Assessing soil quality using indicators: a review

Christian Bockstaller, Isabelle Cousin

Assessing soil quality using indicators: a review

Christian BOCKSTALLER[1], Isabelle COUSIN[2]

[1] Université de Lorraine, INRAE, LAE, 68000 Colmar, France

[2] INRAE, Info&Sols, 45075 Orléans, France

Corresponding author: christian.bockstaller@inrae.fr

Abstract

Soil underpins the entire agricultural ecosystem and plays a major role in both production and in the ecosystem services that regulate production. Agroecological transition involves transforming farming systems by replacing synthetic inputs with ecosystem services. To support these efforts, assessment methods are needed to perform an initial diagnosis and evaluate the changes produced by the transition. Generally speaking, soil quality and health cannot be measured directly. Instead, a range of indirect environmental assessment indicators must be used. This article reviews the indicators available for assessing the impact of agricultural management on soil fertility, quality and health. For these factors, the most commonly used indicators are based on field measurements. We also look at the predictive indicators used by agronomists striving to improve cropping systems and design innovative systems. Deeper investigation is warranted into several areas, such as the reference value and the predictive quality of indicators in relation to ecosystem services like pest regulation.

Keywords: agroecological transition, soil fertility, soil health, ecosystem service, biological activity, model, biological index

1. Introduction

Soil underpins the entire agricultural ecosystem and plays a major role both in agricultural production and in providing the various ecosystem services that regulate production (Obiang Ndong et al., 2020a). Rising environmental concerns in terms of sustainability and the agroecological transition have led to a proliferation of scientific publications on the links between the state of soil and the coverage of these issues. Several key concepts have been successively introduced, with the oldest term ‘fertility’ being the most widely used since the 1950s. In the 1990s, the term ‘soil quality’ emerged, followed by ‘soil health’. Soil fertility is defined as the set of physical, chemical and biological factors that support crop growth and productivity. Other factors have gradually been added, such as crop quality and sustainability (Bünemann et al., 2018). This broadening of the criteria to consider has led to the concept of ‘soil quality’, defined as ‘the capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation’ (Karlen et al., 1997). The concept of soil health emerged following the development of the ecosystem services framework, defined as the processes or components from which humans can derive benefit (Tibi & Therond, 2017). At the European level, soil is considered to be in good physical, chemical and biological health if it is able to provide various ecosystem services, namely biomass production, protection of groundwater bodies, biodiversity support and carbon sequestration.[1] It should be noted, however, that in a human-made system – which is the case for agriculture – a distinction must be made between what is truly an ecosystem service and what results from human activity and external inputs (Soulé et al., 2023).

The agroecological transition aims to transform agricultural systems to replace external inputs that consume non-renewable resources and are harmful to the environment with ecosystem services (Therond et al., 2017). Such a change can only be achieved by acquiring new knowledge about the agroecological

[1] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021DC0699

functioning of farming systems. System redesign efforts must go beyond improving efficiency or simply replacing inputs. Achieving this level of change requires the support of assessment procedures throughout the process, not only to perform a diagnosis of the initial situation but also to monitor the changes brought about by the transition, with a view to making possible readjustments to the trajectory. The ‘fertility’, ‘quality’ and ‘health’ qualifiers attached to soils cannot typically be measured directly, which means using indicators which often take various forms in environmental assessments (Bockstaller et al., 2015). This article reviews the indicators available to assess the impact of agricultural practices on soil fertility, quality and health. To do this, we will draw in large part on the review by Bünemann et al. (2018) and our own expertise.

To organise how we present existing indicators, we will draw on the typology of Bockstaller et al. (2015), which distinguishes between:

- *Causal indicators*, which are typically easy to implement (provided that data are available) but provide information of low predictive quality for a given effect (soil compaction, erosion, etc.). These indicators are generally used for causal variables or simple combinations of causal variables, which relate to soil and climate practices and variables.
- *Measured effect indicators*, based on measurements, counts or observations, are usually much more difficult to obtain but offer a more accurate ‘snapshot’ of the effect.
- *Predictive effect indicators*, produced by operational models (with few accessible input variables) and complex models. These indicators represent a compromise between the two previous indicator categories, with the dual advantage of being able to link causes to effects and carry out ex ante (a priori) assessments.

When assessing soil quality, the most commonly used indicators are those based on field measurements. We will now look at the predictive indicators used by agronomists seeking to improve cropping systems or design innovative systems to address sustainability challenges, especially through efforts to maintain or restore soil quality. This article provides an overview of the available indicators, highlighting their strengths and weaknesses, and discusses areas for future research.

2. Measured effect indicators: from chemical and physical indicators to biochemical and biological indicators

- **Chemical indicators**

In their review article, Bünemann et al. (2018) identified and classified the soil quality indicators from 65 sets of indicators, excluding all articles that focused only on biological indicators (Figure 1). The three most frequently used indicators are chemical indicators from soil analyses: soil organic matter (90% of cases), pH (around 80% of cases) and available phosphorus (just over 70%). Total nitrogen (50%) and available potassium (40%), both measured by soil analysis, were also commonly found. Finally, indicators based on measuring electrical conductivity and which require special technology and include clay, water and ion contents (Busselen, 2018), were used in 30% of cases. Interpreting these indicators can be challenging.

Soil organic matter was also recognised by farmers as the key indicator for assessing soil quality in a survey of 28 farmers in Wisconsin (USA), who also ranked this indicator first among 50 soil properties (Romig et al., 1995). Soil analysis is the most common method for measuring soil organic carbon (SOC) content. A rough estimate can be made by visual observation (McGarry, 2005). The importance of organic matter is clear in its central involvement in providing soil-related ecosystem services such as soil structuring, erosion control and the supply of water and nitrogen to crops (Therond & Duru, 2019).

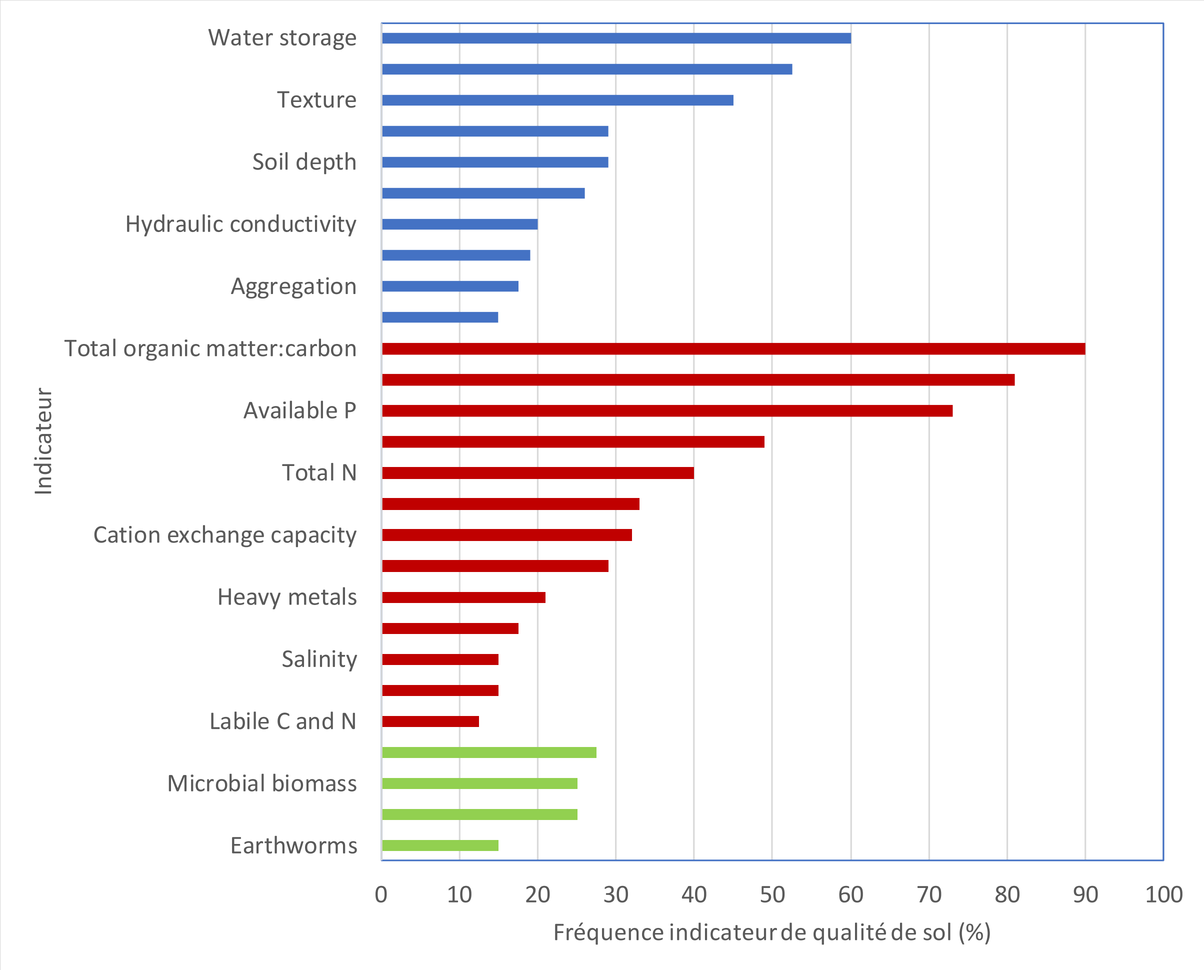

Figure 1: Frequency of soil quality indicators appearing in publications included in the review by Bünemann et al. (2018) that included 65 sets of indicators. Articles dealing solely with biological indicators were excluded from the review.

- <u>**A soil quality indicator derived from the characterisation of soil organic matter**</u>

Research by Johannes et al. (2017) on soil samples from 161 sites in Switzerland shows that the ratio of SOC content to clay content is more discriminating than measured soil organic matter content in terms of soil structure quality (Sq, assessed using the Visual Evaluation of Soil Structure, or VESS method; see Table 1). The approach was adapted to soil samples using a qualitative scale ranging from 1 (very good structure) to 5 (very poor structure). Two threshold values and a target value were proposed for this ratio: an SOC:clay ratio of 1:8 is the limit above which most soils have a very good structure (Sq < 2 in Figure 2), while most soils at the lower ratio limit of 1:13 have a very poor structure (Sq > 4, Figure 2). This indicator has been used by other authors (Misslin et al., 2022). It should be noted that the study by Misslin et al. (2022) was carried out on a range of soils with clay contents between 10 and 34%, which excludes dense soils such as those observed in Lorraine. The SOC:clay ratio has been the subject of critical analysis by several authors, particularly with regard to soil health (Mäkipää et al., 2024).

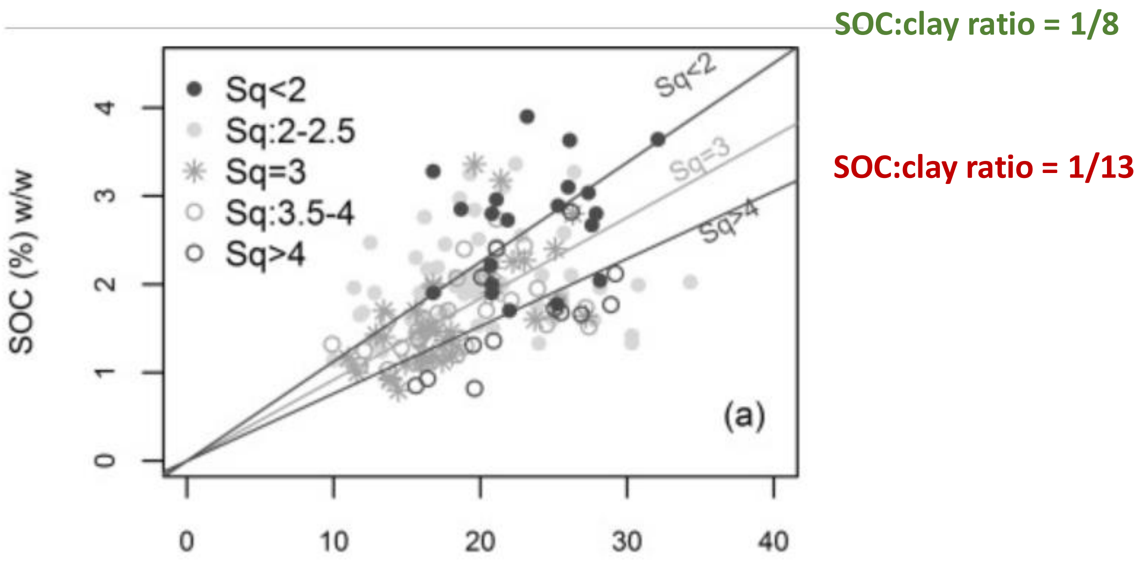

Figure 2: Determination of thresholds for the soil organic carbon (SOC) to clay ratio to discriminate between soils based on their structure quality (Sq). Sq visual scores ranged from 1 (very good) to 5 (very poor) for 161 sites in Switzerland (Johannes et al., 2017).

2.1. Physical indicators

To assess physical soil quality, the three indicators most frequently cited in the review by Bünemann et al. (2018) are water storage (60%), bulk density (just over 50%) and texture (45%). Three other indicators were cited slightly less often (20–30%): structural stability, soil depth and penetration resistance.

While texture is easily measured by soil analysis, the other indicators are much less accessible and are not routinely measured. So-called pedotransfer functions have been suggested to estimate the soil's available water capacity, one of the soil water content indicators used by agronomists. These pedotransfer functions use soil properties that are relatively easy to measure (textural element content, organic matter, bulk density, etc.) and take different forms, such as linear regressions, decision trees or neural networks (Wösten et al., 2001). Bulk density and penetration resistance are indicators of soil compaction but are not so easy to obtain or interpret. To overcome these metrological difficulties, several visual methods have been proposed for assessing soil structure using field tools (e.g. a knife, spade) and describing it using visual descriptors such as the shape and condition of the soil clods.

Bünemann et al. (2018) compared 7 methods (Table 1), including the '*profil cultural*' (cultural profile) method developed since the 1980s in France. The French method involves digging a trench, while the German method (M-SQR) uses a pit and the others are performed using a spade. In addition to structure, a range of other variables are estimated, including texture (based on feel), aggregate size and shape, and variables linked to water and biological properties (rooting, earthworms). The VS-Fast method includes a soil pH and labile C measurement (in the field) and observations of the surface condition (soil crusting), like for the VSA method. The VSA method includes erosion observations, while the M-SQR method includes slope observations.

Table 1: Features of 7 field methods to assess soil structure and other properties (adapted from Bünemann et al. (2018)).

METHOD NAME	SOILPAK	CULTURAL PROFILE	VS-FAST	PEERLKAMP*	VSA	VESS	M-SQR
COUNTRY	Australia	France	Australia	UK	New Zealand	Brazil/UK	Germany
REFERENCE ** FOR	McKenzie (2001)	Roger-Estrade et al. (2004)	McGarry (2006)	Ball et al. (2007)	Shepherd et al. (2008)	Guimarães et al. (2011)	Mueller et al. (2014)
OBJECTIVE	Soil structure and compatibility for cultivation	Soil structure	Land degradation	Soil structure	Soil quality	Soil structure	Soil properties linked to potential yield
TYPE OF TEST	Spade	Trench	Spade	Spade	Spade	Spade	Pit
TIME REQUIRED (MIN)	25–90	60–180	?	5–15	25	5–15	10–40
OBSERVATION OTHER THAN THE STRUCTURE							
TEXTURE			X		X		X
AGGREGATE SIZE			X	X	X	X	X
AGGREGATE SHAPE	X						
CONSISTENCY	X		X				
POROSITY	X			X	X	X	
COLOUR	X		X		X		
AVAILABLE WATER							X
WATER INFILTRATION			X				
ROOT DEVELOPMENT	X		X	X		X	
POTENTIAL ROOTING DEPTH					X		X
EARTHWORMS			X		X		

* This method later became the VESS method
** See Bünemann et al. (2018) for references. The year of publication does not necessarily correspond to the year when the method was designed.

2.2. Biochemical and biological indicators

A major limitation of the most commonly used chemical indicators (Figure 1) is their lack of susceptibility to changes in practices due to their long response times. Practitioners need indicators that alert them early of issues so they can implement corrective measures as soon as possible (Christel et al., 2021; Paz-Ferreiro & Fu, 2016). Although soil structure assessment methods can be used to observe effects on soil quality, they are generally limited to physical parameters that do not take overall soil functioning into account. These methods are also destructive and require a certain amount of investment and know-how. Over the last 40 years, these issues have spurred work on biotic indicators, using measurements of soil enzyme activity or the abundance and diversity of living organisms. Bünemann et al. (2018) identified the four most commonly used of these indicators, although they lagged behind chemical and physical indicators (Figure 1): soil respiration (around 30%), microbial biomass, nitrogen mineralisation (both around 25%) and earthworm density/diversity (15%).

Microbial biomass carbon measured using a chloroform fumigation-extraction method was considered in the 1990s by Chaussod (1996) as one of the only reliable, operational and interpretable biological indicators. This indicator was also expressed relative to the quantity of organic carbon. Thus, the microbial quotient is an indication of organic substrate availability with regard to soil microbes (Chaussod, 1996; Paz-Ferreiro & Fu, 2016). For soil respiration measured by CO_2 emissions per unit of soil, an indicator based on the metabolic quotient has also been developed and expresses a rate of renewal of the microbial biomass. Activities by various enzymes (e.g. protease, urease, phosphatase) have been used as indicators of soil biological quality (Petitjean et al., 2019). Thresholds have been set for these various indicators, although they have yet to be specified for enzyme activities. For the microbial quotient, a threshold of 2% has been proposed, below which the soil is considered to be in a state of organic matter depletion. It is easy to see how this set of measurements, which account for both the biological life of the soil and the restitution of mineral nutrients available to plants (through microbial enzyme activity), could serve as an objective assessment of the potential for biological activity, which is very much in line with agroecological needs.

Advances in molecular biology techniques, and more specifically the democratisation of PCR techniques, make it possible to measure the quantities of a genetic sequence (especially regions of the 16S rRNA gene for bacteria). As a result, it is now easier and faster to estimate the sizes of the bacterial and fungal compartments than with the fumigation approach. Similarly, pyrosequencing techniques provide access to the total diversity of microbial communities. Bioinformatics approaches have also been developed and enable very powerful data analyses to be carried out on large data sets, particularly at taxonomic level. For example, bacterial communities have been mapped across France using samples from the Soil Quality Measurement Network (Réseau de Mesures de la Qualité des Sols – RMQS) and grouped into 16 habitats based on pH, C:N ratio and land-use type (Karimi et al., 2020). Other studies have taken a functional approach to studying bacterial interaction networks via co-occurrence analyses, which have made it possible to differentiate network structures according to land use (forest, grassland, arable farming, viticulture) (Karimi et al., 2019) and distinguish between organic and conventional cropping systems that are ploughed or unploughed (Hartman et al., 2018). In any event, although these increasingly advanced molecular approaches are opening up new fields of investigation, their predictive quality is still under discussion (Bünemann et al., 2018).

The review by Bünemann et al. (2018) also shows that other indicators based on counts and identification of organisms such as earthworms are also commonly used (see Figure 1). In France, analysis of this taxonomic group is used alongside other taxa, namely by the Agricultural Biodiversity Observatory (Observatoire Agricole de la Biodiversité – OAB[2]), the network of 500 field plots under the French Ecophyto plan set up to assess the unintended effects of pesticides (500 ENI[3]), the Noé Association,[4] and the European BioBio project (Bockstaller et al., 2019). Data on other soil organisms, such as nematodes, microarthropods, mesoarthropods (springtails, etc.) and macroarthropods (ground and rove beetles, etc.), are also used. A recent meta-analysis comparing the effects of conventional, organic and conservation agriculture on soil quality gives a broader view of their use (Christel et al., 2021). These field measurements involve fairly sophisticated trapping techniques and time-consuming identification work that requires specific skills for identification at species level. Advances in digital technology could conceivably reduce these methodological constraints over time. There may be a need to start thinking about how extended knowledge of the biodiversity hosted in a soil could be made available to all farmers to support their management choices. It is currently possible to show that intensive farming practices

[2] https://www.observatoire-agricole-biodiversite.fr/

[3] https://ecophytopic.fr/pic/exposition-et-impacts/reseau-500-eni-biovigilance

[4] https://noe.org/noe-publie-recueil-indicateurs-biodiversite-agricoles

leave their mark on the living organisms in soil. However, much more must be done to show that the biodiversity present in a field can support natural pest regulation and enable agroecological management.

2.3. Soil quality indices

The review by Bünemann et al. (2018) focused on studies using a range of chemical, physical and biological indicators, while a study by Petitjean et al. (2019) dealt with the measurement of several enzyme activities. Another approach is that of Biofunctool®, which is based on 12 indicators linked to three soil ‘aggregate functions’: soil structure maintenance, nutrient cycling and carbon transformation (Thoumazeau et al., 2019). Such multi-indicator approaches always raise the question of how to synthesise results that may be contradictory. One possibility is a multivariate approach as implemented by Petitjean et al. (2019), but results obtained using this approach will depend on the range of variation of the indicators sampled. To overcome this issue, other authors have proposed aggregating several indicators into composite indices. Examples taken from the review article by Paz-Ferreiro & Fu (2016) are presented in Table 2. This work illustrates the levels of complexity with geometric mean, weighted sum and more complex formula calculations. In contrast, two approaches for the visual assessment of soil structures described by Bünemann et al. (2018) – VS-Fast and M-SQR – are based on a weighted sum of visual criterion ratings. All these approaches succeed in producing a single value to qualify soil quality. This facilitates monitoring over time and comparison between situations, but also calls into question the scientific validity of the weightings and the degree of accuracy of the predictive value.

Table 2: Examples of biological indices adapted from Paz-Ferreiro & Fu (2016). See the original article for references.

REFERENCES	MATHEMATICAL EXPRESSION	UNIT
HINOJOSA ET AL. (2004)	GMea = (acid phosphatase × alkaline phosphatase × β-glucosidase × arylsulphatase × urease)$^{1/5}$	µmol product g^{-1} h^{-1}.
BASTIDA ET AL. (2006)	MDI = [0·89(1/(1 + (dehydrogenase/4·87)$^{-2·5}$)] + [0·86(1/(1 + (WSCh/11·09)$^{-2·5}$)] + [0·84(1/(1 + (urease/1·79) $^{-2·5}$)] + [0·75(1/(1 + (WSC/95·03)$^{-2·5}$)] + [0-72 (1/(1 + (respiration/18·01)$^{-2·5}$)]	dehydrogenase and urease (mg product g^{-1} h^{-1}), WSCh and WSC (mg kg^{-1}) respiration (mg CO_2-C kg^{-1} soil).
PUGLISI ET AL. (2006)	AI 1 = −21·30 · arylsulphatase + 35·2 · β-glucosidase − 10·20 · phosphatase − 0·52 · urease − 4·53 · invertase + 14·3 · dehydrogenase + 0·003 · phenoloxidase	µmol product g^{-1} h^{-1}.
	AI2 = 36·18 · β-glucosidase − 8·72 · phosphatase − 0·48 · urease − 4·19 · invertase	
	AI3 = 7·87 · β-glucosidase − 8·22 · phosphatase − 0·49 · urease	
GARCÍA-RUIZ ET AL. (2008, 2009)	GMea = (acid phosphatase × alkaline phosphatase × β-glucosidase × arylsulphatase × dehydrogenase × PN)$^{1/6}$	µmol product g^{-1} h^{-1}.
PAZ-FERREIRO ET AL. (2012B)	GMea = (phosphatase × β-glucosidase × arylsulphatase × dehydrogenase)$^{1/4}$	µmol product g^{-1} h^{-1}.

*GMea: geometric mean for several enzyme activities; MDI: microbiological index of soil degradation; WSCh: water soluble carbohydrates; WSC: water soluble carbon; PN: potential rate of soil ammonium oxidation; AI: enzymatic activity index

2.4. Predictive effect indicators

With regard to assessing changes in soil organic matter, Manzoni & Porporato (2009) listed 74 predictive models, including the Hénin–Dupuis model developed in 1945. Similarly, the contribution of erosion to soil degradation and soil quality has also been widely covered. A total of 435 models and their various versions were reviewed by Borrelli et al. (2021). However, there are far fewer models for modelling changes in soil structure (Roger-Estrade et al., 2009).

In addition to this work carried out by soil quality specialists, agronomists involved in evaluating cropping systems have developed predictive indicators based on simplified models to link farming practices to their effects on soil quality components, particularly soil biology. Several indicators that are related to a certain degree have been developed using the DEXi tool (Bohanec et al., 2008) to assess direct impacts in the field in order to aid innovative system design. Other research has been carried out in the area of life cycle assessment (LCA), which requires more quantitative approaches. LCA looks at the environmental impacts throughout a product's life cycle; it includes the direct impacts of production as well as indirect impacts, both upstream related to input production and downstream linked to product use and waste management. LCA can provide comprehensive environmental assessments and identify impact transfers throughout the product life cycle. LCA is based on an emissions inventory, the degree of resource consumption and the integration of the other effects of (human) activities, all aggregated in an impact indicator.

2.5. Indicators developed with the DEXi tool

Figure 3 shows the mechanisms involved in soil functioning that are increasingly taken into account, since the approach developed for MASC 2.0 (Craheix et al., 2012) or I-BIO (Soulé et al., 2023) and DEXiSol (Thibault et al., 2018). Soil organic matter (with or without inputs), pesticides and crop diversity are considered by all three methods. In I-BIO and DEXiSol, the effects of fertilisation and tillage are also taken into account. In I-BIO, no distinction is made between bacterial and fungal communities, whereas DEXiSol differentiates between them and adapts the monitored variables accordingly. However, I-BIO does distinguish between the direct effects on the food web of tillage and inputs, and the indirect effects via soil organic matter and the diversity of root substrates of the crops in rotation. A similar or even greater gradient can be observed for soil macrofauna. It should be noted that DEXiSol also incorporates organic, phosphorus and pH soil fertility indicators, as does MASC 2.0.

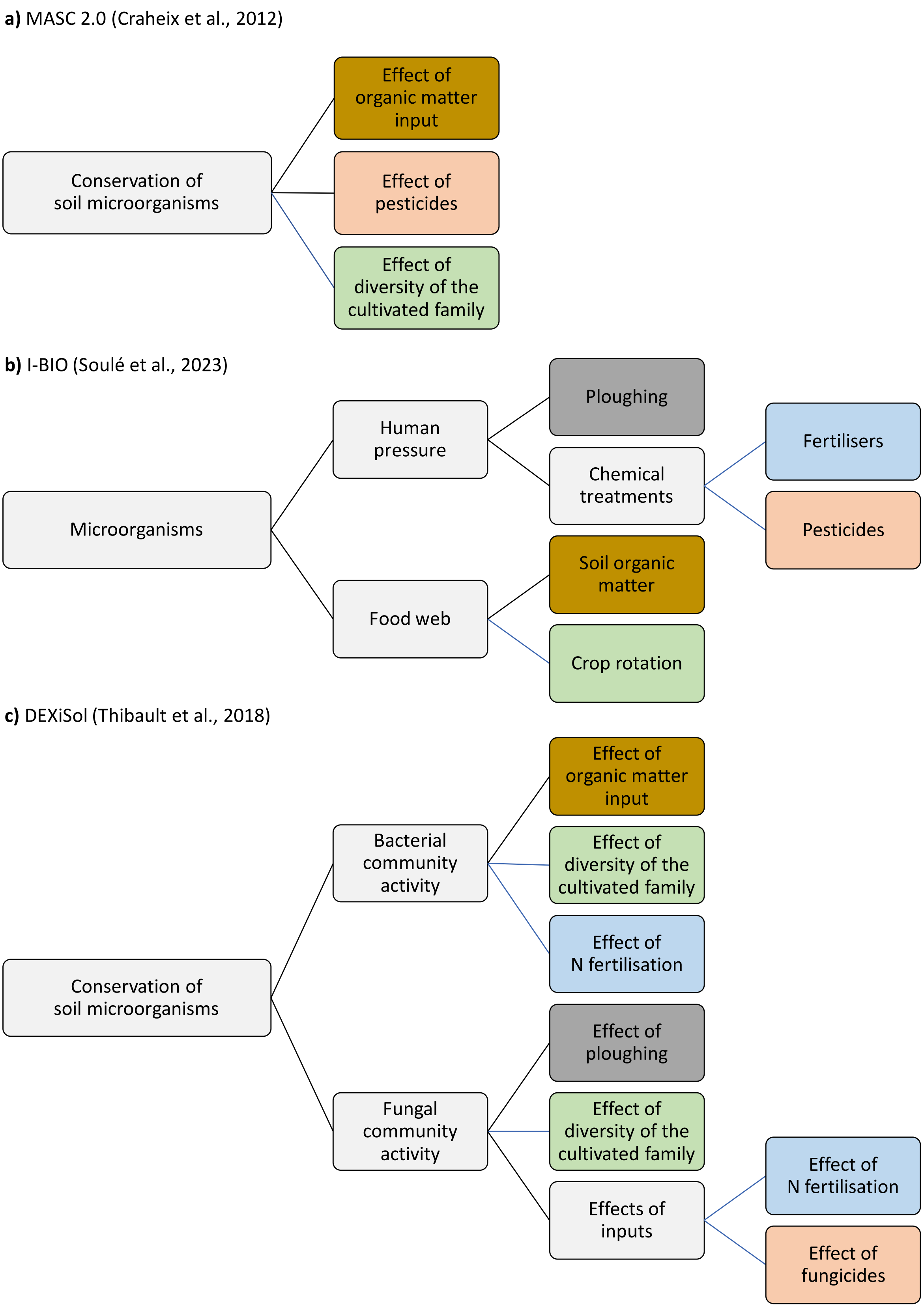

Figure 3: Structure of three predictive indicators assessing the impacts of agricultural practices on soil microorganisms, based on the DEXi tool (decision trees with if/then rules and qualitative classifications (e.g. low/medium/high) (Bohanec et al., 2008).

2.6. Soil quality indicators for life cycle assessment

We identified two very different approaches developed within the LCA framework. The SALCA soil quality (SALCA-SQ) method developed by Agroscope Zurich includes a variety of practices and a few environmental variables that generate impact scores according to simplified decision rules. These decision rules are aggregated into nine impact indicators: three physical, three chemical and three biological (Oberholzer et al., 2012). In contrast to this simplified approach, Garrigues et al. (2012) at INRAE Rennes adapted essentially mechanistic models for three impacts: the Roth-C model for organic matter, RUSLE for erosion and COMPSoil for soil structure. In each case, these approaches focus only on direct impacts in the field and can be implemented in a non-LCA context.

2.7. Soil ecosystem service indicators

As mentioned in the introduction[1] ecosystem services are central to the definition of soil health at European level. In the review by Obiang Ndong et al. (2020a), agricultural production was mentioned in 100% of the articles, climate regulation in 83%, water quantity regulation in 65%, recreation and tourism in 55%, nutrient regulation in 43%, and erosion regulation in over 30%. In one example of arable farming in the central and northern plains of France, Obiang Ndong et al. (2020b) used the STICS model to predict agricultural production and calculated 5 soil-related ecosystem service indicators: amount of nitrogen supplied to crops, green water provision to crops, blue water provision, the amount of nitrogen not leached and the amount of carbon sequestered. Using a multivariate regression tree, they identified 5 ecosystem services provided by agricultural systems and established the minimum thresholds to be respected in the relevant area, i.e. an area under cover crops of ± 16%, a soil pH > 6.75 and, for situations with > 16% cover crops and a pH > 6.75, a frequency of sugar beet of ± 36 % in the rotation

In the methodological framework combining impact and ecosystem service indicators, Soulé et al. (2023) used the AMG model (Clivot et al., 2019) to assess carbon sequestration capacity. They also used semi-quantitative indicators noting the potential ecosystem services related to crop rotation for soil structure, erosion protection, nitrogen provision, water consumption, etc. (Keichinger et al., 2021). Finally, they used a newly developed indicator to assess soil and canopy albedo (i.e. the capacity of the soil and canopy to reflect radiation), which has a positive effect on greenhouse gas emissions. This last development highlights the way soil use and input characteristics are connected to efforts to limit climate change.

3. Discussion

This article addresses the question of how to assess soil quality and health using indicators, given that direct measurements are impossible due to the complexity of the concept. Until now, little attention has been paid to this issue in multicriteria analysis methods for assessing agricultural system sustainability. A review of 262 methods used to assess the environmental impact of agricultural systems showed that two of the ten most frequently covered themes were related to soil quality, but that soil quality in and of itself was not addressed (Soulé et al., 2021). Soil erosion ranked fifth, after biodiversity, greenhouse gases, and pesticide and fertiliser management. Soil organic matter came ninth, corroborating the observations of Bünemann et al. (2018). Soil quality assessment has mainly been performed by specialists because of the complex interactions between soil properties (Garrigues et al., 2012).

We have based this review on the typology of indicators developed by Bockstaller et al. (2015), which differentiates between causal and effect indicators, with the latter category divided into measured effect indicators and model-derived predictive effect indicators. We have left out causal indicators, which have a low predictive value (see more on this issue below) and are linked to different impacts. Each category contains multiple indicators, as detailed at the beginning of the article for the category of indicators that can be obtained by direct measurement. Researchers have proposed a number of models to account for the physicochemical components of soil quality (mainly understood in terms of organic matter and susceptibility to erosion). These models are not always easy to use, although some have been adapted for use by practitioners, such as the AMG model for soil carbon (Bouthier et al., 2014). Very little attention has been paid to the biological dimension due to complex processes involved. A few approaches to predictive indicators are available and focus on assessing the impact of practices on biological and physicochemical factors.

Faced with so many indicators, potential users must chose which type of indicators as well as the actual indicators to use depending on the objectives being pursued. Several articles stress the need to precisely determine the usage situation or each user's prior choices to guide the choice and find a method that meets the user's needs (Bockstaller et al., 2015; Leclerc et al., 2011). The purpose of the assessment and the beneficiaries concerned are the two key use descriptors. For example, if the purpose is to report on an action aimed at reducing environmental impacts, or to monitor changes in the state of the environment, indicators of measured effects are undoubtedly the most appropriate choice. These indicators are designed to provide as accurate a picture of reality as possible. At a later stage, other questions will help to refine the choice of methods/indicators, such as the scale and number of plots to be assessed. Similarly, at the temporal level, it is important to consider the response time of the variable behind the indicator used to describe the effects. In this case, biological indicators will be more useful than chemical or physical indicators, which are slow to react to changes (Christel et al., 2021; Paz-Ferreiro & Fu, 2016). Finally, users will have to make do with the time and resources they have available. If users are involved in designing new cropping systems or supporting farmers in making systemic changes, predictive indicators that link impacts to causes will be much more useful, particularly in an ex ante or a priori assessment phase on virtual systems. Such approaches will enable them to identify practices to be improved or to answer questions such as 'What happens if I change a particular practice'?

However, for an indicator to be useful, it must be interpretable and have an available reference value (Bünemann et al., 2018). For chemical indicators, threshold values have long been established and are periodically revised depending on changes in the state of knowledge and objectives set for agricultural systems. Thus, given the need to reduce inputs for economic and environmental reasons, the thresholds for offsetting exports of P and K have been greatly reduced (Jordan-Meille et al., 2021). For biological indicators and indices, the lack of reference values is one of the main limitations. However, it has been established that in all cases, these reference values depend on soil and climatic conditions and the situation in which they are used. This means that investment in field campaigns is needed to set reference values, which are typically statistical (e.g. mean, median, quartile). This begs the question of what these reference values signify: better does not always mean sustainable. The work of Johannes et al. (2017) is an example of an attempt to establish thresholds on absolute values based on field measurements, although this work has since been criticised (Mäkipää et al., 2024).

Another point raised by Bünemann et al. (2018) deals with the validity or predictive quality of indicators, i.e. the link between the indicator value and a state or process measured experimentally. This question is especially pertinent regarding approaches based on molecular biology. It is generally rare for this step of defining validity parameters to be taken, although there are exceptions. Van Eekeren et al. (2010) identified several indicators on 20 permanent production grasslands that could be linked to soil-related ecosystem services: soil structure maintenance, water regulation and nutrient supply, and agricultural production. For example, earthworm activity was linked to soil structure maintenance, while organic matter content and water supply were linked to grass production. For predictive indicators using the DEXi method, only Soulé et al. (2023) confirmed the indicator outputs with field measurements. They observed a qualitative correlation between the subindicators linking the effect to microorganisms or earthworms and counts of these organisms in the field. Similarly, the SALCA-SQ method (Oberholzer et al., 2012) was compared with data from a long-term trial in Switzerland and with calculations for typical crop management sequences in order to assess the consistency of the indicator's outputs. A very detailed analysis was performed, taking into account the simplicity of the model and the data sets. Overall, the indicator can be used to differentiate between situations with organic fertilisation and situations with mineral fertilisation or without fertiliser inputs, in line with field measurements.

4. Conclusion

In conclusion, a wide range of indicators based on field measurements exists and includes some predictive indicators, which are mainly aimed at agronomists involved in designing new cropping systems. Potential users should take care to clarify their needs and usage situation (purpose, scale, resources, etc.). The Biofunctool® method offers a description of precise and affordable protocols that fall within the R&D field (Thoumazeau et al., 2019). Farmers who do not have the time to implement such measures will be more likely to turn to laboratory services, such as those offered by Auréa,[5] the result of an R&D project conducted with Arvalis and other partners. While these methods are based on a set of operational indicators, aggregation issues and the study of synergies and antagonisms between these indicators need further attention. Evaluating functions such as the regulation of soil pests is an additional area of research to explore, as are the keys to interpreting the enormous masses of data generated by new molecular approaches. Finally, developing more knowledge on soil contributions and how to make the ecosystem services that are directly linked to soil more reliable is another challenge to address in the absence of widespread agroecological practices.

Ethics

The authors declare that the experiments were carried out in compliance with all applicable national regulations.

Declaration on the availability of data and models

The data supporting the results presented in this article are available on request from the author of the article.

Declaration on generative artificial intelligence and artificial intelligence assisted technologies in the writing process.

The authors used artificial intelligence in the translation process from French to English.

Author ORCIDs

CB: 0000-0001-8880-4908
IC: 0000-0002-8114-7113

Authors' contributions

CB: conceptualisation, writing – original draft, review and editing; IC: conceptualisation

Declaration of interest

The authors declare that they do not work for, advise, own shares in, or receive funds from any organisation that could benefit from this article, and declare no affiliations other than those listed at the beginning of the article.

Acknowledgements

The authors would like to thank the reviewer who helped to improve the article.

Declaration of financial support

The authors declare that they received no financial support for the research, authorship and/or publication of this article.

[5] https://www.aurea.eu/conseil-2/agroecosol-2/

References

Bockstaller C., Feschet P., & Angevin F. (2015). Issues in evaluating sustainability of farming systems with indicators. *Oléagineux Corps Gras Lipides*, *22*(1). https://doi.org/10.1051/ocl/2014052

Bockstaller C., Lassere-Joulin F., Meiss H., Sausse C., van der Werf H., Denoirjean T., Ranjard L., Angevin F., Manneville V., Michel N., Tosser V., & Plantureux S. (2019). Les indicateurs de biodiversité pour accompagner les agriculteurs : embarras du choix ou pénurie ? *Innovations Agronomiques*, *75*, 73-86. https://doi.org/10.15454/bzmzzf

Bohanec M., Messean A., Scatasta S., Angevin F., Griffiths B., Krogh P. H., Znidarsic M., & Dzeroski S. (2008). A qualitative multi-attribute model for economic and ecological assessment of genetically modified crops. *Ecological Modelling*, *215*(1-3), 247-261. https://doi.org/doi:10.1016/j.ecolmodel.2008.02.016

Borrelli P., Alewell C., Alvarez P., Anache J. A., Baartman J., Ballabio C., Bezak N., Biddoccu M., Cerdà A., Chalise D., Chen S., Chen W., De Girolamo A. M., Gessesse G. D., Deumlich D., Diodato N., Efthimiou N., Erpul G., Fiener P., ... Panagos P. (2021). Soil erosion modelling: A global review and statistical analysis. *Science of the Total Environment*, *780*, 146494. https://doi.org/10.1016/j.scitotenv.2021.146494

Bouthier A. ., Duparque A. Mary B., Sagot S., Trochard R., Levert M., Houot S., Damay N., Denoroy P., Dinh J.-L., Blin B., & Ganteil F. (2014). Adaptation et mise en œuvre du modèle de calcul de bilan humique à long terme AMG dans une large gamme de systèmes de grade cultures et de polyculture-élevage. *Innovations Agronomiques*, *34*, 125-139. https://doi.org/10.17180/rgmy-kq04

Bünemann E. K., Bongiorno G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J. W., & Brussaard, L. (2018). Soil quality – A critical review. *Soil Biology and Biochemistry*, *120*, 105-125. https://doi.org/10.1016/j.soilbio.2018.01.030

Busselen T. (2018).*Cartographie de la conductivité électrique de la zone racinaire du sol par géogradar aéroporté opérant à basses fréquences* (Publication No. thesis:17282) [Master's thesis, UCLouvain]. DIAL.mem. http://hdl.handle.net/2078.1/thesis:17282

Chaussod R. (1996). La qualité biologique des sols : Évaluation et implications - AFES - Association Française pour l'Étude du Sol. *Etude et Gestion Des Sols*, *3*, 261-278. https://www.afes.fr/ressources/la-qualite-biologique-des-sols-evaluation-et-implications/

Christel A., Maron P.-A., & Ranjard L. (2021). Impact of farming systems on soil ecological quality: a meta-analysis. *Environmental Chemistry Letters 2021*, *1*, 1-23. https://doi.org/10.1007/s10311-021-01302-y

Clivot H., Mouny J.-C., Duparque A., Dinh J.-L., Denoroy P., Houot S., Vertès F., Trochard R., Bouthier A., Sagot, S., & Mary B. (2019). Modeling soil organic carbon evolution in long-term arable experiments with AMG model. *Environmental Modelling & Software*, *118*, 99-113. https://doi.org/10.1016/j.envsoft.2019.04.004

Craheix D., Angevin F., Bergez J. E., Bockstaller C., Colomb B., Guichard L., Reau R., & Doré T. (2012). MASC 2.0, un outil d'évaluation multicritère pour estimer la contribution des systèmes de culture au développement durable. *Innovations Agronomiques*, *20*, 35-48. https://doi.10.17180/bx81-1x20

Garrigues E., Corson M. S., Walter C., Angers D. A., & van der Werf H. M. G. (2012). Soil-quality indicators in LCA: method presentation with a case study. *8th International Conference on LCA in the Agri-Food Sector*, 343-348.

Hartman K., van der Heijden M. G. A., Wittwer R. A., Banerjee S., Walser J.-C., & Schlaeppi K. (2018). Cropping practices manipulate abundance patterns of root and soil microbiome members paving the way to smart farming. *Microbiome*, *6*(1), 14. https://doi.org/10.1186/s40168-017-0389-9

Johannes A., Matter A., Schulin R., Weisskopf P., Baveye P. C., & Boivin P. (2017). Optimal organic carbon values for soil structure quality of arable soils. Does clay content matter? *Geoderma*, *302*, 14-21. https://doi.org/10.1016/j.geoderma.2017.04.021

Jordan-Meille L., Mollier A., Montagnier C., Véricel G., Tauvel P., & Denoroy P. (2021). Réévaluation des seuils de réponse des cultures à la teneur en phosphore biodisponible du sol. *Rencontres Comifer-Gemas, Nov 2021*.

Karimi B., Dequiedt S., Terrat S., Jolivet C., Arrouays D., Wincker P., Cruaud C., Bispo A., Chemidlin Prévost-Bouré N., & Ranjard L. (2019). Biogeography of soil bacterial networks along a gradient of cropping intensity. *Scientific Reports*, *9*(1), 1-10. https://doi.org/10.1038/s41598-019-40422-y

Karimi B., Villerd J., Dequiedt S., Terrat S., Chemidlin-Prévost Bouré N., Djemiel C., Lelièvre M., Tripied J., Nowak V., Saby N. P. A., Bispo A., Jolivet C., Arrouays D., Wincker P., Cruaud C., & Ranjard L. (2020). Biogeography of soil microbial habitats across France. *Global Ecology and Biogeography*, *29*(8), 1399-1411. https://doi.org/10.1111/geb.13118

Karlen D. L., Mausbach M. J., Doran J. W., Cline R. G., Harris R. F., & Schuman G. E. (1997). Soil quality: a concept, definition, and framework for evaluation (A Guest Editorial). *Soil Science Society of America Journal*, *61*(1), 4-10. https://doi.org/10.2136/sssaj1997.03615995006100010001x

Keichinger O., Viguier L., Hellou G., Messéan A., Angevin F., & Bockstaller C. (2021). Un indicateur évaluant la diversité globale des rotations : de la diversité des cultures aux services écosystémiques. *Agronomie, Environnement & Sociétés*, *11*(1), 183-201.

Leclerc C., Attoumani-Ronceux A., Bockstaller C., & Galan M. B. (2011). Usages des méthodes d'évaluation environnementale. *Ecologisation des Politiques et des Pratiques Agricoles*, 1-8.

Mäkipää R., Menichetti L., Martínez-García E., Törmänen T., & Lehtonen A. (2024). Is the organic carbon-to-clay ratio a reliable indicator of soil health? *Geoderma*, *444*, 116862. https://doi.org/10.1016/j.geoderma.2024.116862

Manzoni S., & Porporato A. (2009). Soil carbon and nitrogen mineralization: Theory and models across scales. *Soil Biology and Biochemistry*, *41*(7), 1355-1379. https://doi.org/10.1016/j.soilbio.2009.02.031

McGarry D. (2005). *A methodology of a visual soil-field assessment tool. Natural Resources Sciences. Queensland, 50 p;*

Misslin R., Clivot H., Levavasseur F., Villerd J., Soulié J. C., Houot S., & Therond O. (2022). Integrated assessment and modeling of regional recycling of organic waste. *Journal of Cleaner Production*, *379*, 134725. https://doi.org/10.1016/j.jclepro.2022.134725

Oberholzer H. R., Knuchel R. F., Weisskopf P., & Gaillard G. (2012). A novel method for soil quality in life cycle assessment using several soil indicators. *Agronomy for Sustainable Development*, *32*(3), 639-649. https://doi.org/10.1007/s13593-011-0072-7

Obiang Ndong G., Therond O., & Cousin I. (2020a). Analysis of relationships between ecosystem services: A generic classification and review of the literature. In *Ecosystem Services* (Vol. 43, p. 101120). Elsevier B.V. https://doi.org/10.1016/j.ecoser.2020.101120

Obiang Ndong G., Villerd J., Cousin I., & Therond O. (2020b). Using a multivariate regression tree to analyze trade-offs between ecosystem services: Application to the main cropping area in France. *Science of the Total Environment*, 142815. https://doi.org/10.1016/j.scitotenv.2020.142815

Paz-Ferreiro J., & Fu S. (2016). Biological indices for soil quality evaluation: perspectives and limitations. *Land Degradation & Development*, *27*(1), 14-25. https://doi.org/10.1002/ldr.2262

Petitjean C., Philibert A., Manneville V., Amiaud B., Perrin A.-S., Charrier X., Gastal F., de Vliegher A., Willekens K., Montenach D., Houot S., Morvan T., & Piutti S. (2019). Biomasse microbienne carbonée et activités enzymatiques : gammes de valeurs obtenues pour différents sols agricoles français et belges - AFES - Association Française pour l'Étude du Sol. *Etude et Gestion des Sols*, *26*, 81-92. https://www.afes.fr/ressources/biomasse-microbienne-carbonee-et-activites-enzymatiques-gammes-de-valeurs-obtenues-pour-differents-sols-agricoles-francais-et-belges/

Roger-Estrade J., Richard G., Dexter A. R., Boizard H., De Tourdonnet S., Bertrand M., & Caneill J. (2009). Integration of soil structure variations with time and space into models for crop management. A review. *Agronomy for Sustainable Development*, *29*(1), 135-142. https://doi.org/10.1051/agro:2008052

Romig D. E., Garlynd M. J., Harris R. F., & McSweeney K. (1995). How farmers assess soil health and quality. *Journal of Soil and Water Conservation*, *50*(3), 229-236.

Soulé E., Charbonnier R., Schlosser L., Michonneau P., Michel N., & Bockstaller C. (2023). A new method to assess sustainability of agricultural systems by integrating ecosystem services and environmental impacts. *Journal of Cleaner Production*, *415*, 137784. https://doi.org/10.1016/j.jclepro.2023.137784

Soulé E., Hawes C., Young M., Henckel L., Michel N., Michonneau P., & Bockstaller C. (2023). A predictive indicator assessing effect of cropping system and surrounding landscape on biodiversity. *Ecological Indicators*, *151*, 110289. https://doi.org/10.1016/j.ecolind.2023.110289

Soulé E., Michonneau P., Michel N., & Bockstaller C. (2021). Environmental sustainability assessment in agricultural systems: a conceptual and methodological review. *Journal of Cleaner Production*, *325*, 129291. https://doi.org/10.1016/j.jclepro.2021.129291

Therond O., & Duru M. (2019). Agriculture et biodiversité : les services écosystémiques, une voie de réconciliation ? *Innovations Agronomiques*, *75*, 29-47. https://doi.org/10.15454/gldz6i

Therond O., Duru M., Roger-Estrade J., & Richard G. (2017). A new analytical framework of farming system and agriculture model diversities. A review. *Agronomy for Sustainable Development*, *37*(3), 24. https://doi.org/10.1007/s13593-017-0429-7

Thibault C., Cavan N., Labreuche J., Métais P., & Angevin F. (2018). Multicriteria assessment of the effects of tillage practices on cropping systems: development of the decision support tool DEXiSol. *21st International Soil Tillage Research Organization (ISTRO) Conference, ISTRO, September 2018*, 1-2.

Thoumazeau A., Bessou C., Renevier M. S., Trap J., Marichal R., Mareschal L., Decaëns T., Bottinelli N., Jaillard, B., Chevallier T., Suvannang N., Sajjaphan K., Thaler P., Gay F., & Brauman A. (2019). Biofunctool®: a new framework to assess the impact of land management on soil quality. Part A: concept and validation of the set of indicators. *Ecological Indicators*, *97*, 100-110. https://doi.org/10.1016/j.ecolind.2018.09.023

Tibi A., & Therond O. (2017). *Évaluation des services écosystémiques rendus par les écosystèmes agricoles*. Une contribution au programme EFESE. [Research report] INRA, 118 p. https://doi.org/10.15454/1h4z-tq90

Van Eekeren N., de Boer H., Hanegraaf, M., Bokhorst J., Nierop D., Bloem J., Schouten T., de Goede R., & Brussaard L. (2010). Ecosystem services in grassland associated with biotic and abiotic soil parameters. *Soil Biology and Biochemistry*, *42*(9), 1491-1504. https://doi.org/10.1016/j.soilbio.2010.05.016

Wösten J. H. M., Pachepsky Y. A., & Rawls W. J. (2001). Pedotransfer functions: bridging the gap between available basic soil data and missing soil hydraulic characteristics. *Journal of Hydrology*, *251*(3-4), 123-150. https://doi.org/10.1016/S0022-1694(01)00464-4