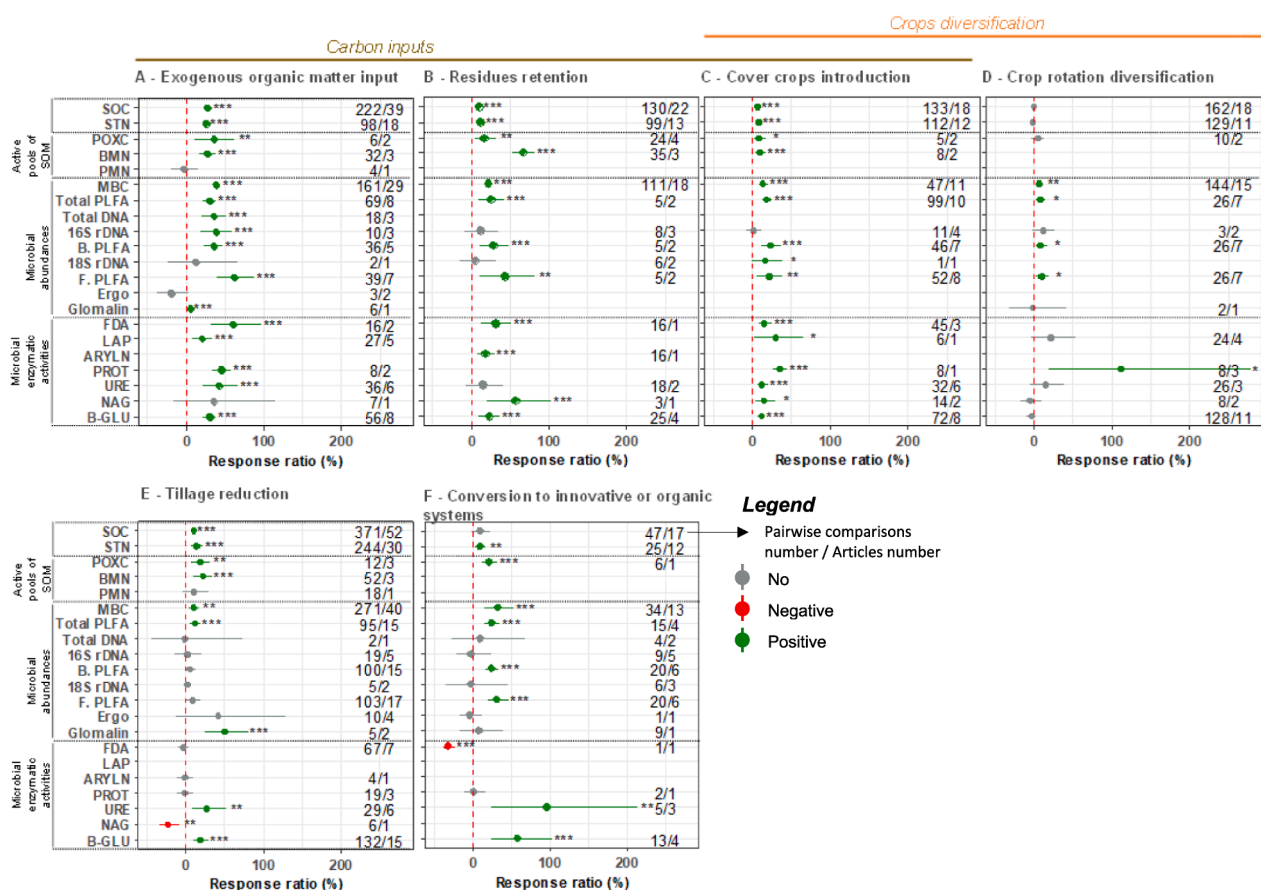


Fig. 2. Response ratio of physico-chemical, active pools of SOM and microbiological soil variables to different agricultural practices: A – Exogenous organic matter input, B – Residues retention, C – Cover crops introduction, D – Crop rotation/ diversification, E – Tillage reduction, F – Conversion to innovative or organic systems. A, B and C correspond to practices involving direct C inputs in soils and C and D to practices increasing crop diversification. The horizontal bars correspond to 95 % confidence intervals for each overall model. The significance level of each model is indicated at the right of each bar (p-value < 0.05: *, p-value < 0.01: **, p-value < 0.001: ***).

crop RR (+31 % for FDA, +19 % for ARYLN, +23 % for B-GLU, and +67 % for BMN) (Fig. 2E).

The RR practice had positive and robust effects on various soil variables, with residue retention leading to increases in soil organic C, N, microbial biomass, bacterial and fungal PLFA abundances, and microbial activities. The detailed percentage increases provide insights into the specific improvements in soil health and functioning associated with crop RR.

3.2.3. Cover crop introduction (CC)

The effects of cover cropping were studied on 16 soil indicators by analyzing data from 32 papers. The effect size was significant for 15 models. Eleven of these models were considered robust according to their Rosenberg fail-safe number (POXC, BMN, 18S rDNA, and LAP models were non-robust) (Table S4). Positive LRR values of robust models indicated an increase in soil variables caused by CC introduction (Fig. 2A). CC practice caused an increase in soil physico-chemical variables: 7 % for SOC and 8 % for STN contents (Fig. 2B). Cover cropping enhanced total microbial biomass (by 14 and 19 % for MBC and total PLFA, respectively), bacterial biomass by 24 % (bacterial PLFA), and fungal biomass by 22 % (fungal PLFA). A positive effect of cover crops was also found for enzyme activities (+11 % for B-GLU, +13 % for URE, +16 % for FDA, and +35 % for PROT) (Fig. 2B). Cover cropping had positive and robust effects on various soil variables, leading to increases in SOC, nitrogen, microbial biomass, bacterial and fungal biomass, and enzyme activities. The detailed percentage increases provide insights into the specific improvements in soil health and functioning associated with cover cropping practices.

3.2.4. Crop rotation/ diversification (CR)

The effects of the CR practice were studied on 14 soil indicators using data from nine articles. The effect size was significant in five models. All these models were considered robust according to their Rosenberg fail-safe number (Table S4). Results showed that crop rotation with species diversification caused an increase of total microbial biomass (+7% for MBC and +8 % for total PLFA), bacterial and fungal biomasses determined by PLFA (+9% for bacteria and +10 % for fungi), and PROT enzyme activity (+112 %) (Fig. 2D). The crop rotation practice involving species diversification had positive effects on microbial biomass and enzyme activity. The findings suggest that this agricultural practice contributes to enhancing soil health and functioning. The robustness of the models adds confidence to these observed effects.

3.2.5. Tillage reduction (TR)

The effects of TR were studied on 20 soil indicators using data from 73 papers. The effect size was significant in 10 models. All these models were considered robust according to their Rosenberg fail-safe number (Table S4). The positive LRR for 9 out of 10 significant robust models highlighted the global increase of soil variables in response to TR practice. The relative increase reached 10 % and 14 % for SOC and STN and 11 % for microbial biomass abundances determined by MBC and total DNA. URE and B-GLU activities increased by 28 % and 19 %, respectively. TR also positively impacted the soil glomalin content, which increased by 51 % (Fig. 2C). It should be noted that TR caused a decrease of about 23 % only for NAG activity (Fig. 2C).

3.2.6. Transition from conventional to innovative or organic farming systems (IOS)

The effects of IOS practice were analyzed using data from 22 papers, and the study included 16 soil indicators. The effect size was significant for 9 out of the 16 models studied. Eight of these significant models were considered robust according to Rosenberg's fail-safe criterion (Table S4). The STN model was non-significant (Fig. 2F). The results of the robust models indicated that IOS practice led to an increase in several soil variables: POXC increased by 22 %, total microbial biomass increased by 24 % for total PLFA and 34 % for MBC. Bacterial and fungal

PLFA increased by 25 % for bacteria and 32 % for fungi. Some enzyme activities involved in N and C cycles were stimulated by IOS practice: URE activity increased significantly by 97 %, and B-GLU activity increased by 58 %. IOS practice led to a 31 % reduction in the value of FDA activity.

4. Discussion

4.1. The impact of moderators on the sensitivity of soil indicators during the transition to sustainable management practices

Our study highlighted that climatic moderators (site elevation, air temperature, and precipitations) did not strongly influence soil indicators' responses to management practice changes, which aligns with Eze et al. (2023). They demonstrated that early indicators of SOC stock changes are more influenced by soil C inputs than climate factors across a global dataset. Similarly, Cong et al. (2015) found that soil OM dynamics were more responsive to management practices than precipitation and temperature regimes. This implies that the effects of agricultural practices on soil indicators are primarily driven by the management practices themselves rather than being modulated by climatic conditions.

The negative modulating effect of high clay content on the response of STN, MBC, F. PLFA, and B-GLU indicators supports the mechanistic understanding that clays can bind and stabilize OM compounds through mineral-organic associations (Belayneh et al., 2019; Schweizer et al., 2021). This binding limits the bioavailability of nutrients and the cycling of OM (Vogel et al., 2015). Clay OM complexes are particularly stable (Bruun et al., 2010), potentially restraining indicator responses. Soils with high OM content (such as those in the control treatments) also negatively modulated the responses of SOC and B. PLFA indicators. This likely reflects the fact that these soils are approaching what scientists sometimes refer to as maximum C saturation levels, where additional C inputs become ineffective. In other words, soils with high OM content may be closer to their maximum storage capacity for C and N accumulation than soils with lower OM content (Angers et al., 2011; Hassink, 1997; Husain & Dijkstra, 2023; Matus, 2021), resulting in smaller observable effects from practices involving C inputs. This negative modulating effect could also be related to substrate saturation kinetics that constrain microbial growth responses (Jones et al., 2018).

The observed negative impact of high pH on the responses of STN, F. PLFA, and B-GLU indicators aligns with the literature, indicating that pH is a strong driver of the soil microbiome and associated functions (Lauber et al., 2009; Rousk et al., 2010). Moreover, the length of the trials had a positive effect on the responses of STN, 16S rDNA, and FDA indicators. Longer trial periods showed more pronounced responses of indicators. This highlights that changes in soil OM pools and microbial communities in response to new practices may require extended periods to fully manifest, as observed in long-term trials (Diaz-Zorita and Grove, 2002; Nunes et al., 2020; Ren et al., 2019a). Lag periods are necessary for new steady-state conditions in C flows and nutrient cycling to be established (Smith et al., 2014), thereby making the effects of these new practices more evident as farming practices proceed over time.

The negative relationship between soil sampling depth and the response of indicators suggests that the assessment of soil properties in response to these changes shows more significant effects for the upper soil layers. Studies have shown that microbial biomass decreases with soil depth (Naylor et al., 2022). This decrease is particularly pronounced for reduced tillage practices due to the stratification of OM and microbial communities (Büchi et al., 2017a; He et al., 2023b). Thus, sampling depth is an important aspect to consider, especially for practices like reduced tillage. Observations of more significant indicator responses in the upper soil layers align with the understanding that the impacts of agricultural practices are often most pronounced in the surface horizons, where OM inputs and microbial activity are concentrated. The stratification of OM and microbial communities under reduced tillage practices

further reinforces the importance of considering sampling depth when assessing the effects of such practices on soil indicators.

This study highlights the need to consider moderating factors such as soil properties (clay content, OM, pH), trial duration, and sampling depth when assessing the impact of agricultural practices changes on soil indicators. Soil characteristics can significantly influence indicator responses due to mechanisms involving OM stabilization, C and N storage limits, and pH effects on microbial communities. Longer trials reveal more pronounced changes in biological indicators, reflecting the time required for sustainable management practices to affect soil health and functioning. Nevertheless, some bioindicators do not respond to trial length, suggesting a quicker reactivity to changes in practices. Additionally, it is essential to focus sampling strategies on the upper soil layers, where the effects of management practices are most pronounced, to accurately capture the responses of sensitive indicators, particularly for management practices such as reduced tillage, which induces vertical stratification of OM and microbial communities. By taking these moderating factors into account, we can make informed decisions and develop effective management strategies to improve soil sustainability in various agrosystems.

This study also highlights the importance of considering moderators related to soil properties, such as clay content, OM levels, and pH, as well as the duration of the trial and the sampling depth for the monitoring and interpretation of microbiological indicators of soil health. This is particularly crucial in the context of changing management practices.

4.2. Assessing the sensitivity of active SOM pools and microbiological indicators in discriminating between sustainable management practices and conventional practices

To extend the routine physico-chemical soil analysis to include

indicators linked to active SOM pools and the microbiological state of the soil, it is essential that these new indicators present a discrimination threshold equal to or greater than that of the conventional reference indicators, namely SOC and STN. SOC and STN are widely recognized for their effectiveness in standard soil health assessments, particularly during the transition from conventional to sustainable management practices (Benintende et al., 2015). Our study, as summarized in Table 3, presents a comprehensive overview of these findings. The farming practices studied included three practices involving C inputs to soils: EOM, CC, and RR; two crop diversification practices: CC and CR; the reduction of tillage: TR; and crop system conversion: IOS.

SOC and STN showed positive responses to agricultural practices involving C inputs (EOM, crop RR, cover cropping) and TR. The addition of OM provides a direct source of organic C and N to the soil (Lal, 2020; Tian et al., 2020), while reduced tillage minimizes soil disturbance, leading to lower aeration and slower OM decomposition rates (Balesdent et al., 2000; Six et al., 2002). Reduced tillage also promotes soil aggregate formation, physically protecting OM from microbial decomposition within these aggregates (Six et al., 2004). These mechanisms contribute to the accumulation of SOC and STN by increasing OM inputs, reducing decomposition, and promoting physical protection. However, SOC and STN did not exhibit significant sensitivity to crop rotation diversification or conversion to innovative/organic farming systems within the study time frames. This could be attributed to the fact that changes in total SOC and STN represent cumulative effects over extended periods, often requiring years to be detected (Nair et al., 2019; Pulleman et al., 2000). Additionally, soils may have already reached an equilibrium state under previous management, and significant changes may not occur until a new equilibrium is established with new practices (Poeplau et al., 2011; Smith, 2004).

Microbial biomass indicators such as MBC and PLFA exhibited sensitivity to practices involving C inputs, crop diversification (cover

Table 3

Overview table of the response of physio-chemical, active pools of SOM and microbiological indicators to the sustainable management practices. SOC and STN are considered as reference indicators as they are commonly used in routine soil analysis.

Soil analytical indicators		Exogenous organic matter input	Residues retention	Crop rotation/diversification	Tillage reduction	Conversion to innovative or organic systems		
SOC		***	***		***			
STN		***	***		***			
Active pools of SOM								
	POXC	**	**		**	***		
	BMN	***	***		***			
	PMN							
Microbial abundances								
	MBC	***	***	**	**	***		
	Total	***	***	*	***	***		
	PLFA							
	Total DNA	***						
	16S rDNA	***						
	B. PLFA	***	***	*		***		
	18S rDNA							
	F. PLFA	***	**	*		***		
	Ergo							
	Glomalin				***			
Microbial enzymatic activities								
	FDA	***	***			***		
	LAP	***						
	ARYLN		***					
	PROT	***		*				
	URE	***			**	**		
	NAG		***		**			
	B-GLU	***	***		***	***		
		-50	0	50	100	150	NS or non-robust	No data

SOC: Soil Organic Carbon; STN: Soil Total N; POXC: Permanganate Oxidizable Carbon; BMN: Biologically Mineralizable Nitrogen; PMN: Potentially Mineralizable Nitrogen; MBC: Microbial biomass carbon; Total PLFA: Total Phospholipid fatty acid; Total DNA: Microbial molecular biomass; 16S rDNA: Bacterial 16S rDNA genes copy number; B. PLFA: Total bacterial PLFA; 18S rDNA: Fungal 18S rDNA genes copy number; F. PLFA: Total fungal PLFA; Ergo: Ergosterol; Glomalin: Glomalin; FDA: Fluorescein diacetate hydrolase; LAP: Leucine aminopeptidase; ARYLN: Arylamidase; PROT: Protease; URE: Urease; NAG: N-acetylglucosaminidase; B-GLU: Beta-glucosidase.

Notes: Significance level: *: p-value < 0.05, **: p-value < 0.01, ***: p-value < 0.001.

cropping and rotations), TR, and conversion to innovative/organic systems. This responsiveness aligns with research showing rapid changes in microbial communities induced by shifts in OM inputs and management practices (Insam and Munder, 2021; Zhang et al., 2020). The mechanisms underlying this sensitivity include increased availability of organic substrates, creation of favorable micro-habitats, and improved soil habitats stimulating microbial growth and activity from C input practices (Bölscher et al., 2017; Bünemann et al., 2018; Hu et al., 2018; Lal, 2016; Mbuthia et al., 2015). Crop diversification provides diverse root exudates, changes rhizosphere interactions, and influences nutrient cycling patterns, supporting diverse microbial communities (Coskun et al., 2017; McDaniel et al., 2014; Tiemann et al., 2015; Venter et al., 2016). Reduced tillage minimizes physical disturbance while maintaining suitable moisture and temperature regimes, preserving favorable micro-habitats (Lal, 2016; Mbuthia et al., 2015; Shi et al., 2019). Innovative/organic systems combine diversified inputs, crop diversification, and other practices, creating a favorable range of substrates and habitats for microbial proliferation (Hartmann et al., 2015; Lori et al., 2017). Notably, MBC and PLFA outperformed SOC and STN in sensitivity to crop rotation, suggesting their potential as more sensitive indicators for soil diagnostics due to the rapid turnover and direct responsiveness of microbial biomass to changes in substrate availability and soil conditions (Bünemann et al., 2018; Chen et al., 2020).

Enzyme activities such as FDA, B-GLU, and URE showed sensitivity to practices involving C inputs and TR, consistent with the well-documented links between OM inputs, microbial activity, and enzyme production in soils (Adetunji et al., 2020; Karolin et al., 2022). The addition of OM provides substrates that stimulate microbial growth and consequent production of enzymes involved in C, N, and phosphorus cycling (Brockett et al., 2012). Reduced tillage minimizes soil disturbance, preserving favorable habitats for microbial communities and their associated enzyme activities (Dai et al., 2020). The study also highlighted the positive impact of conversion to innovative/organic systems on B-GLU and URE activities, potentially reflecting the stimulation of specific microbial functional groups involved in C and N cycling under these management regimes (Prommer et al., 2020; Rahmann et al., 2021). Overall, these practices involving C inputs, reduced disturbance, and diversified systems enhance microbial activity and create conditions favorable to increased enzyme production and activities in the soil by providing substrates, preserving habitats, and supporting functionally diverse microbial communities.

Some microbiological variables, such as 16S rDNA and enzymatic activities involved in the N cycle (URE, NAG, and LAP), exhibited varying sensitivities to different C input practices. This suggests that the sensitivity of these variables is influenced by the quantity and quality of C inputs, aligning with findings from previous studies that highlight the importance of C input characteristics on microbial community structure and functions (Bastida et al., 2008; Trivedi et al., 2013). Specifically, the sensitivity of 16S rDNA, a marker for bacterial abundance, and enzymatic activities involved in the N cycle suggest that these indicators are responsive to changes in soil management practices that modify OM inputs. This aligns with research indicating that microbial community composition and enzyme activities are directly influenced by the amount and biochemical quality of organic amendments applied to the soil (Allison and Martiny, 2008; Burns et al., 2013). For instance, high-quality organic inputs, rich in labile C, tend to enhance microbial activity and diversity due to the higher availability of energy released from the decomposition of fresh OM (Fontaine et al., 2003).

However, our study did not find significant relevance in using glomalin, ergosterol, and potentially mineralizable nitrogen (PMN) as soil indicators for diagnosing the effects of C input practices on microbiological soil state. This lack of significance may be due to the limited number of studies available on these indicators, leading to insufficient data for a robust analysis. Glomalin, a glycoprotein produced by arbuscular mycorrhizal fungi, has been recognized for its role in soil structure and C sequestration (Rillig, 2004), but its response to different

agricultural practices is not well-documented. Similarly, ergosterol, a fungal biomarker, and PMN, an indicator of the soil's capacity to mineralize organic nitrogen, have shown potential in some studies but lack comprehensive validation across diverse soil types and management practices (Joergensen and Wichern, 2008; Keeney and Bremner, 1966). Therefore, while 16S rDNA and some enzymatic activities are recognized as sensitive and effective indicators, the underrepresentation of other indicators in the research literature highlights a gap that needs to be addressed for a better assessment of their sensitivity to agricultural practices. Expanding the scope of studies to include these less commonly used indicators could enhance our ability to assess and manage soil health more comprehensively in the future (Lehman et al., 2015).

Active SOM pools, represented by POXC and BMN, exhibited sensitivity to practices involving C inputs, TR, and conversion to innovative/organic systems. This observation aligns with the understanding that these labile fractions can respond more rapidly to management changes compared to total SOM content (Nair et al., 2019; Pulleman et al., 2000). The addition of fresh OM through amendments, crop residues retention, or cover crops directly contributes to these active pools and reduces their decomposition rates (Balesdent et al., 2000; Haynes, 2005; Six et al., 2002). Reduced tillage promotes soil aggregate formation, physically protecting labile SOM fractions within aggregates from decomposition while preserving favorable micro-habitats for their persistence (Ashraf et al., 2022; Mbuthia et al., 2015; Six et al., 2004). In innovative/organic systems, the combination of diverse organic inputs and shifts in microbial community composition and activity influence the cycling and accumulation of these active SOM fractions (Hartmann et al., 2015; Hu et al., 2018; Lori et al., 2017; Prommer et al., 2020). The higher sensitivity of POXC and BMN compared to total SOM content is attributed to their more rapid turnover rates and direct responsiveness to changes in C inputs and soil disturbance regimes (Haynes, 2005; Nair et al., 2019; Pulleman et al., 2000a).

The study highlighted the importance of considering sampling depth when interpreting the responses of soil indicators, particularly for TR practices. This is because reduced tillage systems generate stratification of OM, with accumulation at the soil surface. Consequently, the responses of indicators like SOC, STN, MBC, and PLFA, and enzyme activities were moderated by sampling depth (Büchi et al., 2017b; Nunes et al., 2018). Under reduced tillage, there is minimal soil inversion and mixing, leading to the concentration of OM inputs, microbial biomass, and associated enzymatic activities in the upper soil layers (Balota et al., 2003; He et al., 2023a). This vertical stratification results in depth gradients, where indicator values can differ significantly between surface and subsurface soils. The accumulation of OM and level of microbial activity at the surface under reduced tillage systems can lead to vertical gradients in indicator responses, emphasizing the importance of sampling depth. Failing to account for this by sampling only at a single depth may not accurately capture the full effects of reduced tillage on soil properties and processes. This finding reinforces the need for appropriate sampling strategies that account for depth-related variations in soil properties and microbial communities when assessing indicator responses, particularly in reduced tillage systems (Büchi et al., 2017a; Nunes et al., 2018).

Soil microbiological properties constitute the living, dynamic compartment driving many crucial ecosystem services in agroecosystems. While chemical and physical indicators provide a general assessment of soil condition, microbiological indicators offer insights into soil functions. Evaluating microbiological indicators related to active soil OM fractions, microbial biomass, community structure, and enzymatic activities informs on key processes governing nutrient cycling, OM transformations, and the maintenance of favorable soil structure (Angers et al., 2011; Cong et al., 2015; Jones et al., 2018). By integrating assessments of microbial biomass C/N, PLFA, enzyme activities, and labile C pools, we highlight the link between nutrient retention and erosion mitigation (Delgado-Baquerizo et al., 2016; Malik et al., 2016). Rather than only detecting changes, a comprehensive

biological analysis reveals how agricultural practices can modify the capacity of the soil microbiome to provide these valuable functions and ecosystem services (Díaz-Zorita & Grove, 2002; Nunes et al., 2020; Ren et al., 2019b). For instance, soils with high microbial biomass, diverse enzyme activities covering C/N/P acquisition pathways, and sufficient labile soil OM indicate a robust capability to sustain nutrient recycling and primary productivity (Pulleman et al., 2000b; Thiessen et al., 2021). Microbial communities enriched with fungi and bacteria involved in aggregate formation promote favorable soil structure for water/gas transport and erosion limitation (Bach et al., 2022; Mbutia et al., 2015). Similarly, high N-acquiring enzyme activities and N-fixing populations mean sufficient N supply, while phosphate solubilizers enhance phosphorus availability for plant uptake (Calderon et al., 2016; Kamaa et al., 2021).

In addition to physico-chemical indicators, the assessment of microbiological indicators reflects the dynamics, activities, and functional diversity of soil microbial communities linked to soil biological fertility (Bünemann et al., 2018; Lehman et al., 2015; Pulleman et al., 2012). Evaluating soil processes and functions through the analysis of microbiological indicators enables the strategic use of management practices to optimize beneficial soil microbiological states, aligning with the expected multifunctionality of soils, particularly for sustainable productivity and environmental quality goals in agrosystems.

5. Conclusion

Our study underscores the necessity for integrating the active pool of SOM and microbiological (e.g., MBC, PLFA, and B-GLU) indicators into the assessment of agricultural soil fertility and health, particularly during transition from conventional to sustainable management practices. We found that climatic factors such as altitude, MAT, and precipitation do not significantly influence the responses of soil microbiological indicators, which are primarily driven by agricultural management practices. Soil clay content, OM levels, and pH strongly modulate the response of these indicators. The duration of trials and the age of agricultural practices play a crucial role, as longer periods are necessary to observe significant changes in indicators linked to SOM. Sampling depth is also critical, with more pronounced responses of indicators in the upper soil layers, especially under reduced tillage practices.

An active pool of SOM indicators such as POXC and BMN and microbiological indicators such as microbial biomass C, phospholipid fatty acids, and enzyme activities demonstrate greater sensitivity to agricultural management practices than traditional indicators like SOC and total N. Microbiological indicators provide essential insights into soil functions such as nutrient cycling, OM transformation, and soil structure maintenance, allowing for a more effective assessment of soil health. By integrating microbiological indicators with traditional measurements and considering factors such as soil properties, duration from management practices change, and sampling depth, it is possible to develop efficient agricultural management strategies to enhance soil sustainability and productivity in agroecosystems.

CRedit authorship contribution statement

Elodie Cusset: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Nadia Bennegadi-Laurent:** Writing – review & editing. **Sylvie Recous:** Writing – review & editing, Conceptualization. **Pierre-Yves Bernard:** Writing – review & editing. **Anne-Sophie Perrin:** Writing – review & editing, Resources. **Romain Tscheiller:** Writing – review & editing. **Isabelle Trinsoutrot-Gattin:** Writing – review & editing, Project administration, Investigation, Funding acquisition, Conceptualization. **Wassila Riah-Anglet:** Writing – review & editing, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2024.112706>.

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