European Journal of Soil Science

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European Journal of Soil Science

METHODS ARTICLE OPEN ACCESS

SoilManageR—An R Package for Deriving Soil Management Indicators to Harmonise Agricultural Practice Assessments

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Received: 30 September 2024 | **Revised:** 21 March 2025 | **Accepted:** 25 March 2025

Funding: This work was funded under the European Joint Program for SOIL (EJP SOIL), which has received funding from the European Union's Horizon 2020 research and innovation programme: Grant agreement No 862695.

Keywords: earthworm | monitoring | software | soil degradation | soil health | soil organic matter | soil threat

ABSTRACT

Understanding the effects of agricultural soil management on the soil system and its functions is crucial to ensure the sustainable use of soil. Due to the countless ways in which soil can be managed, it is not an easy task to compare soil management practices across different locations and over time. One approach to making soil management comparable is the use of numerical soil management indicators. However, due to the lack of standardisation of soil management data and indicators, the comparability of results across studies remains limited. To address these shortcomings, we developed SoilManageR, an accessible R package. The first version of SoilManageR calculates numerical soil management indicators for carbon (C) input, tillage intensity, soil cover duration, nitrogen (N) fertilisation, equivalent livestock units per area, and plant diversity. In this paper, we present the functionality of SoilManageR and demonstrate its capabilities with three case studies. The cases were selected to compare soil management across space, time and context, as well as to relate soil management to soil quality. For this, we calculated soil management indicators for 16 experimental treatments from six agricultural long-term experiments and for 18 farmers' fields in Switzerland. We found that experimental treatments were representative of the management of the farmers' fields in terms of tillage intensity and soil cover, but that farmers' fields tended to exhibit higher livestock integration, leading to higher C and N inputs through organic amendments. We related soil management indicators to selected soil quality indicators in experimental treatments and showed that tillage intensity is the most important management driver of earthworm biomass, whereas C and N inputs were the best predictors of the organic carbon content of the topsoil. Finally, we applied SoilManageR to three sites of the Swiss Soil Monitoring Network and identified significant reductions of N inputs across time in two sites. We demonstrate that SoilManageR is a versatile tool for quantifying multiple aspects of soil management intensity, which can be useful to analyse how policy changes affect soil management. Additionally, SoilManageR can be used to assess soil management impacts on soil quality and provide guidance based on these insights.

Raphaël Wittwer and Thomas Keller are authors contributed equally.

Summary

- R package to calculate numerical soil management indicators
- Demonstration of the package's ability to assess agricultural practices and impacts
- Comparing management intensities of experimental treatments and farmers' fields
- Identifying drivers of soil quality and temporal trends in soil management

1 | Introduction

Sustainable agricultural soil management is essential for restoring, maintaining, and enhancing the functioning of the soil system, and for the provision of soil-derived ecosystem services (Lal 2009; Helming et al. 2018). To evaluate management practices, numerous field experiments and meta-analyses compare individual management factors, for example, no-till versus conventional tillage (e.g., Pittelkow et al. 2015; Mondal and Chakraborty 2022; Bagnall et al. 2023), presence versus absence of cover crops (e.g., Blanco-Canqui and Ruis 2020; Bagnall et al. 2023), or different organic fertilisation levels (e.g., Chen et al. 2018; Bagnall et al. 2023). However, the narrow focus on isolated management practices may overlook the influence of confounding management factors that affect outcomes and their interpretation. Furthermore, on-farm studies have revealed that classifying fields into broad categories, such as organic, no-till, and conventional systems, can hide significant management variations within each category (Büchi et al. 2019). Transforming complex soil management information into continuous, numerical soil management indicators (e.g., intensities of tillage, soil cover or fertilisation) offers an approach to analysing gradients in soil management intensities and overcoming the drawbacks of dichotomous comparisons. While more studies are adopting soil management indicators (e.g., Armengot et al. 2011; Tiemann et al. 2015; Williams et al. 2020; Garland et al. 2021; Büchi et al. 2022; Dupla et al. 2022; Edlinger et al. 2023; Walder et al. 2023; Pearsons et al. 2023; Reumaux et al. 2023; Chassain et al. 2024) the choice and calculation of indicators remain study-specific. Thus, the comparability of results across studies is hindered by the lack of standardised agricultural management data and readily available tools for calculating soil management indicators in a harmonised manner.

To tackle these limitations, we developed the SoilManageR package for R (R Core Team 2024). This software package includes a comprehensive template for collecting management information in different contexts (e.g., field experiments, soil monitoring programs, and farm networks) and routines for deriving selected soil management indicators to represent different aspects of soil management. The first version of SoilManageR contains a suite of equations to calculate indicators for carbon (C) input into the soil system, tillage intensity, soil cover duration, nitrogen (N) fertilisation, equivalent livestock units (LSU) per area, and plant diversity. This set of indicators quantifies differences in soil management based solely on management information. In this way, we hope to contribute to an evidence-based discussion on sustainable soil management (FAO-ITPS 2020), soil-conserving management (FAO 2023), and soil-regenerating management (Paustian et al. 2020). Here, we present the new R package and illustrate the utility of the SoilManageR by comparing the soil management of six Swiss agricultural long-term experiments with the soil management of two farm networks. Additionally, we apply SoilManageR to show that the soil management indicators can be used in statistical modelling to predict management-dependent soil quality indicators and demonstrate their use in identifying trends in management intensities over time.

2 | The SoilManageR Package

The SoilManageR software calculates selected numerical indicators to quantify various aspects of soil management, based on the provided management information. After a review of the literature on soil management metrics, the suite of selected management indicators was based on the work of Büchi et al. (2019), with adaptations to reduce the reliance on site-specific soil and climate information. The selection aims to integrate the major aspects of arable soil management and to keep the amount of necessary input data as low as possible. SoilManageR is fully open source and available on CRAN (Heller and Wittwer 2024a), enabling experienced R users to adapt and extend its functionalities. The indicators currently implemented are:

1. Carbon (C) input (Mg C ha^{-1} year^{-1}): represents the amount of organic carbon supplied to the soil system.
2. Soil tillage intensity (year^{-1}): quantifies the mechanical disturbance of the soil through primary tillage, seedbed preparation, seeding, and stubble cultivation.
3. Soil cover duration (days year^{-1}): evaluates the duration of soil cover by plants or plant residues.
4. Nitrogen (N) input (kg N ha^{-1} year^{-1}): represents the amount of nitrogen added to the soil by mineral and organic fertilisers.
5. Equivalent livestock unit per area (LSU ha^{-1} year^{-1}): reflects the number of livestock units (LSU, numerically equivalent to one dairy cow) necessary to supply the animal-derived organic amendments.
6. Plant diversity: three metrics to quantify plant diversity in a crop rotation or a cropping sequence (i.e., number of sown species, Crop Diversity Index and the Shannon Index).

The SoilManageR package is designed so that it can be used either fully or partially. When used fully, all soil management indicators are calculated from a soil management data template. The partial option allows users to customise the output, calculate only selected soil management indicators from a reduced set of management information, or only apply specific functions or default values.

2.1 | Management Data Template

To collect data on a broad range of soil management operations and to compute soil management indicators in a standardised manner, a template has been developed. The template is distributed together with the SoilManageR software package and is available on Zenodo (Heller, Wittwer et al. 2024). The template includes a hierarchical three-level structure, classifying individual soil management events into six broad management categories, associated operations and devices using a defined nomenclature. Together with the date of the field operation, an optional numerical value with a corresponding unit (e.g., tillage depth in cm or fertilisation in kg N ha^{-1}) can be entered for a more precise calculation of the indicators. For each of the six main categories—tillage, sowing, fertilisation, irrigation, crop protection, and harvest—a set of default operations and devices is provided. The set of default operations was derived from the RUSLE2 framework (USDA-NRCS 2023), the German KTBL (Bischoff et al. 2020), the SARE handbook on weed management (Mohler et al. 2021) and Blanchy et al. (2024) and was extended based on the management records of Agroscope-run LTEs and farmer-managed fields presented in the case studies. In total, 78 management operations are available in the current template, which can be extended in the future. Because tillage operations can be difficult to unambiguously identify, a booklet with illustrations of tillage, sowing, and mechanical weeding operations has been compiled and is available on Zenodo (Heller and Wittwer 2024b).

2.2 | Description of Indicators

2.2.1 | Carbon Inputs Into the Soil System (C Input)

2.2.1.1 | Carbon Inputs by Crops and Crop Residues. The C input by crops is estimated based on crop yield using the allometric functions and reference values provided by Bolinder et al. (2007) and subsequent studies (see below). We chose the approach of Bolinder et al. (2007) over others (see Riggers et al. (2019) for examples) because parameters for a wide range of crops grown in temperate climates are readily available (Bolinder et al. 2007, 2015; Keel et al. 2017; Fan et al. 2017; Taghizadeh-Toosi et al. 2020; Wüst-Galley et al. 2020). The equations are as follows:

$$C_{\text{main Product}} = \text{Yield} * \text{CC}_{\text{main Product}} \tag{1a}$$

$$C_{\text{Residues}} = \text{Yield} * \frac{1 - \text{HI}}{\text{HI}} * \text{CC}_{\text{Residues}} \tag{1b}$$

$$C_{\text{Root}} = \frac{\text{Yield}}{\text{SRR} * \text{HI}} * \text{CC}_{\text{Root}} \tag{1c}$$

$$C_{\text{Exudates}} = \text{C}_{\text{Root}} * \text{REF} \tag{1d}$$

where C is the C amount (kg C ha^{-1}) and CC is the C content of a given crop component (kg C Mg DM^{-1}; DM: dry matter), by default 450 kg C Mg DM^{-1} (Bolinder et al. 2007). Yield is the dry matter yield of the main product (e.g., grain) of a crop (Mg DM ha^{-1}). If no specific crop yields are provided by the user, reference yields derived from Sinaj et al. (2017) are assumed. HI is the harvest index (ratio of main product to the total aboveground biomass that comprises the main product and the straw or residue), SRR is the ratio of the aboveground biomass to the root biomass, and REF is the root exudation factor (i.e., the ratio of the root exudated C to the C in the root biomass). All components are multiplied with crop specific S-factors that determine the share of the fraction that enters the soil systems. In the case of residue removal, the S-factor for the residue fraction is set to 0. Crop-specific parameters are taken from Bolinder et al. (2007), Bolinder et al. (2015), Keel et al. (2017), and Wüst-Galley et al. (2020). We apply the yield dependent harvest index ($\text{HI} = \text{Intercept} + \text{Product} * \text{Slope}$) proposed by Fan et al. (2017) for cereals, faba beans, peas, corn, rapeseed, and soybeans. For temporary leys, we assume yield-independent annual belowground C input $\left(C_{\text{Root}} + C_{\text{Exudates}}\right)$ of 2.25 Mg C ha^{-1} as suggested by Taghizadeh-Toosi et al. (2020) who showed that fixed below ground C inputs are more adequate than fixed SRR for leys. Similarly, the below ground C inputs $\left(C_{\text{Root}} + C_{\text{Exudates}}\right)$ of grain maize, silage maize and cereals are fixed to 460, 1100and 600 kg C ha^{-1} respectively, independent of the crop yield (Hirte et al. 2018). All default values and parameters are provided in Supporting Information S1.

2.2.1.2 | Carbon Input by Cover Crops. The C input by cover crops is estimated with the same formulas as the C input by arable crops. The C in the above ground biomass ($C_{\text{cover crop}} = C_{\text{main Product}}$ in Equations 1a–1d) is a function of the time a cover crop is established (Seitz et al. 2022). Based on the cover crop C input estimations for arable soils in Germany of Seitz et al. (2022) a minimum and a maximum cover crop biomass are assumed for a growing period shorter than 180 and longer than 240 days, respectively, and linearly interpolated for the period in between.

$$C_{\text{cover crop}} = \begin{cases} 1253\ \text{kgC ha}^{-1}, \text{duration} < 180\ \text{days} \\ 1253\ \text{kgC ha}^{-1} + (\text{duration} - 180\ \text{days}) \\ \quad * \dfrac{663\ \text{kgC ha}^{-1}}{60\ \text{days}}, 180\ \text{days} \le \text{duration} \le 240\ \text{days} \\ 1916\ \text{kgC ha}^{-1}, \text{duration} > 240\ \text{days} \end{cases} \tag{2}$$

The remaining parameters to calculate the C input by cover crops are HI = 1, SRR = 3.67, and REF = 0.31, all derived from Seitz et al. (2022). Note that with these assumptions, the C input of short term cover crops (e.g., few weeks) is overestimated.

2.2.1.3 | Carbon Input by Organic Amendments. The C input by organic amendments is calculated based on the dry matter content (DMC) and the C content of the dry matter of each amendment. If the contents are unknown, default values from the Swiss fertiliser recommendations (Sinaj et al. 2017) are used (Supporting Information S1). The default dilution of liquid organic amendments such as slurries is assumed to be 50% organic amendment and 50% water.

2.2.2 | Soil Tillage Intensity

We incorporate the soil tillage intensity rating (STIR), which was introduced by the RUSLE2 framework (USDA-NRCS 2023), is widely applied (e.g., Büchi et al. 2019; Dupla et al. 2022; Bagnall et al. 2023) and allows a nuanced comparison of tillage practices. For each tillage and sowing operation, a STIR value is calculated with the following formula (USDA-NRCS 2023) that we transformed to metric units:

$$\mathrm{STIR} = (0.8045 * \mathrm{Speed}) * (3.25 * \mathrm{TTM}) * 2.54 * \mathrm{Depth} * \mathrm{Area}_{\mathrm{disturbed}} \quad (3)$$

where Speed is the speed of the operation in km / h, TTM is the tillage type modifier, Depth is the depth of the operation in cm and the $\mathrm{Area}_{\mathrm{disturbed}}$ is the share of the surface that is disturbed by the operation. By definition, the tillage type modifier is 1.0 for inversion operations (e.g., mouldboard plough), 0.7 for mixing operations (e.g., rotary harrow), 0.8 for mixing and some inversion operations (e.g., disc harrow or spading machine), 0.4 for lifting and fracturing operations (e.g., subsoiler), and 0.15 for compression operations (e.g., rollers). Because detailed information on tillage operations may not be readily available in many situations, we derived representative default values for 50 tillage operations from USDA-NRCS (2023). These default values are available in Supporting Information S1 (Figures S1 to S6).

2.2.3 | Soil Cover Duration

Soil cover duration is evaluated by the number of days per year with a cover by plants and by plant residue of at least 30% (Büchi et al. 2016). The soil cover by crops and cover crops is calculated as the percentage of soil cover based on crop type and days since sowing (Supporting Information S1), following the work of Mosimann and Rüttimann (2006). Soil cover by crop residues is estimated as done by Büchi et al. (2016) and Steiner et al. (2000):

$$\mathrm{cover}_{\mathrm{residues}} = \left(1 - e^{-k*M}\right) * 100\,\% \quad (4)$$

where M is the residue mass ($\mathrm{g\,m^{-2}}$) and k is a cover coefficient ($\mathrm{m^2\,g^{-1}}$) that is assumed to be 0.0175 (Steiner et al. 2000). The residue mass M is dependent on the residue supply by crops, residue decay, and residue incorporation by tillage operations (Büchi et al. 2016). Residue supply is estimated with the yield-dependent residue C (see Equations 1a–1d) and a C content of 450 mgC gDM^{-1}. If residues are removed, the residue mass is subtracted. Residue decay is calculated using the formula of Steiner et al. (1999):

$$M_t = M_{t-1} * \left(1 - k_{\mathrm{decay}}\right) \quad (5)$$

where M_{t-1} is the residue mass of the prior day ($g\,m^{-2}$) and k_{decay} is the daily decay rate, assumed to be 0.028 $\mathrm{g\,g^{-1}}$ for simplicity. This value represents the average decomposition rate of winter wheat straw reported by Steiner et al. (1999). Residue incorporation by tillage is estimated with the burial coefficients specific to each operation (USDA-NRCS 2023) that are provided in Supporting Information S1.

2.2.4 | Nitrogen Fertilisation (N Input) and Equivalent Livestock Units (LSU) per Area

Nitrogen (N) input by fertilisation [$kg\,N\,ha^{-1}$] is calculated as the combined total N input by mineral and organic fertilisation. The N input from organic amendments is calculated in a similar way as the C input from organic amendments (see section 2.2.1). The equivalent livestock unit (LSU) per area is calculated by dividing the animal-derived N, such as the N in slurry or manure, by the yearly N excretion of a hypothetical livestock unit equivalent to a dairy cow (EUROSTAT 2025). The yearly N excretion per LSU is assumed to be 105 $kg\,N$ (Swiss Federal Council 2023).

2.2.5 | Plant Diversity

Plant diversity refers to the variety of plants, including main crops and cover crops, sown throughout a crop rotation on a single field. It is assessed using three metrics: the total number of sown species per crop rotation or cropping sequence, the crop diversity index (CDI) from Tiemann et al. (2015), and the Shannon Index (SI; Shannon 1948; Spellerberg and Fedor 2003) for the sown species in the rotation. The CDI is given as (Tiemann et al. 2015):

$$\mathrm{CDI} = \overline{S_{\mathrm{year}}} * S_{\mathrm{rotation}} \quad (6)$$

where $\overline{S_{\mathrm{year}}}$ is the average number of sown species per year and S_{rotation} is the total number of species in the crop rotation or cropping sequence. The SI is given as (Shannon 1948):

$$\mathrm{SI} = -\sum_{i=1}^{S} \left(p_i * ln(p_i)\right) \quad (7)$$

where i is sown species, S is the total number of species, and p_i is the relative abundance of each species within a crop rotation or a cropping sequence.

All three plant diversity indicators are calculated for a defined reference period. To enable meaningful comparisons of soil management across fields, this reference period must be standardised, as indicator values are sensitive to the length of the assessment period. In the absence of a fixed crop rotation, which is common in on-farm conditions, we propose assessing plant diversity based on cropping sequences spanning five to 10 years to ensure comparability of calculated metrics.

2.3 | Temporal Aggregation of Indicators

To facilitate comparisons across time and sites, the estimated C input, STIR values, soil cover duration, and N inputs are summed annually. These yearly sums are then calculated as an arithmetic mean for the period of interest, which is typically one full crop rotation. The diversification indicators are calculated for the entire evaluation period (see Section 2.2.5).

3 | Cases Studies

The SoilManageR allows the quantitative and objective comparisons of soil and crop management strategies across diverse datasets and study types. It aims to facilitate the evaluation and monitoring of changes in agricultural management over space and time, offering valuable insights for farmers and policymakers. To test these capabilities, we applied SoilManageR to three different datasets from Switzerland. First, we assessed if the soil management intensities of experimental treatments were representative for the soil management intensities of farmers' fields. Second, we related the soil management intensities of the experimental treatments to selected key soil quality indicators. Finally, we analysed temporal trends in soil management intensities of monitoring sites to identify if and how management has changed over time.

3.1 | Case 1: Comparison of Experimental Treatments and Farmers' Fields

We extracted soil management information from farm management information systems of nine farmers' fields from the "Terres Vivantes (TV)" project in the Canton of Jura (Johannes et al. 2023) and of nine arable sites of the Swiss soil monitoring network (NABO; Gross et al. 2021) distributed across Switzerland. The selected 18 fields represent arable practices in Switzerland. For each field, we calculated and averaged the management indicators for the years from 2020 to 2022 for TV, and for the last 3 years where data was available for the NABO sites. We calculated management indicators for 16 experimental treatments of six agricultural long-term experiments. The experiments are all situated on the Swiss plateau and exhibit relatively similar pedo-climatic conditions (Table 1). We averaged the management indicators across the last full rotation (Table 1), except for the SSO trial (Table 1), where there was no fixed rotation, and we calculated the indicators for the entire duration of the experiment. For each experimental treatment, the crop yields were averaged across spatial (DOK, FAST, SSO, P24A, ZOFE; Table 1) or temporal replicates (OBAC; Table 1). We assessed the correlation of management indicators separately for farmers' fields and experimental treatments, as well as collectively across the entire dataset (Figure 1, upper triangle). Then, we compared the management indicators of the farmers' fields to the management indicators of the experimental treatments with a Welch two samples *t*-test accounting for unequal variance in R (R Core Team 2024).

3.2 | Case 2: Relating Soil Management to Soil Quality

For all experimental treatments (Table 1), we compiled data on two important soil quality indicators that are frequently used to assess the sustainability of soil management practices (see for example FAO-ITPS 2020), namely we collected legacy data on earthworm biomass ($g\,m^{-2}$) and topsoil SOC ($g\ C\ kg^{-1}$). Earthworms were collected by hand-sorting of a soil block of 20 cm depth combined with expulsion by either formaldehyde or mustard solution in at least three pseudo-replicates per plot. SOC was obtained from mixed soil samples from 0 to 20 cm or 7.5 to 12.5 cm depth (depending on the experiment, see Figure 2) by wet oxidation according to the Swiss reference method (Agroscope 2020). We averaged the soil quality indicators per treatment. The relations between soil management and soil quality were then analysed with linear mixed-effect models that accounted for random effects on the level of the experiment. The model fitting was performed with the lme4 and lmerTest packages (Bates et al. 2015; Kuznetsova et al. 2017). In order to test which management indicators are influencing the soil quality indicators the most, we performed model selection with the MuMIn package (Bartoń 2024). For the model selection, we used the soil quality indicators as dependent variables and a selection of management indicators (C input, STIR, soil cover, N input and livestock integration) as potential predictor variables. For further analysis and discussion, we chose the best performing models for each soil quality indicator based on the lowest AICc value. The model fits of the best models were visually evaluated for normality and homoscedasticity of the residuals with the R package sjPlot (Lüdecke 2024) and considered to be appropriate. We calculated the share of the total variance that can be explained by the fixed effects alone (R^2_{maginal}) and by the fixed effects and the random effects together ($R^2_{\text{conditional}}$) for each of the best models with the MuMIn package (Bartoń 2024). Finally, we extracted the relative importance of the variables within the best SOC model by hierarchical variance partitioning with the glmm.hp package (Lai et al. 2023).

3.3 | Case 3: Assessing Long-Term Soil Management Trends

Temporal trends in management intensities may lead to changes in soil quality. To show that the soil management indicators can be used to identify temporal management trends, we calculated the management indicators of nine sites of the Swiss soil monitoring network (NABO; Gross et al. 2021) where management data were readily available in sufficient quality for a period of 26 to 36 years. We then assessed the long-term trends in management intensities with a linear regression for each management indicator at each site. Lastly, we identified three sites with contrasting management trends (e.g., different temporal trends) to be presented and discussed in this paper. Due to confidentiality reasons, we refer to the chosen NABO sites as site A, B, and C.

4 | Results

4.1 | Case 1: Soil Management Indicators of Experimental Treatments and Farmers' Fields

The soil management indicators of experimental treatments and farmers' fields are depicted in Figure 1. Additionally, the numeric indicator values of the experimental treatments are reported in Table 2. Overall, the management indicators of farmers' fields (Figure 1, in green) showed stronger correlation to each other than the indicators of the experimental treatments. In the experimental treatments, we found a significant positive correlation between soil cover and C input (Figure 1, in blue). Contrastingly, for farmers' fields, we found a significant negative correlation between *C* input and soil cover as well as between STIR and soil cover. Furthermore, significant positive correlations were found between STIR and *C* input, as well as between total N input and LSU.

The *t*-test comparison of experimental treatments and farmers' fields revealed that the intensities of the two groups were generally in a similar range (Figure 1). However, farmers' fields had higher livestock intensity values than experimental treatments ($p = 0.02$). The farmers' fields also showed higher inputs of C ($p = 0.08$) and higher N fertilisation intensity ($p = 0.06$) as compared to experimental treatments.

TABLE 1 | Description of the six Swiss long-term field experiments and the 16 treatments for which the soil management indicators were calculated.

Experiment (sources)	Place (coordinates, elevation)	Soil type/Soil texture[a]/MAP[c]/MAT[b]	Since	Crop rotation	Treatment	Description
DOK (Krause et al. 2020)	Therwil (47.502582, 7.539340, 306 m.a.s.l.)	Pseudogleyic Luvisol/Silt Loam/929 mm/10.8°C	1978	Soybean Winter Wheat[d] Potato Winter wheat Temporary ley (2 years) Silage maize[d]	MIN	Inversion tillage, mineral fertilisation
					CON	Inversion tillage, combined mineral and organic fertilisation with manure and slurry
					ORG	Organic farming system, inversion tillage, organic fertilisation with manure and slurry
					DYN	Bio-dynamic farming system, organic fertilisation with composted manure and slurry
FAST (Wittwer et al. 2021)	Rümlang (47.438889, 8.527778, 443 m.a.s.l.)	Calceric Cambisol/Loam/1063 mm/9.7°C	2009	Grain maize Spring pea[d] Winter wheat Temporary ley (2 years) Winter wheat[d]	CIT	Inversion tillage, mineral fertilisation
					CNT	No-till farming system, mineral fertilisation.
					OIT	Organic farming system, inversion tillage, organic fertilisation with slurry
					ORT	Organic farming system, reduced tillage, organic fertilisation with slurry
Oberacker (OBAC) (Martínez et al. 2016a & 2016b)	Zollikofen (46.989608, 7.461849; 555 m a.s.l.)	Eurtic Cambisol/Sandy Loam/1026 mm/9.3°C	1994	Silage maize Winter pea[d] Winter wheat[d] Spring faba bean[d] Spring barley[d] Sugar beet[d]	IT	Inversion tillage, mineral fertilzation
					NT	No-till farming system, mineral fertilisation
SSO (Keller et al. 2017)	Zürich (47.430188, 8.521243; 440 m a.s.l.)	Endogleyic Cambisol/Silt Loam/1063 mm/9.8°C	2014	Spring triticale Silage maize Winter wheat Winter rapeseed Winter barley Silage maize Winter wheat Winter wheat Winter barley	IT	Inversion tillage, mineral fertilisation
					NT	No tillage, mineral fertilisation

(Continues)

TABLE 1 | (Continued)

Experiment (sources)	Place (coordinates, elevation)	Soil type/Soil texture[a]/MAP[c]/MAT[b]	Since	Crop rotation	Treatment	Description
ZOFE (Oberholzer et al. 2014)	Zürich (47.426805, 8.518893; 438 m a.s.l.)	Haplic Luvisol/Sandy Loam/1063 mm/9.8°C	1949	Grain maize Winter wheat[d] Spring wheat[d] Spring barley Temporary ley (2 years) Winter wheat[d] Grain maize Potato Winter wheat[d]	MIN COM	Inversion tillage, mineral fertilisation Inversion tillage, combined mineral fertilisation and organic fertilisation with compost
P24A (Maltas et al. 2018)	Duillier (46.400410, 6.229573, 446 m.a.s.l.)	Calceric Cambisol/Loam/950 mm/10.8°C/	1976	Grain maize Winter wheat Spring barley Winter rapeseed Spring oat Winter wheat	MIN FYM	Inversion tillage, mineral fertilisation Inversion tillage, combined mineral and organic fertilisation with manure

[a]According to USDA textural classes (Soil Science Division Staff 2017).
[b]Mean annual precipitation 1991–2020 (MeteoSwiss 2024).
[c]Mean annual temperature 1991–2020 (MeteoSwiss 2024).
[d]Crop followed by a cover crop.

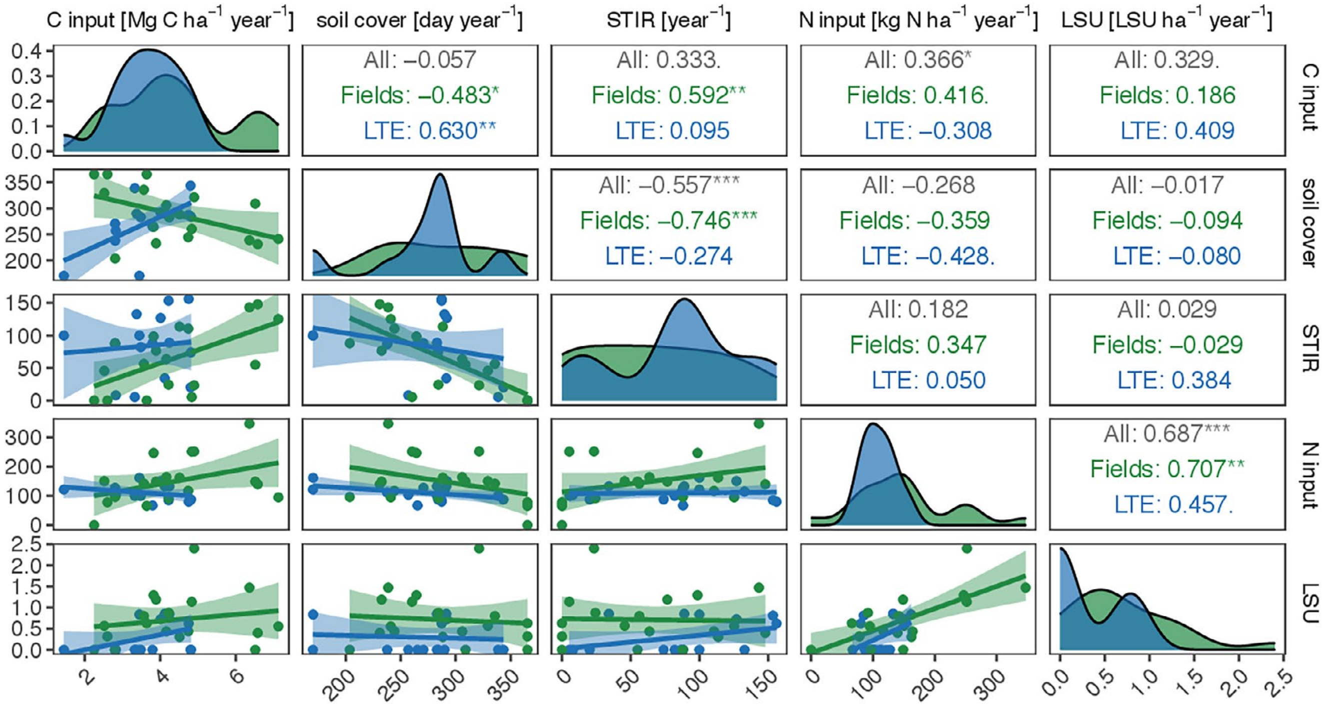

FIGURE 1 | Comparison of management indicators from 16 treatments of six Swiss long-term field experiments (LTE, blue) and 18 farmers' fields (green). The diagonal plots represent the density distribution functions of the indicators. The scale for the density distribution is on the left of the top left box (0.0 to 0.4). The scatter plots below the diagonal show the average values of the soil management indicators per experimental treatment and farmers' field, respectively, with linear regressions for the two groups. The coloured areas represent the 95% confidence interval of the linear regressions. The values above the diagonal represent the linear correlation coefficients between the indicators (grey: All observations, green: farmers' fields, blue: LTE treatments).

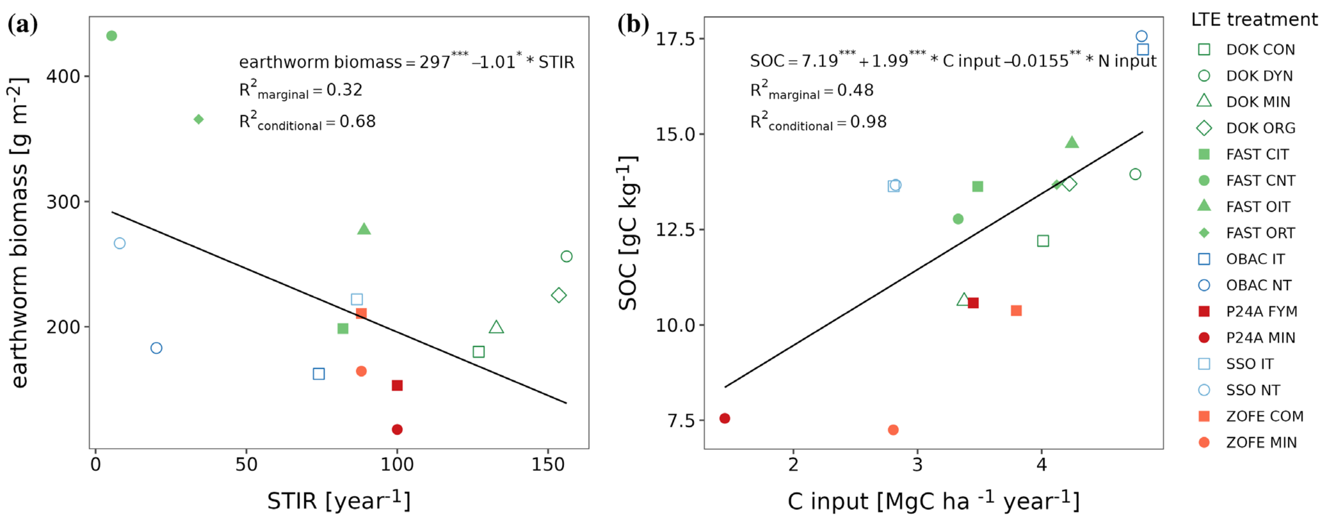

FIGURE 2 | (a) Earthworm biomass as a function of tillage intensity (STIR) and (b) soil organic carbon content of the topsoil (SOC) as a function of estimated carbon input (C input) for 16 treatments of six Swiss long-term field experiments (LTE). The empty symbols refer to experimental treatments where the SOC content was measured for the 0–20 cm depth interval, whereas the filled symbols refer to treatments where the SOC content was measured in the 7.5–12.5 cm depth interval. The equations in (a) and (b) display the estimates of the best performing linear mixed-effect models for the respective soil quality indicator. Only the estimates for the intercept and the fixed effects are reported, whereas the random effects that account for site-specificity (i.e., the experiment) are omitted. The * signs denote the *p*-values of the respective estimate (* < 0.05, ** < 0.01, *** < 0.001). The $R^2_{marginal}$ is the proportion of the variance explained by the fixed effects alone, whereas the $R^2_{conditional}$ is the proportion of the variance explained by the fixed and the random effects together. The lines represent the predicted response variable of the mixed-effect model (earthworm biomass and SOC). For prediction with the SOC model, the N input was fixed to the average N input across all experimental treatments (110 kg N ha^{-1} year^{-1}). The legend of the symbols is the same for both parts of the figure; for treatment abbreviations see Table 1.

TABLE 2 | Soil management indicators of the experimental treatments.

Experiment	Treatment	C input (Mg C ha^{-1} $year^{-1}$)	Soil cover (day $year^{-1}$)	STIR ($year^{-1}$)	N input (kg N ha^{-1} $year^{-1}$)	LSU[a] (LSU ha^{-1} $year^{-1}$)
DOK	MIN	3.4	290	133	115	0
	CON	4	292	127	151	0.73
	ORG	4.2	287	154	85	0.81
	DYN	4.8	287	156	80	0.62
FAST	CIT	3.5	283	82	100	0
	CNT	3.3	339	5	100	0
	OIT	4.2	283	89	133	0.85
	ORT	4.1	292	34	133	0.85
OBAC	IT	4.8	284	74	88	0
	NT	4.8	344	20	88	0
SSO	IT	2.8	238	87	111	0
	NT	2.8	257	8	104	0
ZOFE	MIN	2.8	271	88	128	0
	COM	3.8	265	88	67	0
P24A	MIN	1.4	170	100	122	0
	FYM	3.4	170	100	162	0.83

[a]LSU: livestock unit intensity, calculated based on the use of organic amendments. 105 kg of animal-derived N is equivalent to one LSU.

4.2 | Case 2: Soil Management and Soil Quality Indicators

The best model for earthworm biomass accounted for tillage intensity only (earthworm biomass~STIR), whereas the best model for SOC accounted for C and N inputs (SOC~C input + *N* input). Figure 2 depicts the statistics of the two models alongside the earthworm biomass and SOC data. The model selection tables, the fixed and random effect estimates of the best models, as well as the distributions of the residuals (normality, homoscedasticity) can be found in the Supporting Information S2. The intercept of 297 g m^{-2} and the fixed effect of the tillage intensity of −1.01 g m^{-2} $STIR^{-1}$ of the best earthworm model accounted for 32% of the variability ($R^2_{marginal}$). The site-specific random effects on earthworm biomass were estimated between 52 and 62 g m^{-2} and increased the explained variability in earthworm biomass to 68% ($R^2_{conditional}$).

In the best performing SOC model, the intercept of 7.19 g SOC kg^{-1} and the fixed effect estimates of 1.99 g SOC kg^{-1} (Mg C ha^{-1} $year^{-1}$)$^{-1}$ for the C input and of −0.02 g SOC kg^{-1} (kg N ha^{-1} $year^{-1}$)$^{-1}$ for the N input accounted for 48% of the variability within the SOC data ($R^2_{marginal}$). The hierarchical variance partitioning attributed 91% of the explained variance (i.e., 91% of 48%) to the differences in C input and 9% to the differences in N input. Due to the relatively small importance of the N input, we do not show the variation in N input in Figure 2. The site-specific random effects were estimated to be between −3.4 and 2.5 g SOC kg^{-1}, and when included, the share of the explained variability in SOC increased to 98% ($R^2_{conditional}$).

4.3 | Case 3: Long-Term Soil Management Trends of Farmers' Fields

The long-term management trends differed between the three selected sites (Figure 3). The C input and the N input decreased significantly over time on site A. On site B, the N input and the tillage intensity decreased, whereas the soil cover increased significantly with time. For site C, no significant temporal trends in any management intensities were found.

5 | Discussion

5.1 | Lower Livestock Integration in Experimental Treatments Than Farmers' Fields

The comparison of soil management intensities showed that the soil cover and tillage intensities of the experimental treatments were similar to those of farmers' fields, hence experiments are representative of on-farm conditions. However, our analysis revealed that the livestock integration in farmers' fields is often higher than in the experimental treatments, resulting in higher C and N inputs. This indicates that experimental treatments may be biased towards low stocking densities, C and N inputs. This indication is further supported by the fact that the livestock integration of all experimental treatments was smaller than 1 LSU ha^{-1}, a value well below the legal limit for Switzerland of three LSU ha^{-1} (Swiss Federal Assembly 2023). Therefore, future experiments could explore the effect of higher stocking densities that are representative

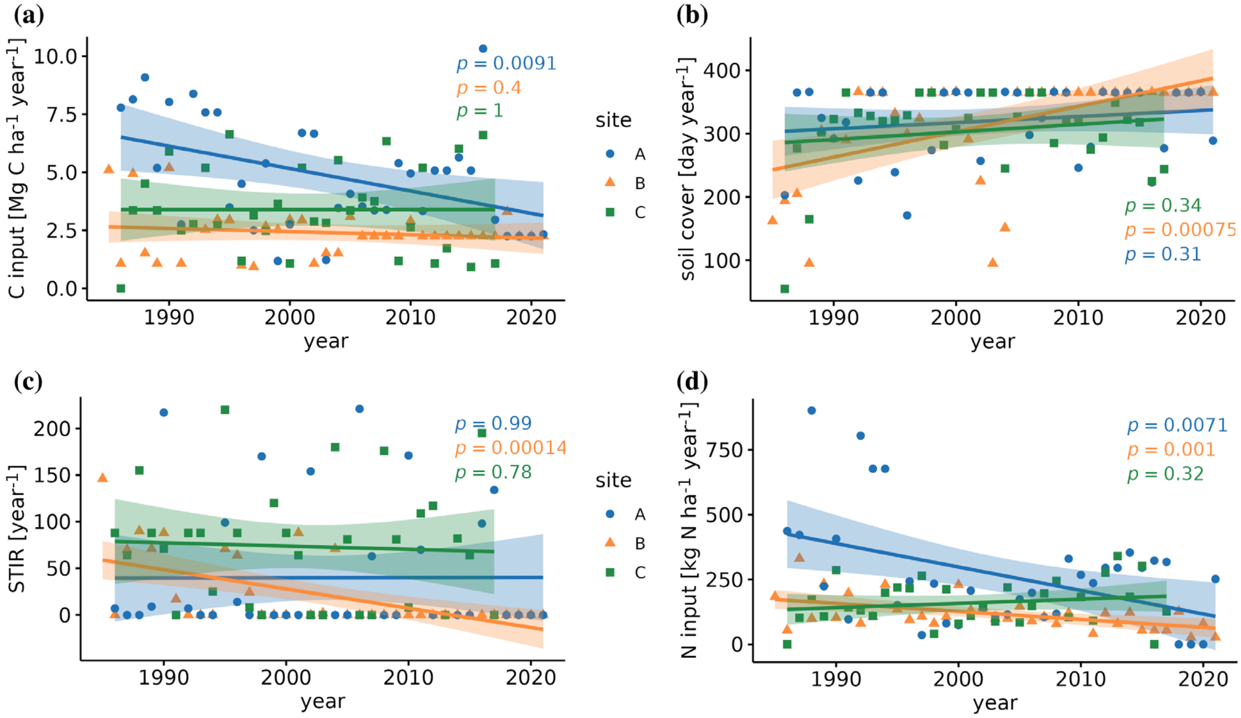

FIGURE 3 | Long-term trends in soil management intensities of three sites of the Swiss Soil Monitoring Network. The displayed management intensities are (a) estimated carbon (C) input, (b) soil cover, (c) tillage intensity, and (d) nitrogen (N) fertilisation. The colours refer to the sites; the dots are the indicator values of a single year. The lines are the linear regressions of each management intensity across time for each site. The coloured areas are the 95% confidence interval of the linear regression. The displayed *p*-values refer to the slope of the linear regressions.

for mixed farming in the Swiss context, similar to the Flemish BOPACT trial (D'Hose et al. 2016).

The estimated C inputs of the experimental treatments ranged from 1.4 to 4.8 Mg C $ha^{-1}year^{-1}$, whereas for farmers' fields they were estimated to be between 2.3 and 7.1 Mg C $ha^{-1}year^{-1}$. Due to different assumptions made in estimating C inputs from crops and cover crops, our values are consistently higher than the ones reported for the same experiments by Keel et al. (2019). For example, we have considered *C* inputs of cover crops to be dependent on the duration during which a cover crop was growing, whereas Keel et al. (2019) assumed fixed *C* inputs for cover crops. Our estimated *C* input values are within a similar range as the estimated C inputs into French arable soils (1 to 8 Mg C $ha^{-1}year^{-1}$, Martin et al. 2021), but in most cases above the estimated average *C* inputs of European wheat fields of 2.6 Mg C $ha^{-1}year^{-1}$ (Wang et al. 2016). The higher estimated *C* inputs in Switzerland likely are due to relatively high adoption rates of cover cropping, diverse crop rotations, and organic amendments (Heller, Bene et al. 2024).

Based on the USDA-NRCS (2008) benchmarks of a maximum average STIR of 15 for no-till systems (with no single year above a STIR of 30), and of 60 for conservation tillage systems, we identified only two no-till systems (SSO NT, FAST CNT; Table 1) and two conservation tillage systems (FAST ORT, OBAC NT; Table 1) across our LTEs. The no-till treatment of the Oberacker trial (OBAC NT) had unexpectedly high STIR values, which were due to the sugar beet harvest, but qualified as a no-till system if the sugar beet harvest was excluded from the calculations. In contrast, 10 out of 18 farmers' fields had a STIR value of less than 60 and would therefore qualify as conservation tillage systems. In 2022, 23.9% of Switzerland's arable land was subjected to conservation tillage (German: "Mulchsaat") and 3.5% to no-till (FOAG 2023). Thus, we conclude that conservation tillage approaches were underrepresented in the experimental treatments that we assessed. Contrastingly, in the farmers' fields, conservation tillage seemed to be overrepresented (55% of fields), most likely due to the presence of temporary ley in the rotation. This apparent overrepresentation suggests that the USDA-NRCS (2008) STIR benchmarks for conservation tillage are not directly applicable in mixed farming systems with ley in the rotation. A suitable adaptation would be the introduction of an upper single-year STIR limit of 60.

The annual soil cover days of experimental treatments clustered around 280 days, with the exception of the no-till treatments that exhibited higher values. Only the P24A treatments without cover cropping (Table 1) showed lower values (170 days). The clustering around 280 days can be attributed to strict crop rotations in field experiments that incorporate autumn-sown crops, spring-sown crops, and winter cover crops. In contrast, the soil cover indicators of farmers' fields ranged from 203 to 365 days and were less clustered due to less strict crop rotations and variable shares of temporary ley in the rotations.

The correlation of soil cover and *C* input that was found in experimental treatments was expected because treatments with higher soil cover typically include cover crops that also contribute to the *C* inputs. This link between soil cover and the *C* input may explain the positive impact of soil cover on soil quality indicators found by Garland et al. (2021). The correlations that were found in farmers' fields can mostly be explained by the comparably high reliance on animal manure for N fertilisation that is typical for Switzerland (Spiess 2011). Higher overall N inputs by manure were the reason for the higher livestock intensity in farmers' fields. Additionally, the amended manure was incorporated into the soil by tillage, which led to the negative association of tillage intensity and *C* input.

5.2 | Tillage Intensity Reduced Earthworm Biomass, and Carbon and Nitrogen Input Determined Soil Organic Carbon Content

We used SoilManageR to assess the impact of management intensity on soil quality indicators across long-term field experiments and found that earthworm biomass was driven by tillage intensity, whereas SOC levels were influenced by *C* and N inputs. The relationship between earthworm biomass and tillage intensity is well-established in qualitative terms (Chan 2001; Capowiez et al. 2009; Jossi et al. 2011; van Capelle et al. 2012; Vidal et al. 2023). For example, Capowiez et al. (2009) and Jossi et al. (2011) have reported lower abundance of anecic earthworm species in conventionally tilled fields, resulting in reduced total earthworm biomass compared to fields with reduced or no tillage. Our study systematically related earthworm biomass to a numerical soil management indicator across multiple sites and found that the STIR value alone explained 32% of the total variance in the earthworm data. This is a significant proportion considering that earthworm biomass is strongly influenced by site-specific factors such as climate, soil type, and soil texture (Phillips et al. 2019; Edwards and Arancon 2022). These site-specific effects were captured by the random effects in our model. However, some treatment-specific effects, which have contributed to the overall variability in earthworm biomass, were not accounted for in our model (see DOK, ZOFE and P24A in Figure 2a). Examples of such unaccounted treatment-specific effects are differences in feed quantity and quality in organic amendments (Leroy et al. 2008), as well as the impact of crop protection products (Pelosi et al. 2014) and synthetic fertilisers on earthworms (Edwards and Lofty 1982).

The C and N input together explained 48% of the variability within the SOC data. The considerable random effects that were found point to the fact that SOC levels are strongly influenced by site characteristics like climate, texture, and soil type (Cotrufo and Lavallee 2022) that cannot be changed by management. Soils with higher sand content or slightly warmer and drier climates (ZOFE, DOK, P24A; Table 1) exhibited lower SOC levels compared to sites with colder, more humid climates or higher clay content (OBAC, SSO, FAST; Table 1). Because SOC changes are slow processes (decades), the different durations of the experiments (10 to 75 years) may have contributed to the site-specific random effects. Interestingly, the slope of the relationship between *C* input and SOC appears to be similar for all trials ($\sim 2\,\mathrm{g\ SOC\ kg^{-1}\ [Mg\ C\ ha^{-1}\ year^{-1}]^{-1}}$), indicating that long-term *C* input rates have led to comparable differences in SOC regardless of the site conditions (Figure 2b). Whether this relation holds true for higher and lower *C* input levels and for a wider pedoclimatic context needs further investigation.

5.3 | Decrease in N Input at Farm Level due to Changes in Legislation

We assessed temporal trends in management intensities of farm fields and identified three soil monitoring sites with differing management trends. At site A, a substantial decline in C and N inputs was observed (Figure 3a,d). Historically, site A received significant applications of pig and dairy cow manures; however, lowered legal limits for the application of fertilisers in the 1990s (Herzog et al. 2008) led to a marked reduction in the application of animal manures. In fact, since 2001 the farm at site A has been obligated to export animal manure to other farms. The same legislative changes likely also influenced site B, leading to a significant, but less marked, reduction in N inputs. Additionally, at site B, there was a transition from arable cropping to grassland in 2004, resulting in almost permanent soil cover and STIR values indicative of no tillage activity (Figure 3b,c). In a follow-up study, the impact of these changes on soil quality and crop productivity could be investigated. Additionally, the quantification of the management intensities with SoilManageR may help to disentangle the contributions of different drivers of soil quality changes (e.g., relative impacts of climate change and management change).

5.4 | SoilManageR Allows Comparison of Soil Management Across Space, Time, and Contexts

The three case studies showed that the soil management indicators calculated with SoilManageR allowed a comparison of soil management across space, time, and contexts (experimental treatments, on-farm studies and monitoring programmes). The SoilManageR package is designed such that users can either derive the full suite of management indicators from a management data template, calculate a single indicator or parts thereof from a limited amount of soil management information, or use single functions (e.g., calculation of STIR value of a single tillage operation or estimate C input by a single organic fertilisation operation). SoilManageR includes literature-based default values for various parameters, such as carbon (C) and nitrogen (N) contents in organic amendments, time to soil cover of 30% by plants after sowing, or the depth of tillage operations. These default values often include assumptions about the climatic and agricultural conditions of temperate regions in Europe, focusing on Switzerland. Users who apply SoilManageR outside temperate Europe should assess whether the assumptions, including those related to plant growth, organic amendments, and tillage operations, are representative of their agroecosystems. To accommodate different contexts, all default values and assumptions can be customised when users have locally relevant data. We envision that future studies on soil management use and potentially extend SoilManageR, and that the common use of the soil management indicators will allow the direct comparison of results across studies.

5.5 | Future Perspectives

The suite of soil management indicators currently implemented in SoilManageR and presented in this study could be expanded in the future. Discussions with scientists across disciplines identified additional aspects of soil management that could be integrated: plant protection intensity (e.g., Pelosi et al. 2013), energy use efficiency (e.g., Pervanchon et al. 2002), biological nitrogen fixation inputs (e.g., Nucera et al. 2023), machine traffic intensity, animal grazing intensity, and additional fertilisation intensities including phosphorus input. The integration of more than one indicator per soil management aspect, such as multiple ways to assess the supply of organic matter, would reduce the dependence on a single approach and could further enhance the robustness of the findings produced with SoilManageR. Furthermore, additional crops, the representation of different cover crops and cover crop mixtures, and the integration of additional management practices like mixed cropping and relay intercropping could be implemented. The open-source nature of the SoilManageR packages allows these additions and other changes to be made by advanced R users.

To enhance the use of soil management indicators beyond academia, selected soil management indicators from SoilManageR could be integrated into online applications or farm management information systems. This integration would enable farmers and other decision-makers to assess current soil management practices and to compare different management scenarios.

6 | Conclusions

Our study demonstrates the ability of SoilManageR-derived soil management indicators to discern differences and similarities in soil management intensities across different sites. SoilManageR can be used to analyse soil management intensities in field experiments, on-farm studies, and monitoring programmes across time and space. In our case studies, we found higher livestock-derived C and N inputs in farmers' fields than in field experiments, identified tillage intensity as the main management driver of earthworm biomass and C input as the main management driver of SOC in experimental settings, and found policy-driven long-term reductions in N inputs on monitoring sites. The publicly available SoilManageR package contributes to standardising soil management information and to harmonising the calculation of soil management indicators. We are confident that this standardisation will foster the generation of comparable soil management knowledge and information across sites, and provide a scientific basis for advice to farmers and policymakers.

Author Contributions

Olivier Heller: conceptualization, investigation, writing – original draft, methodology, software, formal analysis, data curation, visualization, writing – review and editing. **Andreas Chervet:** data curation, writing – review and editing, investigation. **Fabien Durand-Maniclas:** investigation, writing – review and editing, data curation. **Thomas Guillaume:** investigation, writing – review and editing, data curation. **Franziska Häfner:** investigation, writing – review and editing, data curation. **Michael Müller:** investigation, writing – review and editing, data curation. **Raphaël Wittwer:** conceptualization, writing – original draft, writing – review and editing, methodology, software, data curation, supervision, investigation. **Thomas Keller:** conceptualization, funding acquisition, writing – original draft, methodology, writing – review and editing, supervision.

Acknowledgements

We thank Sonja Keel (Agroscope, Switzerland), Martin Bolinder (SLU, Sweden), Giulio Feruzzi (USDA-NRCS, United States of America), and Lucie Büchi (University of Greenwich, United Kingdom) for their advice and support in developing the SoilManageR package. Luca Bragazza, Shiva Ghiasi, Jochen Mayer, Marcel van der Heijden (all Agroscope, Switzerland) and Peter Hofer (Bern Office of Agriculture & Nature, Switzerland) are thanked for contributing soil and/or management data for experimental treatments. We thank Alice Johannes (Agroscope, Switzerland) for providing management data for farmers' fields. We thank Dominik Schittli (Switzerland) for the support in collecting soil quality indicator data. Juliane Hirte and Florian Walder (both Agroscope, Switzerland) are thanked for contributing statistical expertise. Last but not least, we thank Wolfgang G. Sturny (Swiss No-Till, formerly Soil Conservation Service of the Canton of Berne) for carefully reviewing an advanced version of the manuscript. This work was funded under the European Joint Program for SOIL (EJP SOIL), which has received funding from the European Union's Horizon 2020 research and innovation programme: Grant agreement No 862695.

Data Availability Statement

The SoilManageR and all code that was used for this publication can be found on CRAN (https://doi.org/10.32614/CRAN.package.SoilManageR) and on gitlab (https://gitlab.com/SoilManageR). The management data template and the illustrated guide on soil management operations can be found on zenodo (https://zenodo.org/communities/soilmanager). For confidentiality, the management data that was used as input into SoilManageR can only be made available on motivated request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.