



Contrasting roles of inherent soil characteristics, climate, and management for soil property states and changes – Long-term observations from arable soil monitoring sites in Switzerland

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ABSTRACT

Soil properties such as soil organic carbon (SOC), nitrogen (TN), phosphorus (PTP), and bulk density (BD) underpin soil fertility and ecosystem functioning, yet the relative importance of factors controlling their long-term states and short-term changes remains poorly quantified. Here, we analyse 35 years of data from 26 arable soil monitoring sites in Switzerland to (i) quantify temporal trends in soil properties across crop rotation types and sites; (ii) identify management, soil, and climate predictors of soil property states and annual changes; and (iii) assess the contexts in which different modelling frameworks provide suitable insights into soil dynamics. We combined indicator-based management and pedoclimatic data and applied linear mixed-effects and nonlinear modelling approaches. Across sites, SOC, TN, and PTP show no consistent trends, while BD decreases slightly over time. Soil texture and pH explain most of the variation in soil property states, whereas climate and management play a stronger role in explaining their changes. As a key management indicator, soil cover days are positively related to SOC and TN states and changes. Linear models provide robust rankings of dominant predictors, while nonlinear models identify context-dependent thresholds and climatic constraints on management responses. Soil organic carbon and TN show meaningful responsiveness to management over time periods of several years, whereas PTP remains constrained by soil buffering, and BD varies primarily with climatic conditions. Overall, soil management and policy should prioritize the continuity of protective measures and site-adapted management that reduces soil degradation risks and aligns practices with local soil and climate conditions.

1. Introduction

Sustaining soil properties such as organic carbon content, nutrient contents, and bulk density at adequate levels is fundamental to long-term soil productivity. Soil organic carbon (SOC) regulates nutrient and energy cycling, supports the formation of stable soil aggregates, and contributes to carbon storage, thereby linking soil fertility with climate change mitigation (Janzen, 2024). Nutrient availability, shaped by mineral composition, organic matter, and soil chemistry, is essential for plant nutrition and crop performance (Telo da Gama, 2023). Bulk density (BD) influences soil rootability, water infiltration, and water-holding capacity, thereby affecting plant growth under diverse environmental conditions (Blanchy et al., 2023). Hence, these properties underpin sustained agricultural productivity and agroecosystem

resilience.

Most soil properties display substantial site-specific responses driven by inherent site conditions, whereas their temporal change occurs only gradually (Abu-Hashim et al., 2022; Klöffel et al., 2024; Tomaz et al., 2022). Strong site effects linked to inherent soil characteristics and climate often obscure management influences (Blair et al., 2024; Feng et al., 2022; Peri et al., 2016; Zeller et al., 2001). Because spatial variability often exceeds the magnitude of short-term change, long-term, multi-site soil monitoring is essential to detect trends, understand drivers, and support effective soil management. Yet, those data sets remain scarce and temporal trends in key soil properties often remain unclear or cannot be robustly detected.

These patterns reflect the dual nature of soil development. The long-term state of soil, shaped by mineralogy, topography, vegetation, and

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climate, develops over centuries to millennia (Jenny, 1994; Norfleet et al., 2003). These inherent factors define baseline fertility, water-holding capacity, and structural characteristics, ultimately setting the ceiling for agricultural productivity and agroecosystem resilience (Mueller et al., 2010). In contrast, short-term responsiveness—the rate at which soil properties change over years to decades—is governed by management and environmental perturbations such as crop rotation, fertilization, organic amendments, or tillage, as well as drought, flooding, erosion, or extreme temperatures (Crystal-Ornelas et al., 2021; Heikkinen et al., 2022). However, despite recognition of the different processes, the drivers of both the long-term state and the short-term change of soil properties remain insufficiently understood, limiting our ability to determine their manageability within pedoclimatic constraints.

Analyses of drivers of soil properties are strongly shaped by study design choices, including the definition of response variables (state or change), predictor selection, and the response function. Agricultural systems vary widely across soils, climates, and management practices, so factorial designs or paired system comparisons can only capture a limited portion of this complexity (Bai et al., 2018; De Notaris et al., 2021; Young et al., 2021). On-farm studies, by contrast, reflect the diversity of real-world farming conditions but this diversity can make systematic comparisons difficult. Translating management information into quantitative indicators enables the detection of management gradients and system-independent drivers (e.g., Büchi et al., 2019; Walder et al., 2023; Williams et al., 2020), though indicator construction remains context-specific and labor-intensive (Büchi et al., 2019). Tools such as the OBIC and SoilManager R packages (Heller et al., 2025; Ros et al., 2022) facilitate reproducible indicator calculation, enabling the use of consistent and comparable predictors across studies.

Functional relationships between predictors and responses can be modeled using linear or nonlinear approaches. Models that support statistical inference and clear interpretation often rely on relatively simple functional forms and may therefore have limited ability to capture nonlinear responses or thresholds (e.g., linear mixed-effects models; Pinheiro & Bates, 2000). In contrast, more flexible modelling approaches can represent nonlinear and context-dependent relationships, although they may offer less straightforward interpretability or formal inference (e.g., multivariate adaptive regression splines; Friedman, 1991). Comparing approaches with different strengths may therefore provide complementary insights into the drivers of soil properties, yet such comparisons have rarely been conducted using consistent long-term datasets.

Assessing the manageability of soil properties enables tailored agricultural advice and informs policies that promote sustainable soil functioning, food security, and environmental protection. With 60% of European soils affected by at least one degradation process, effective soil management is increasingly critical (Arias Navarro et al., 2024). Targeted agri-environmental policies can drive the adoption of sustainable practices and account for much of the variation in soil degradation between countries (Wuepper et al., 2024). Closing knowledge gaps on the link between management and soil properties can help strengthen economic incentives for sustainable soil stewardship (Thorsøe et al., 2023).

Despite its small land area, Switzerland exhibits diverse soils and climates and has experienced notable temperature increases in recent decades (FOEN et al., 2020). Within the Swiss Soil Monitoring Network, data on soil chemical properties and agricultural management have been collected at 26 arable sites since 1985, with bulk density measurements added in 2005 (Gross et al., 2024; Gross et al., 2021). In this study, we used long-term soil, management, and environmental data from these sites to explore the effects of agricultural management and pedoclimatic conditions on SOC, total nitrogen (TN), pseudo-total phosphorus (PTP), and BD. We expected that long-term soil property states would be primarily associated with inherent soil characteristics, whereas short-term changes would be more strongly associated with management and climatic variables. We further expected that nonlinear

modelling would reveal threshold responses and context dependencies that are not captured by linear models. Specifically, we aimed to (i) quantify temporal trends in soil properties in the topsoil across crop rotation types and sites, (ii) identify management, soil, and climate predictors of both state and change of soil properties, and (iii) assess the contexts in which different modelling frameworks provide suitable insights into soil dynamics.

2. Material and methods

2.1. Soil monitoring sites

This study drew on data from 26 arable sites within the Swiss Soil Monitoring Network (NABO), most of which are situated on the Swiss Plateau, the country's main crop-growing region (Supplementary figure 1). The dominant soil type is Cambisol (21 sites; Supplementary table 1), reflecting the main soil type in this region (Jarosch et al., 2026). Crop rotations across sites were classified into four rotation types with different management intensity (based on average fertilizer N inputs; Levers et al., 2016; van der Sluis et al., 2016): (1) cereal, maize, legume rotations with $\geq 50\%$ barley, maize, oats, rye, triticale, wheat, beans, or peas (6 sites; $142 \text{ kg N ha}^{-1} \text{ yr}^{-1}$); (2) tuber, oilseed, vegetable rotations with $\geq 30\%$ beet, potatoes, sunflower, rapeseed, or vegetables (5 sites; $187 \text{ kg N ha}^{-1} \text{ yr}^{-1}$); (3) ley-based rotations with 35–50% ley (5 sites; $197 \text{ kg N ha}^{-1} \text{ yr}^{-1}$), and (4) ley-dominant rotations with $\geq 50\%$ grass-clover ley (10 sites; $212 \text{ kg N ha}^{-1} \text{ yr}^{-1}$; Fig. 1). Remaining proportions consisted of other crops. The fertilizer N inputs were consistent with Swiss fertilization recommendations (Richner & Sinaj, 2017). The farms of all 26 sites complied with the Proof of Ecological Performance (PEP) subsidy scheme and seven farms additionally complied with BioSuisse organic standards.

2.2. Data collection

Soil samples were collected every five years from the same $10 \times 10 \text{ m}$ plot at each site. Since 1985, four composite samples, consisting of 25 individual soil cores, have been taken per site for soil chemical analyses. The samples were collected from the topsoil (0–0.2 m) using a gouge auger (2.5 cm inner diameter). Since 2005, four additional volumetric samples have been collected using an impact probe (5 cm inner diameter) to assess BD. All composite samples were dried at 40°C for 48 h, sieved to 2 mm, and stored at constant temperature of 18°C until analysis. At the end of each 5-year monitoring period, all samples of this period were analyzed in one batch. Soil pH was measured in CaCl_2 solution, total C and TN were analysed by elemental analysis, inorganic C was determined using the Scheibler method, and PTP was extracted with HNO_3 and quantified by ICP-OES (Agroscope, 1996). For samples analysed by elemental analysis, soil organic C was calculated as the difference between total and inorganic C. Until 2014, SOC was determined by wet oxidation. Subsequently, a subset of archived samples was reanalysed by elemental analysis, and site-specific conversion factors were used to transform SOC values obtained by wet oxidation into values equivalent to SOC calculated from total C determined by elemental analysis (Gubler et al., 2018). Bulk density of the fine earth ($< 2 \text{ mm}$) was determined after drying at 105°C and sieving the volumetric samples. Additionally, soil texture was determined once per site using the pipette method, classifying particles as clay ($< 2 \mu\text{m}$), silt ($2\text{--}50 \mu\text{m}$), and sand ($> 50 \mu\text{m}$).

All analyses except for SOC were conducted using consistent analytical protocols throughout the monitoring period. To ensure comparability among monitoring campaigns, archived samples from the previous sampling campaign were reanalysed together with the current samples and used to harmonize analytical results across consecutive batches (Gross et al., 2024). The number of sites included in the analysis of each soil property for each sampling period is provided in Supplementary table 2. For SOC, TN, and PTP, field replicate-level

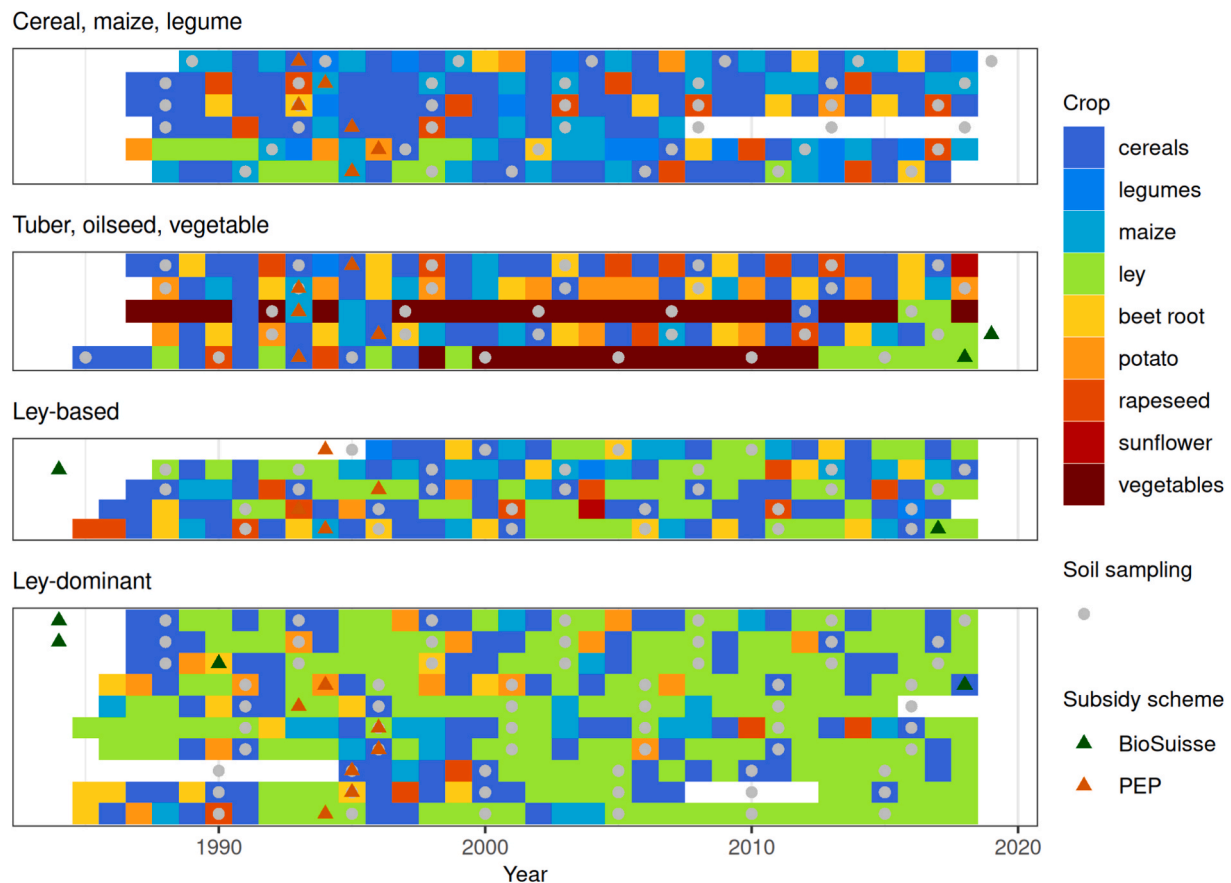


Fig. 1. Crop rotations at the 26 arable sites since the start of monitoring. Each horizontal line represents a single site. Green and orange triangles indicate the year of conversion to the BioSuisse and Proof of Ecological Performance (PEP) subsidy schemes, respectively. Grey dots mark the timing of soil sampling and analysis.

observations were included in the analyses. For BD, only site-year averages across the four field replicates were available and therefore used.

Interpolated daily climate data (mean temperature and the sum of precipitation) for each site were collected from nearby meteorological stations operated by MeteoSwiss. For this study, we used average data for the 30- and 365-day periods before soil sampling, reflecting temperature and precipitation in the month (temp 30 and precip 30, respectively) and year (temp 365 and precip 365, respectively) before sampling.

Management data were provided annually by the farmers and included detailed information on crop type, sowing and harvest dates, organic and mineral fertilization, plant protection measures, and tillage practices (Gross et al., 2021). Since 2013, the data have been systematically quality-checked and curated, while historical records were retrospectively reprocessed and harmonized. For the period between 1992 and 1995, when no management data were collected, information was reconstructed based on site-specific records from preceding and following years and information derived from the Principles of Fertilisation of Agricultural Crops in Switzerland (Richner & Sinaj, 2017).

2.3. Data curation and calculations

In this study, we distinguish between soil-property states and changes. State values represent the measured soil properties at a given sampling date and reflect the cumulative outcome of long-term soil-forming processes and management history. Change values represent the annualized difference between two consecutive sampling events (typically five years apart) and are used as indicators of short-term soil responsiveness to management and climatic variability. Change values per site and year were calculated as follows:

$$\text{change in soil property} = \frac{\text{value}_{\text{sampling year}} - \text{value}_{\text{sampling year}-n}}{n} \times 1000 \quad (1)$$

Where *change* is given in $\text{mg kg}^{-1} \text{yr}^{-1}$ (SOC, TN, PTP) or $\text{mg cm}^{-3} \text{yr}^{-1}$ (BD), *value* is the concentration of SOC, TN, PTP [g kg^{-1}] or value of BD [g cm^{-3}], and *n* is the number of years between two consecutive sampling events. In contrast to a linear regression—which tests for significant changes over the entire time period (Wiesmeier et al., 2025)—this approach does not distinguish between significant and non-significant changes. However, it offers greater flexibility to capture non-linear variability in soil properties over time and to relate these fluctuations to short-term changes in soil management and climate.

Explanatory variables for further analyses were derived from management information as numerical management indicators using the R package SoilManagerR (Table 1; Heller et al., 2025). Initially, the management information was harmonized with the terminology used in SoilManagerR. The management timeline of every site was then checked for completeness and coherence using the data quality check functions of the package (Heller et al., 2025). Missing information was either recovered from the paper archive or estimated based on the management timeline and typical values of crop management and yields for Swiss agricultural practice (Richner & Sinaj, 2017). This way, approximately 100 entries were added to the dataset. The final management dataset consisted of 9'890 operation entries for the 26 sites and covered a time span of 26–38 years (depending on the actual beginning of the monitoring of each site, see Fig. 1). Of these entries, 2'836 were sowing and harvest events, 2'677 plant protection applications, 1'326 organic fertilization events, 1'778 mineral fertilization events, 21 sewage sludge applications, and 1'238 tillage operations. The entries for plant protection were not used in this study because they are highly heterogeneous

Table 1

Overview of management indicators calculated with SoilManagerR (Heller et al., 2025) used in this study, including their abbreviations, data types, measurement units, and the source management information.

Management indicator	Abbreviation	Data type	Unit	Management information (calculated with SoilManagerR)
Soil cover days	soil cover	count	d y ⁻¹	number of days per year with a cover by plants and plant residue of at least 30% (Büchi et al., 2019)
N input by organic and mineral fertilization	N fert	ratio	kg N ha ⁻¹ y ⁻¹	annual amount of N applied to soil via organic and mineral fertilization; if N content of organic fertilizers was unknown, default values from Richner et al. (2017) were used
C input by crop residues	C crop	ratio	kg C ha ⁻¹ y ⁻¹	annual amount of C allocated to soil via above ground crop residues and roots; estimates are based on reference values for crop yields from Sinaj et al. (2017) and allometric functions from Bolinder et al. (2007)
C input by organic fertilization	C fert	ratio	kg C ha ⁻¹ y ⁻¹	annual amount of C applied to soil via organic fertilization; if dry matter content was unknown, default values from Richner et al. (2017) were used
Soil tillage intensity rating	STIR	ratio	y ⁻¹	intensity of tillage and sowing operations; calculated from type of tillage operation, and default values for depth and area of disturbance, as well as machine speed (USDA-NRCS, 2020); summarized per year

with respect to type, intensity, and timing, and their influence on SOC, TN, PTP, and bulk density is expected to be largely indirect and confounded with other management and site factors.

Subsequently, the indicators for soil cover days (soil cover), N input via organic and mineral fertilizers (N fert), C input via above ground residues and roots of the main crops (C crop), C input via organic fertilizers (C fert), and the soil tillage intensity rating (STIR) index were calculated using the function `calculate_indicators()` (Heller et al., 2025), each with a yearly resolution (Table 1; Supplementary figure 2). Annual P fertilizer inputs were not included among the derived management indicators. However, the annual management records indicate that mineral N and P fertilizer applications followed broadly similar temporal patterns across the monitored arable fields (Gross et al., 2021). Together, these indicators describe organic matter and N inputs, soil cover duration, and mechanical soil disturbance, and provide an integrated picture of how management affects SOC and nutrient cycling, sustainable soil functioning, and long-term productivity (Bohoussou et al., 2022; Bolinder et al., 2020; Topa et al., 2021).

To match the 5-year soil sampling intervals, management indicators were grouped into 5-year periods and combined using weighted averages that emphasized recent practices. The indicator value from the year before sampling and the average values from the previous 1–2, 1–3, 1–4, and 1–5 years were summed and divided by five, producing a weighted 5-year average aligned with each soil sampling period:

$$indicator_{weighted} = \frac{value_1 + \bar{x}_{1-2} + \bar{x}_{1-3} + \bar{x}_{1-4} + \bar{x}_{1-5}}{5} \quad (2)$$

Where $value_1$ is the indicator value from the previous year and $\bar{x}_{1-2}$ to $\bar{x}_{1-5}$ are the average values from the previous 1–2 to 1–5 years before sampling.

The final set of management indicators and pedoclimatic variables used in this study comprised:

- Management: soil cover days, N fert, C crop, C fert, STIR (Table 1)
- Soil: pH, sand, clay, initial value (of the soil property at the beginning of the monitoring period; for the change value as response variable only)
- Climate: precip 365, temp 365, precip 30, temp 30

An overview of the average management, soil, and climate indicators per site is given in Supplementary table 3. Correlation among variables was generally weak to moderate, indicating limited multicollinearity and no strong systematic clustering (Supplementary figure 3).

2.4. Data analysis

For general site characterization (descriptive statistics), SOC, TN, PTP, and BD were aggregated per rotation type: mean values were calculated hierarchically, first across field replications (per site and year), then across years (per site), and finally across sites (per rotation type). Standard deviations were computed at the highest hierarchical level, representing variability among sites within each rotation type, therefore accounting for varying management intensities among the crop rotation types.

Long-term trends in SOC, TN, PTP, and BD were assessed both at the site level and aggregated by rotation type. To account for the hierarchical structure of the data and the unexplained variability in soil properties due to random seasonal and spatial effects, linear mixed-effects (LME) models were fitted to the non-aggregated data (Pinheiro & Bates, 2000).

To test for long-term trends per site, the data were subset per site. The soil property was modelled as response variable, with year of sampling included as a continuous fixed effect to estimate the long-term linear trend and as a categorical random effect to account for residual between-year variation not explained by the linear trend. The models were corrected for serial autocorrelation, which was determined by a Durbin-Watson-test:

$$\begin{aligned} \text{soil property} &\sim \text{year} + 1|\text{year}, \\ \text{correlation} &= \text{corAR1}() \end{aligned} \quad (3)$$

To test for long-term trends per rotation type, the entire dataset was used. The soil property was modelled as response variable and year of sampling (numeric) and rotation type with interaction term as fixed effects and year of sampling (nominal) and site as crossed random effects. The models were corrected for serial autocorrelation, which was determined by a Durbin-Watson-test, and the distribution of the model residuals across rotation types was adjusted by a variance function (heteroscedastic model; Pinheiro & Bates, 2000):

$$\begin{aligned} \text{soil property} &\sim \text{year} * \text{rotation type} + 1|\text{site} + 1|\text{year}, \\ \text{weights} &= \text{varIdent(form} = 1|\text{rotation type}), \\ \text{correlation} &= \text{corAR1}() \end{aligned} \quad (4)$$

Significant long-term trends in soil properties were assessed from estimated marginal trends with a significance level of $\alpha < 0.05$.

The influence of management, soil, and climate on SOC, TN, PTP, BD and their respective change variables were evaluated by two different approaches: model averaging of LME models (Burnham & Anderson, 2002) and multivariate adaptive regression spline (MARS) models (Friedman, 1991).

First, we fitted LME models using each soil property—or its annual change—as the response variable. Management, soil, and climate variables were included as fixed effects in linear combination, while sampling year and site were specified as crossed random effects. Prior to model fitting, all explanatory variables were standardized to zero mean and unit variance. The models were then adjusted for spatial autocorrelation, which was assessed using a Durbin–Watson test:

$$\begin{aligned} (\text{change in}) \text{ soil property} &\sim \text{soil cover} + N \text{ fert} + C \text{ crop} + C \text{ fert} + STIR + pH \\ &+ \text{sand} + \text{clay} (+ \text{start value}) + \text{precip } 365 + \text{temp } 365 + \text{precip } 30 \\ &+ \text{temp } 30 + 1|\text{year} + 1|\text{site}, \\ \text{correlation} &= \text{corAR1}() \end{aligned}$$

(5)

Significant coefficients of all models in a range of $\Delta AIC < 7$ relative to the top model (Burnham et al., 2011) were averaged and their 95% confidence intervals calculated. When the 95% confidence intervals excluded zero, the coefficient was considered as consistently significant and the corresponding variable as a robust predictor (Burnham & Anderson, 2002). As all explanatory variables were scaled, a coefficient represented the expected change in the response variable, i.e. the effect size, per one standard deviation increase in the explanatory variable. Model performance was evaluated by examining the range of conditional R^2 values across all models within a $\Delta AIC < 7$ relative to the top model. Finally, the importance of the predictors was assessed by calculating the sum of AIC weights of all models in which each predictor appears, resulting in a proportion value between 0 and 1 for each predictor (Burnham & Anderson, 2002).

Second, MARS models were applied to detect nonlinear relationships between explanatory and response variables using piecewise linear regressions with change points (knots). To ensure comparability with the LME model approach, interaction terms between explanatory variables were not permitted. The model formula included the same explanatory variables as those in the LME approach:

$$\begin{aligned} (\text{change in}) \text{ soil property} &\sim \text{soil cover} + N \text{ fert} + C \text{ crop} + C \text{ fert} + STIR \\ &+ pH + \text{sand} + \text{clay} (+ \text{start value}) \\ &+ \text{precip } 365 + \text{temp } 365 + \text{precip } 30 \\ &+ \text{temp } 30 \end{aligned}$$

(6)

Model complexity was controlled using backward pruning based on generalized tenfold cross-validation (GCV). For each soil property, the best-performing additive model was selected, and performance was evaluated using generalized R^2 and GCV, the latter indicating a model's lack of fit (similar to mean squared error). To aid interpretation and identify nonlinear patterns and change points, partial dependence plots (PDPs) were generated, illustrating the marginal effects of individual explanatory variables on the response variables. Predictor importance was quantified based on how frequently each variable contributed to the model's basis functions. The scores were rescaled so that the most important predictor was assigned a value of 1, and all other predictors were expressed relative to this maximum. A score of 0 indicates that a variable did not contribute to the model (Milborrow et al., 2025).

Importance scores of > 0.5 and > 0 for LME and MARS, respectively, were interpreted as important (Burnham and Anderson, 2002; Milborrow et al., 2025). To obtain the cumulative relative importance of the management, soil, and climate variable groups, the importance scores of all predictors were normalized by the number of variables within each group (management = 5; soil = 3 or 4; climate = 4) and summed.

Finally, the manageability of the state and change parameters was assessed qualitatively from the modelling results rather than directly

inferred by statistical modelling. Categories (very low, low, moderate, high) were assigned by considering the relative contribution of management variables to explained variance and the consistency of management effects across modelling approaches.

2.5. Software

All analyses were performed in the R environment, version 4.2.3 (R

Core Team, 2023), with the R packages SoilManagerR (Heller et al., 2025), tidyverse (Wickham et al., 2019), reshape (Wickham, 2007), reshape2 (Wickham, 2020), and zoo (Zeileis et al., 2014) for data management, car (Fox & Weisberg, 2018), grafify (Shenoy, 2021), emmeans (Lenth and Piaskowski, J., 2026), multcomp (Hothorn et al., 2016), MuMin (Bartoń, 2022), and predictmeans (Luo et al., 2022) for statistical analysis, nlme (Pinheiro, 2011), lme4 (Bates et al., 2015), caret (Kuhn et al., 2015) and earth (Milborrow et al., 2025) for model fitting, and ggplot2 (Wickham & Chang, 2016), ggbiplot (Vu, 2011), ggpubr (Kassambara, 2018), jtools (Long, 2024), pdp (Greenwell, 2017), scales (Wickham et al., 2023), and vip (Bartoszuk & Gagolewski, 2020) for visualization.

3. Results

3.1. Mean values and temporal trends of SOC, TN, PTP, and BD

Mean concentrations of SOC, TN, and PTP over the 35-year observation period were 20, 2.3, and 0.9 g kg⁻¹, respectively (Table 2), but substantial variability was evident among crop rotation types and sites. Averages across rotation types spanned roughly a 1.5-fold range for SOC and PTP and a 2-fold range for TN (Table 2). Site-level variability was considerably larger, with all three properties varying by more than a factor of four across the full data set (data not shown). Bulk density, assessed over a 15-year period, averaged 1.19 g cm⁻³ and showed a comparable pattern to SOC, TN, and PTP: crop rotation types differed little (1.1-fold), whereas values across sites varied by almost a factor of two (data not shown).

Across all 26 sites, only BD showed a significant overall trend, decreasing by -5.9 mg cm⁻³ yr⁻¹ (p = 0.005) over the observation period, whereas SOC (+12.7mg kg⁻¹ yr⁻¹, p = 0.38), TN (+1.6mg kg⁻¹ yr⁻¹, p = 0.39), and PTP (+1.2mg kg⁻¹ yr⁻¹, p = 0.05) exhibited no significant overall trends (data not shown). At the crop rotation type

Table 2
Mean values (± standard deviation) of soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), and bulk density (BD) for arable sites with different crop rotation types over 35 years. Values are hierarchically averaged across field replications (per site and year), years (per site), and sites (per rotation type). Standard deviations refer to the highest hierarchy level (rotation type).

Crop rotation type	SOC [g kg ⁻¹]	TN [g kg ⁻¹]	PTP [g kg ⁻¹]	BD [g cm ⁻³]
Cereal, maize, legume	16 (3)	1.6 (0.3)	0.7 (0.2)	1.17 (0.08)
Tuber, oilseed, vegetable	18 (7)	2.0 (1.0)	1.0 (0.4)	1.26 (0.13)
Ley-based	27 (8)	3.0 (1.1)	1.1 (0.5)	1.12 (0.10)
Ley-dominant	22 (4)	2.4 (0.6)	0.8 (0.2)	1.20 (0.09)
All sites	20 (7)	2.3 (0.9)	0.9 (0.3)	1.19 (0.14)

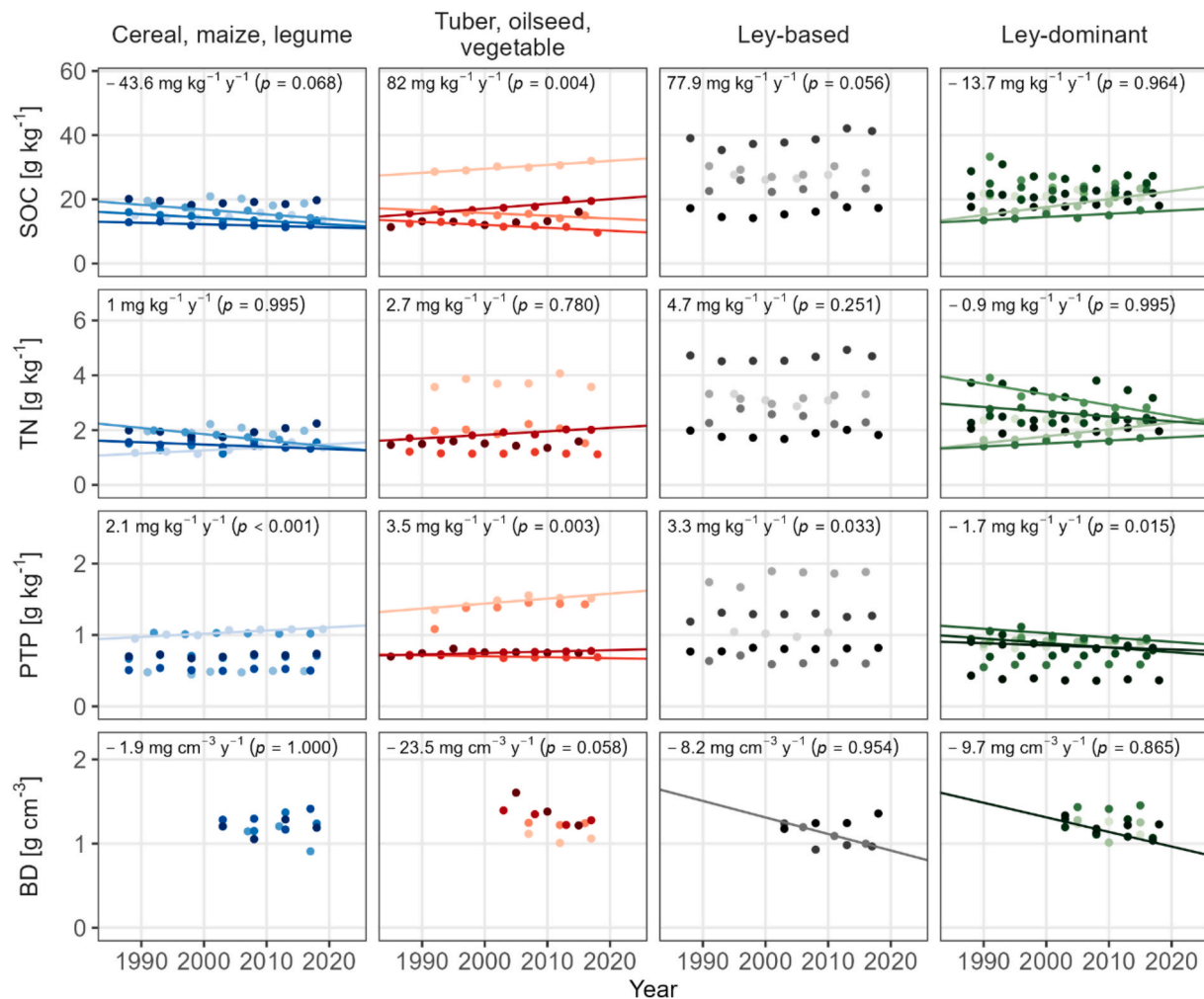


Fig. 2. Long-term trends in soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), and bulk density (BD) at 26 arable sites, grouped by crop rotation type. Points represent mean values per site and year (across 4 field replications, except for BD, where only average values per site and year were available). Trendlines are shown only for sites with statistically significant trends. Different colour families indicate different crop rotation types and different shades indicate different sites within crop rotation types.

level, SOC increased significantly in tuber, oilseed, vegetable rotations ($+82 \text{ mg kg}^{-1} \text{ yr}^{-1}$), while PTP increased significantly in cereal, maize, legume rotations ($+2.1 \text{ mg kg}^{-1} \text{ yr}^{-1}$), tuber, oilseed, vegetable rotations ($+3.5 \text{ mg kg}^{-1} \text{ yr}^{-1}$), and ley-based rotations ($+3.3 \text{ mg kg}^{-1} \text{ yr}^{-1}$), but declined in ley-dominant rotations ($-1.7 \text{ mg kg}^{-1} \text{ yr}^{-1}$). At the site level, significant trends were observed for all soil properties, with SOC, TN, and PTP increasing at 3–4 sites and decreasing at 4–5, and BD decreasing at 2 sites (Fig. 2). Across all sites, estimated coefficients ranged from -292 to $+249 \text{ mg kg}^{-1} \text{ yr}^{-1}$ for SOC, -39.1 to $+25.0 \text{ mg kg}^{-1} \text{ yr}^{-1}$ for TN, -6.3 to $+11.7 \text{ mg kg}^{-1} \text{ yr}^{-1}$ for PTP, and -38.9 to $+10.9 \text{ mg cm}^{-3} \text{ yr}^{-1}$ for BD (Supplementary figure 4).

3.2. Relationships between management, soil, and climate and the state of SOC, TN, PTP, and BD

Effect sizes and relative importance of predictors were first examined using linear models. Several variables showed consistent significant relationships across averaged top models (Fig. 3): SOC and TN were positively related to soil cover days (effect sizes: $+0.4 \text{ g SOC kg}^{-1}$ and $+0.05 \text{ g TN kg}^{-1}$, respectively) and clay ($+3.5 \text{ g SOC kg}^{-1}$ and $+0.4 \text{ g TN kg}^{-1}$), and negatively to precip 30 ($-0.3 \text{ g SOC kg}^{-1}$ and $-0.03 \text{ g TN kg}^{-1}$); PTP was positively related to N fert ($+0.02 \text{ g PTP kg}^{-1}$) and STIR ($+0.01 \text{ g PTP kg}^{-1}$), and negatively to C fert ($-0.02 \text{ g PTP kg}^{-1}$); while BD was positively related to temp 30 ($+0.04 \text{ g cm}^{-3}$). The confidence

intervals for sand and clay were several times larger than those for all other variables. Other management, soil, and climate variables showed significant effects but with inconsistent effect directions across models, and their confidence intervals included zero (Fig. 3). These effects were therefore not considered robust.

Nonlinear relationships among the most influential predictors (as identified by MARS) revealed distinct patterns and thresholds, highlighting inherent soil characteristics as particularly important (Fig. 4). Clay contents above $\sim 30\%$ were associated with strong enhancements of SOC and TN, whereas PTP peaked at both low ($< 20\%$) and high ($> 35\%$) clay levels. Sand content also showed contrasting effects: SOC increased up to $\sim 30\%$ sand before declining again and TN followed a similar although less pronounced trend, while PTP was highest at moderate to high sand contents ($\sim 30\text{--}50\%$). The positive relationship between soil pH and PTP was moderate under acidic conditions and rose sharply above pH 7. Among management and climate variables, only soil cover days and annual precipitation ranked among the top predictors: SOC and TN remained stable up to ~ 250 soil cover days before increasing moderately, whereas BD was lowest at moderate rainfall ($1000\text{--}1500 \text{ mm}$).

The relative importance of predictors was assessed for both linear and nonlinear relationships. Across soil properties, the number of important predictors differed markedly between linear and nonlinear models (Fig. 5). In the linear models, four predictors were highly

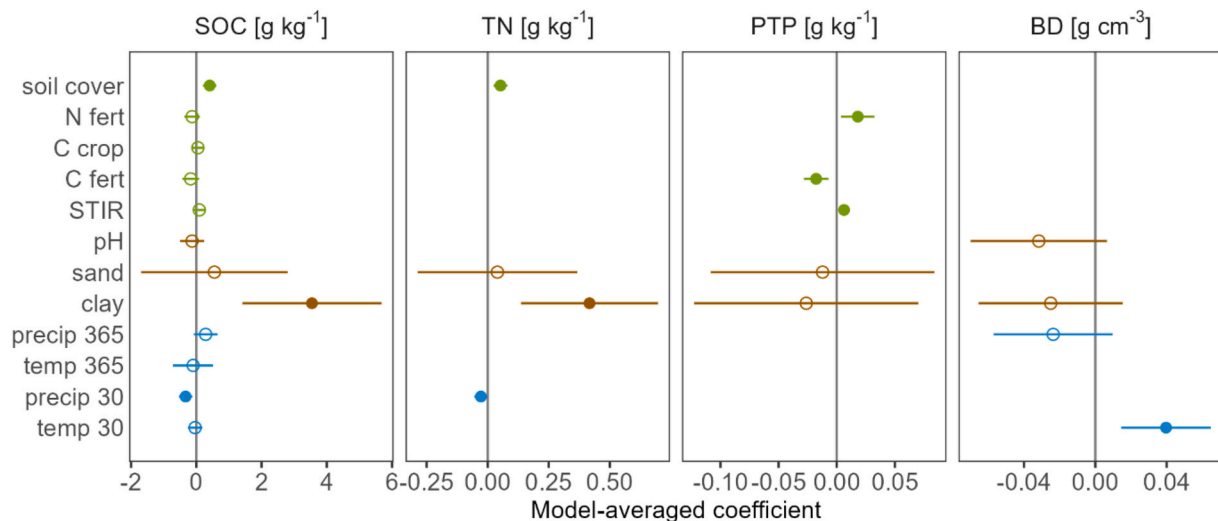


Fig. 3. Model-averaged coefficients with 95% confidence intervals for the explanatory variables included in linear mixed-effects (LME) models, with state values of soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), or bulk density (BD) as response variables. Only significant coefficients from models within $\Delta AIC < 7$ of the top model are shown. Conditional R^2 values of the models range between 0.51 (BD) and 0.97 (PTP; Supplementary table 5). Solid points indicate consistently significant coefficients whose 95% confidence intervals do not include zero, identifying robust predictors. Management variables are shown in green, soil variables in brown, and climate variables in blue.

important for SOC (soil cover days, clay, sand, precip 30), two for TN (soil cover days, clay), and one for PTP (N fert), while none of the predictors for BD reached an importance score > 0.5 . In the nonlinear models, five predictors were important for SOC (soil cover days, clay, sand, C fert, pH), four for TN (soil cover days, clay, sand, C fert), four for PTP (pH, clay, sand, N fert), and one for BD (precip 365). Partitioning cumulative relative importance among management, soil, and climate variables showed distinct contributions across soil properties. In the linear and nonlinear models, management represented 19–34%, soil 46–81%, and climate 0–31% of the normalized relative importance for SOC, TN, and PTP (except for PTP in the linear model: 90% management, 10% soil). For BD, climate variables accounted for most of the relative importance in the models (Fig. 5; Supplementary table 4).

3.3. Relationships between management, soil, and climate and the change in SOC, TN, PTP, and BD

All management, soil, and climate variables showed significant linear relationships to SOC change and PTP change but only a few showed consistent effect directions across averaged top models (Fig. 6): Both SOC and TN change were positively related to soil cover days ($+749 \text{ mg SOC kg}^{-1} \text{ yr}^{-1}$ and $+70 \text{ mg TN kg}^{-1} \text{ yr}^{-1}$) and negatively to their initial values ($-609 \text{ mg SOC kg}^{-1} \text{ yr}^{-1}$ and $-65 \text{ mg TN kg}^{-1} \text{ yr}^{-1}$), while SOC change was also negatively related to sand ($-517 \text{ mg SOC kg}^{-1} \text{ yr}^{-1}$) and precip 30 ($-690 \text{ mg SOC kg}^{-1} \text{ yr}^{-1}$). Phosphorus change was positively related to N fert ($+2.7 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$), C crop ($+1.1 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$), and STIR ($+1.4 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$), and negatively to C fert ($-1.8 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$), sand ($-2.0 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$), and clay ($-2.2 \text{ mg PTP kg}^{-1} \text{ yr}^{-1}$). By contrast, BD change was not significantly related to any variable. The confidence intervals were similarly large for all variables (Fig. 6).

Climate factors, in particular short-term precipitation, displayed the most pronounced nonlinear patterns in relation to changes in soil properties (Fig. 7). Soil organic C, TN, and BD changes peaked under low short-term precipitation up to 50 mm and stabilized around zero (SOC and BD) or declined gradually to negative values (TN) with increasing precipitation up to 250 mm. Short-term temperature also played a key role for BD, which shifted from negative values at 0°C to strongly positive above 20°C with a moderate peak around 10°C . Annual temperature was mainly related to PTP change, showing positive values at

$6\text{--}8^\circ \text{C}$, a drop to zero around 9°C , and a slight increase beyond that point. Soil conditions had comparatively minor effects. Intermediate initial SOC ($25\text{--}35 \text{ g SOC kg}^{-1}$) and PTP levels ($0.7\text{--}0.9 \text{ g PTP kg}^{-1}$) were associated with negative changes in SOC and PTP, respectively. Soil pH > 7 coincided with a sharp rise in PTP change, whereas TN change remained constant under increasing clay content. Among the management factors, soil cover days was the most important. The change in TN remained stable up to ~ 250 days of soil cover days, declined to negative values by ~ 300 days, and peaked positively at ~ 350 days. The change in BD decreased steadily until ~ 300 days, then rose sharply. In addition, N fertilization was also important for SOC change but the response curve showed no clear thresholds.

Similar to the results for the state values of soil properties, the number of important predictors varied markedly among the change values of soil properties in both linear and nonlinear models (Fig. 8). In the linear models, four predictors were highly important for SOC change (soil cover days, initial value, sand, precip 30) and eight for PTP change (soil cover days, N fert, C crop, C fert, STIR, sand, clay, temp 30), while none of the predictors for TN change reached an importance score > 0.5 . For the nonlinear models, five predictors were important for SOC change (N fert, C fert, initial value, precip 30, temp 30), six for TN change (soil cover days, STIR, clay, precip 365, temp 365, precip 30), six for PTP change (soil cover, days, C fert, initial value, pH, clay, temp 365), and eight for BD change (soil cover days, C crop, initial value, precip 365, temp 365, precip 30, temp 30). Across linear and nonlinear models, management accounted for 7–50%, soil 14–65%, and climate 16–66% of the cumulative relative importance for SOC, TN, PTP, and BD changes (Fig. 8; Supplementary table 4).

4. Discussion

4.1. Soil properties and trends over time

The observed soil chemical properties are characteristic of moderately fertile, managed arable soils in Central Europe: $10\text{--}30 \text{ g kg}^{-1}$ SOC (Fernandez et al., 2022; Jacobs et al., 2018), $1.0\text{--}4.0 \text{ g kg}^{-1}$ TN (Fernandez et al., 2022; Matschullat et al., 2018), and $0.5\text{--}2.0 \text{ g kg}^{-1}$ total P (Négre et al., 2024), with $\text{HNO}_3\text{-P}$ often representing a substantial share of operationally defined total P (on average 75%; Chander et al., 2008). Likewise, bulk density values correspond to those generally

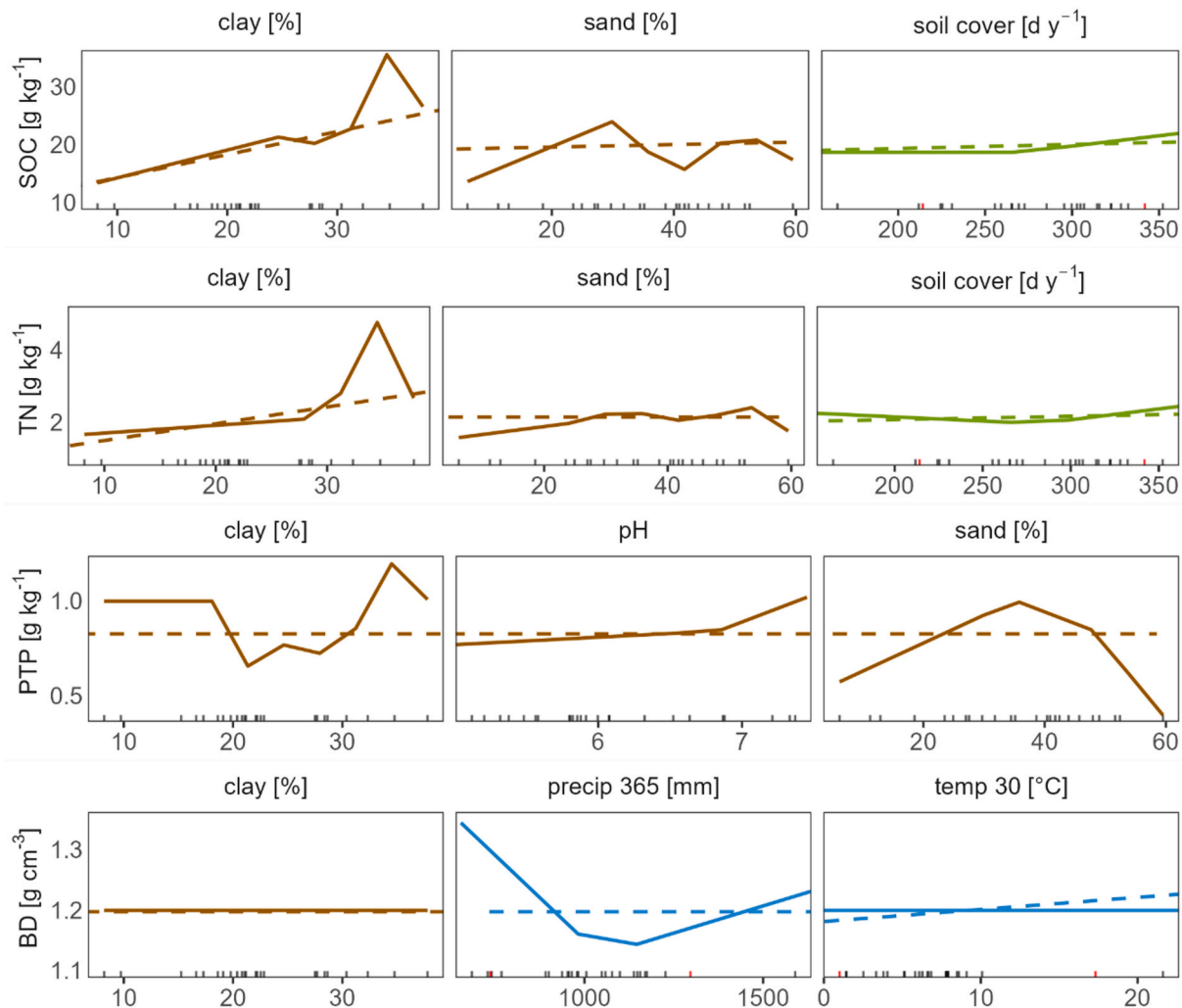


Fig. 4. Partial dependence plots (PDPs) showing the response of soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), and bulk density (BD) to their three most important predictors as identified by the multivariate adaptive regression spline (MARS) analysis (solid lines). Generalized R^2 values of the models range between 0.12 (BD) and 0.89 (TN and SOC; Supplementary table 6). Average model fits of the linear mixed effects (LME) model approach (dashed lines), site-averages of the predictors (black ticks along the x-axis), and 10- and 90-percentiles of the site-year-averages of the predictors (red ticks along the x-axis; management and climate variables only) are given as reference. For BD, only precip 365 was identified as significant predictor in the MARS model, while clay and temp 30 are displayed based on their relevance in the LME model only.

reported for mineral arable topsoils (typically 1.1–1.4 g cm^{-3}) (Jones et al., 2005; Panagos et al., 2024).

The absence of consistent SOC and TN trends highlights heterogeneous trajectories of soil organic matter across sites. Similar spatial variability has been reported in long-term monitoring networks, where changes in SOC and TN often depend on site-specific combinations of management practices, inherent soil characteristics, and climatic conditions (Gubler et al., 2019; Jacobs et al., 2018; Wiesmeier et al., 2025). Parallel SOC and TN dynamics observed at several sites further point to shared controls through organic matter inputs and mineralization processes, particularly where organic amendments contribute to both C and N pools (Johnston et al., 2009; Kögel-Knabner, 2002; van Hijbeek et al., 2017). Although tuber, oilseed, and vegetable rotations are often considered humus-depleting due to high harvest intensity and regular tillage (Kasper et al., 2015), the significant SOC increases observed in our study suggest that additional factors, including management practices such as residue retention (e.g., non-marketable products in vegetable farming), cover cropping, or organic amendments, may contribute to maintaining SOC in intensive crop rotations.

Similarly, PTP does not show a uniform overall trend, but rotation-specific patterns indicate a decline in ley-dominant rotations and

accumulation in arable rotations. Notably, the decline in PTP within ley-dominant rotations despite comparatively high fertilizer inputs suggests that long-term P dynamics are governed by processes beyond nutrient additions alone, including legacy pools and soil buffering mechanisms. This pattern is consistent with the strong legacy effects observed for soil P, where current P levels and changes are consistent with long-term accumulation and buffering processes rather than contemporary management inputs alone (Jarvie et al., 2013).

The only soil property showing a significant trend across sites is BD, decreasing slightly over time. The most plausible explanation for this pattern would be an increase in soil organic matter (Robinson et al., 2022); however, SOC trends were not significantly positive over the time period of BD measurements across all 26 sites ($+0.5 \text{ mg kg}^{-1} \text{ yr}^{-1}$, $p = 0.21$; data not shown). Interpretation remains limited given the short temporal coverage, high variability of BD measurements, and strong influence of tillage and natural loosening processes in the topsoil. More frequent sampling would be required to robustly attribute overall BD trends to management versus climate-related sampling conditions (Baritz et al., 2022).

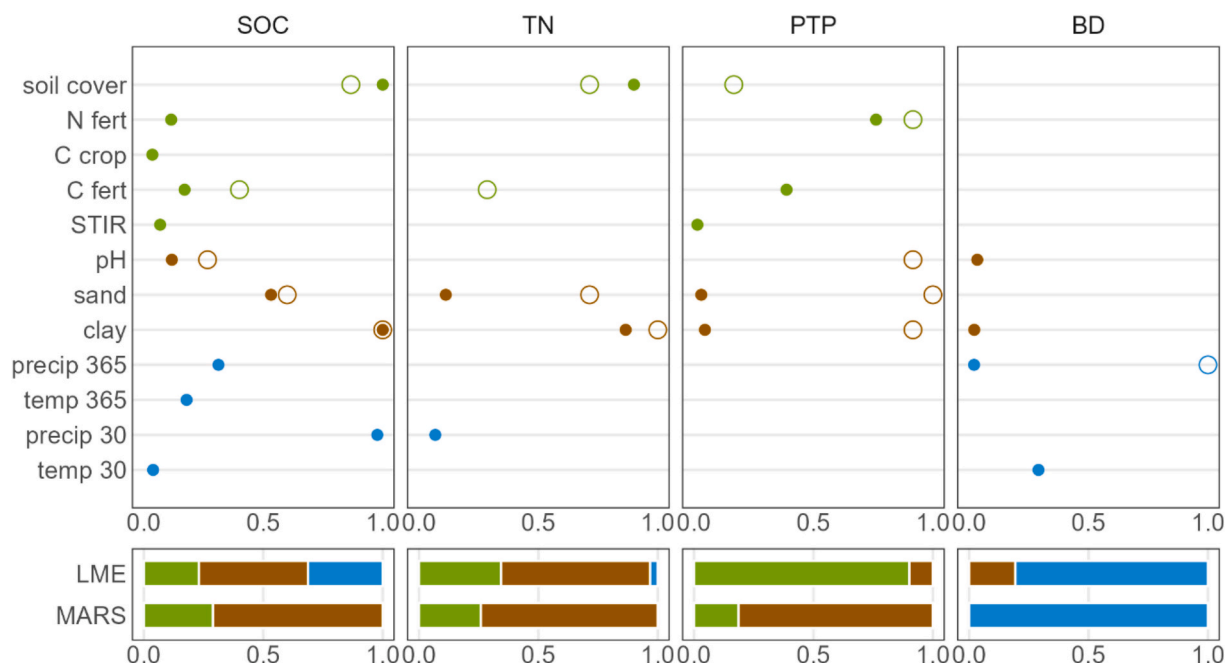


Fig. 5. Normalized relative importance scores (top) and cumulative relative importance (bottom) of management, soil, and climate variables for soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), and bulk density (BD), derived from linear mixed-effects (LME) models (solid dots) and multivariate adaptive regression spline (MARS) models (circles). Conditional R^2 values of the LME models range between 0.51 (BD) and 0.97 (PTP; Supplementary table 5) and generalized R^2 values of the MARS models range between 0.12 (BD) and 0.89 (TN and SOC; Supplementary table 6).

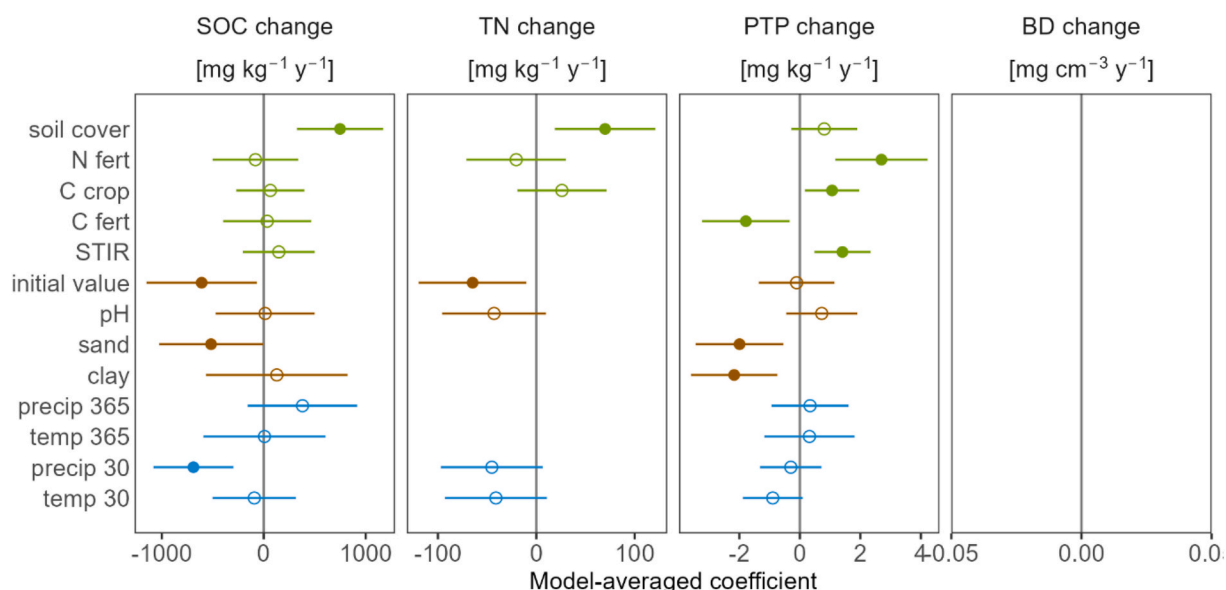


Fig. 6. Model-averaged coefficients with 95% confidence intervals for the explanatory variables included in linear mixed-effects (LME) models, with change values of soil organic carbon (SOC), total nitrogen (TN), pseudo-total phosphorus (PTP), or bulk density (BD) as response variables. Only significant coefficients from models within $\Delta AIC < 7$ of the top model are shown. Conditional R^2 values of the models range between 0.20 (TN) and 0.50 (PTP; Supplementary table 5). Solid points indicate consistently significant coefficients whose 95% confidence intervals do not include zero, identifying robust predictors. Management variables are shown in green, soil variables in brown, and climate variables in blue.

4.2. Predictors of soil property states and changes

The predictors of soil property states and changes show a consistent pattern. Inherent soil characteristics are primarily associated with the long-term levels of SOC, TN, and PTP, whereas climate shows the strongest relation to BD. In contrast, short-term changes in SOC, TN, and BD vary more strongly with varying climatic conditions, while inherent soil characteristics remain the primary predictors of PTP change.

Management shows a moderate but consistent relationship with both states and changes, with slightly stronger effects on the changes. This distinction is expected because long-term soil properties integrate decades of pedogenic development and cumulative management, whereas short-term changes primarily reflect processes operating over individual years or sampling intervals.

As inherent soil characteristics, both soil texture and pH show strong relationships with the state of soil properties. Higher clay content is

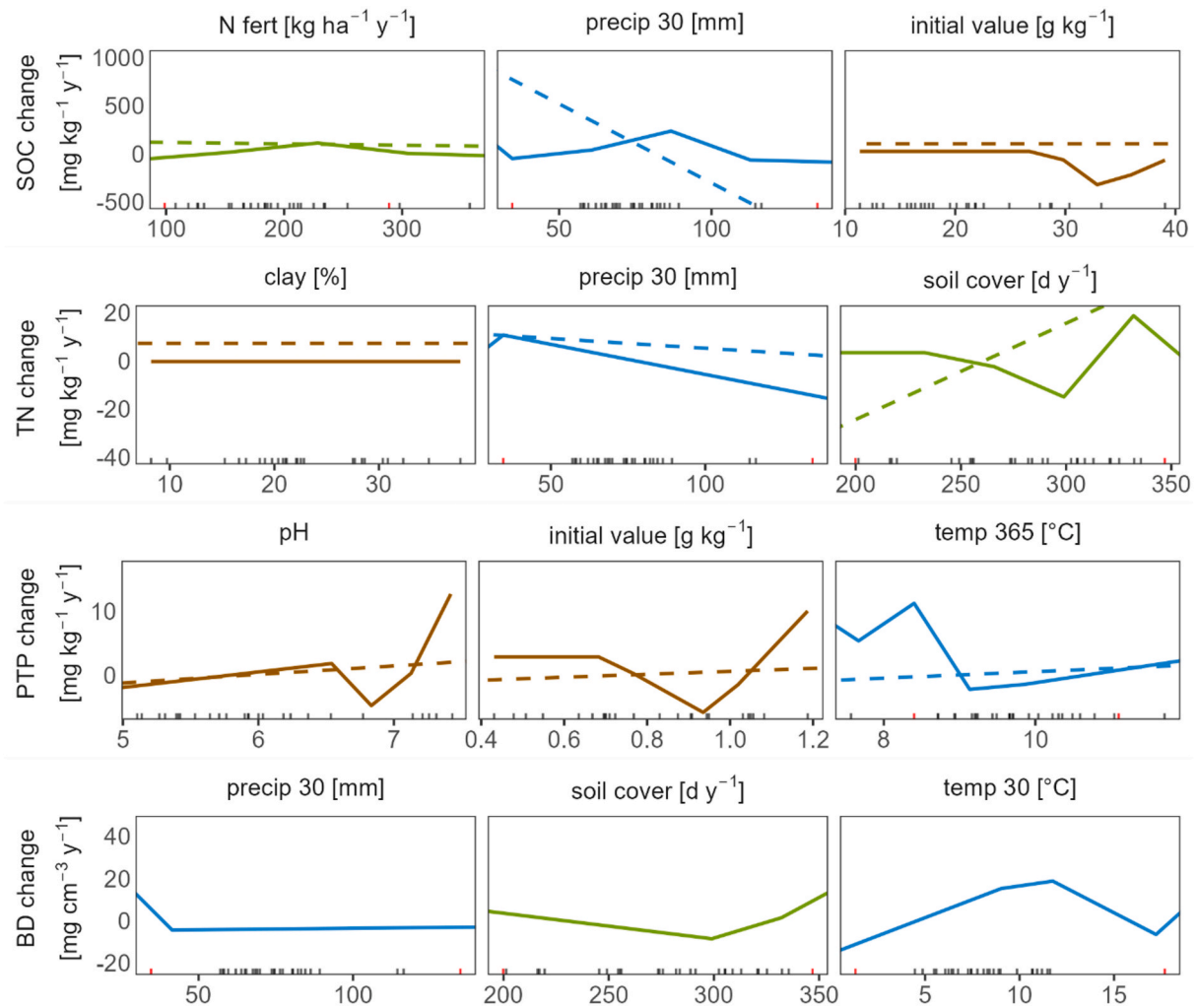


Fig. 7. Partial dependence plots (PDPs) showing the response of soil organic carbon (SOC) change, total nitrogen (TN) change, pseudo-total phosphorus (PTP) change, and bulk density (BD) change to their three most important predictors as identified by the multivariate adaptive regression spline (MARS) analysis (solid lines). Generalized R^2 values of the models range between 0.12 (TN change) and 0.55 (BD change; Supplementary table 6). Average model fits of the linear mixed effects (LME) model approach (dashed lines), site-averages of the predictors (black ticks along the x-axis), and 10- and 90-percentiles of the site-year-averages of the predictors (red ticks along the x-axis; management and climate variables only) are given as reference.

associated with increased SOC and TN through enhanced mineral protection, aggregation, and surface-area-mediated stabilization, while also affecting BD through structural constraints (Bronick & Lal, 2005; Kleber et al., 2015). These relationships are strongly nonlinear, with pronounced thresholds above approximately 30% clay, which may indicate shifts in stabilization pathways toward mineral-associated organic matter (Schweizer et al., 2021). Soil pH is particularly influential for P, with a pronounced increase in PTP levels above pH 7 consistent with a transition from Fe–Al to Ca-dominated sorption mechanisms and reduced buffering capacity (de Sousa et al., 2025; Nobile et al., 2020). In contrast, soil effects on BD operate mainly through physical constraints related to structure, porosity, and moisture regime (Bronick & Lal, 2005; da Silva et al., 1997).

Climate variables show weaker relationships to soil property states than inherent soil characteristics. Long-term climatic influences are likely already embedded in soil development and therefore partly expressed through present-day soil characteristics, reducing the additional explanatory power of contemporary climate for soil-property states. An exception is BD, which is most prominently related to annual precipitation and temperature before sampling. Weather conditions affect soil moisture and physical conditions at the time of sampling during the cool and wet winter–spring period, affecting BD through freeze–thaw dynamics, wetting–drying cycles, and compaction

susceptibility (Leuther & Schlüter, 2021; Nawaz et al., 2013), while long-term climate conditions, in particular moderate soil moisture, are associated with enhanced aggregation (Nunes et al., 2020).

Management effects on long-term soil states are generally secondary, which likely reflects that management inputs accumulate within soil systems whose capacity to retain C, N, and P is constrained by inherent soil properties such as texture, mineralogy, and pH. However, soil cover days emerges as one of the most important predictors for SOC and TN. Longer soil cover is associated with higher SOC and TN levels, consistent with sustained organic inputs, reduced erosion, and the moderation of microclimatic extremes (Ledo et al., 2020). The positive associations of N fertilization and soil disturbance with PTP may reflect broader management intensity within the monitoring network, including the co-application of N and P fertilizers (Duncan et al., 2018; Szegedi et al., 2023). The negative relation to C inputs by organic fertilization may arise from stoichiometric constraints associated with the high C:P ratios of organic fertilizers (Prado et al., 2022). The absence of sharp management thresholds in the nonlinear models indicates that responses are generally gradual, with effects accumulating over time rather than producing abrupt changes.

In contrast to long-term states, short-term changes in soil properties show a stronger sensitivity to both management and climate. Longer soil cover is consistently associated with higher SOC and TN gains, likely by

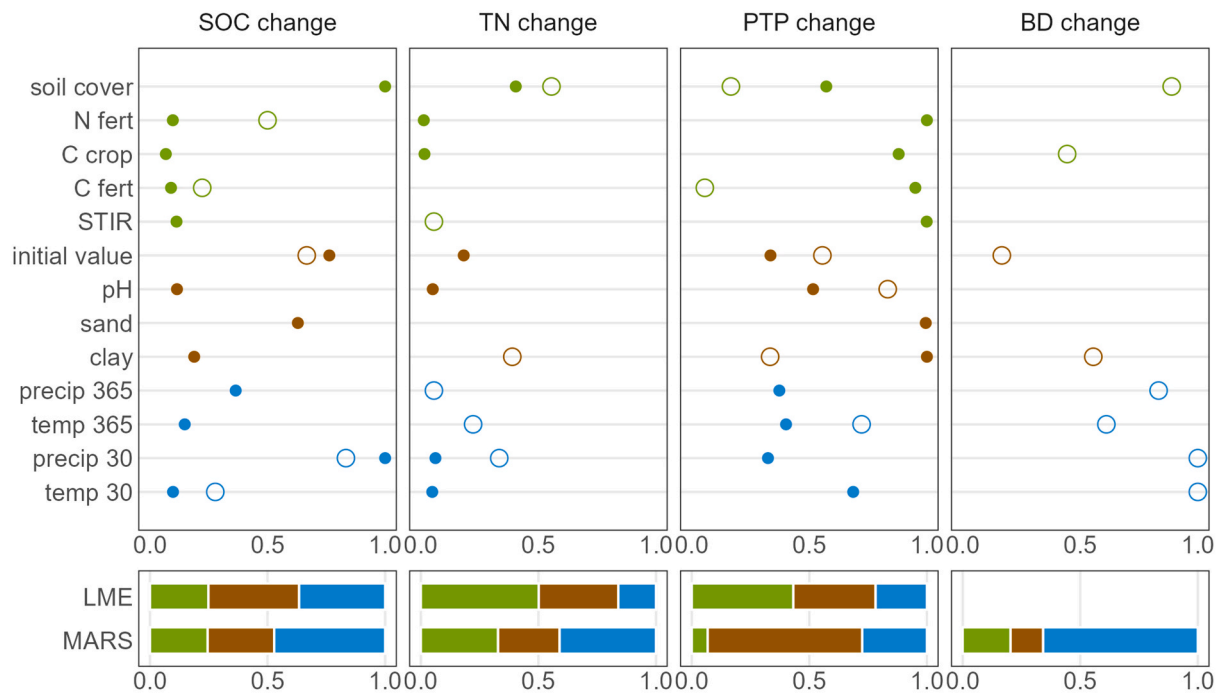


Fig. 8. Normalized relative importance scores (top) and cumulative relative importance (bottom) of management, soil, and climate variables for soil organic carbon (SOC) change, total nitrogen (TN) change, pseudo-total phosphorus (PTP) change, and bulk density (BD) change, derived from linear mixed-effects (LME) models (solid dots) and multivariate adaptive regression spline (MARS) models (circles). Conditional R^2 values of the LME models range between 0.20 (TN change) and 0.50 (PTP change; Supplementary table 5) and generalized R^2 values of the MARS models range between 0.12 (TN change) and 0.55 (BD change; Supplementary table 6).

reducing mineralization of soil organic matter by disturbance, sustaining organic inputs, and buffering soil microclimate (Bolinder et al., 2020; Francaviglia et al., 2023). The nonlinear relation between soil cover days and BD change may reflect a shift from soil loosening by roots and protection from traffic in arable rotations (Shaheb et al., 2021) to soil consolidation in ley-dominated rotations (Peigné et al., 2007). The strong association of PTP change with all management variables except C input from crops most likely reflects management intensity and stoichiometric constraints, mirroring the predictors identified for PTP levels (Prado et al., 2022).

Climate is associated with short-term changes mostly through nonlinear patterns. Moderate short-term precipitation may improve aeration and microbial processing and may thereby favor SOC and TN gains (Hao et al., 2025; Skopp et al., 1990), whereas higher precipitation may suppress aerobic processes and promote leaching and denitrification processes and may level off SOC gains and reverse TN changes to negative values (Manik et al., 2019; Patil et al., 2010; Trost et al., 2013). Bulk density change varies strongly with varying temperature and moisture conditions, reflecting that freeze–thaw processes may reduce BD at low temperatures while warm and dry conditions may increase compaction susceptibility (Saffih-Hdadi et al., 2009; Leuther and Schlüter, 2021). These climatic thresholds suggest that the relationship between management and soil-property changes depends on prevailing climatic conditions.

Inherent soil characteristics and legacy conditions are most prominently related to soil property changes through soil texture and initial values. Higher initial SOC and TN levels constrain accumulation, reflecting legacy effects and regression-to-the-mean artefacts (Poeplau et al., 2011; Slessarev et al., 2023), while sandy soils limit SOC and P gains through weaker aggregation and nutrient retention (Six et al., 2002; van Doorn et al., 2024). Lowest PTP gains at near-neutral pH and intermediate initial PTP levels reflect strong buffering capacity, whereas higher pH and PTP levels indicate reduced buffering and greater net accumulation (van Doorn et al., 2024), underscoring the strong buffering capacity of soils and the dominance of legacy pools (Schärer et al.,

2007). Together, these relationships suggest that the responsiveness of soil properties declines where legacy effects increasingly constrain further change. In contrast, changes in BD show only weak relationships with inherent soil characteristics, consistent with the episodic nature of BD dynamics reported previously (Peigné et al., 2007; Shaheb et al., 2021).

Overall, these results indicate that inherent soil characteristics are primarily associated with the long-term state of soils, while management and climate are increasingly related to short-term variability and change, with nonlinear responses amplifying the role of climatic drivers. This distinction underscores the importance of separating soil property states and changes when evaluating management effectiveness across heterogeneous arable sites.

4.3. Modelling framework

The contrasting patterns observed for soil property states and changes between the LME and the MARS highlight how the choice of modelling framework shapes inference about predictor importance and suitability for different research questions. In observational soil monitoring networks, management cannot be represented through controlled, factorial designs, but rather through aggregated nominal information that reflects real-world agricultural practice (Gubler et al., 2019; Meersmans et al., 2011). Translating such information into numeric indicators enables the joint analysis of management, soil, and climate indicators, but also constrains attribution because management choices are themselves conditioned by inherent soil characteristics and climate. As a result, management effects captured by indicator-based approaches tend to represent broad, systematic influences rather than isolated causal effects, yielding conservative but robust estimates of management importance at larger spatial scales (Harbo et al., 2023; Poeplau et al., 2020; Wiesmeier et al., 2025).

Within this context, LME models provide stable rankings of predictor importance and support transparent inference across heterogeneous datasets. In our analysis, they consistently capture the dominant role of

inherent soil characteristics for long-term soil states and the increasing influence of climate and management for short-term changes, making them well suited for comparative, inference-oriented assessments across soil properties in monitoring networks (Wiesmeier et al., 2025). However, linear formulations necessarily smooth nonlinear responses and threshold behavior, which can obscure important context dependencies. More flexible nonlinear models complement this perspective by identifying response structures not detectable in linear analyses, including soil- and climate-dependent thresholds and buffering behavior for SOC, TN, and BD, as well as the limited responsiveness of PTP to short-term predictors. Consistent with previous studies, increased nonlinear flexibility refines response characterization—such as identifying texture- or climate-dependent thresholds—without altering overall driver hierarchies (De Benedetto et al., 2022; Emamgolizadeh et al., 2015; Leathwick et al., 2006). Accordingly, nonlinear models are most informative for diagnosing conditions under which management effects are amplified or suppressed, rather than for redefining dominant controls.

Variance partitioning provides a complementary metric by expressing the relative contributions of management, soil, and climate as unitless proportions (Legendre & Legendre, 2012). This facilitates comparison across soil properties and between state and change variables, but does not imply independence or causality. The dominance patterns observed here largely reflect co-variation among predictors—management being constrained by inherent soil characteristics and climate co-varying with soil development—rather than separable effects (Dormann et al., 2013). Moreover, some relationships may operate through indirect pathways among variables for example where climatic or management effects on BD are mediated by changes in SOC. Consequently, low or near-zero contributions for specific predictors, especially in nonlinear frameworks, should not be interpreted as irrelevance (Friedman, 1991), but instead reflect buffering processes, legacy effects, or context-dependent constraints that dampen measurable responses. Approaches that explicitly represent causal networks, such as (piecewise) structural equation models, could help disentangle these indirect effects in future analyses.

Taken together, these results show that different modelling frameworks provide complementary insights into the drivers of soil properties. Linear models are best suited for robust ranking of dominant controls and comparative assessments across properties, whereas nonlinear models are most informative for identifying thresholds, buffering behavior, and climatic modulation of management effects. Indicator-based variance partitioning enables synthesis across heterogeneous monitoring data when its limitations are acknowledged. Overall, effective assessment of soil-property predictors benefits from a pluralistic modelling approach in which framework choice is aligned with the specific question being addressed.

4.4. Manageability of soil properties – implications for agricultural practice

The manageability of soil properties in agricultural systems depends strongly on whether long-term states or short-term changes are targeted. Across these 26 arable sites spanning a 35-year monitoring period, variation in soil properties is two to three times higher among sites than among crop rotation types, highlighting the importance of site-specific soil and climatic conditions for management outcomes. Soil organic C, TN, and PTP levels are most strongly related to inherent soil characteristics, while BD shows highest sensitivity to climate conditions. In contrast, short-term changes in soil properties are highly variable across sites, with coefficients spanning both positive and negative ranges and management contributing up to 50% of the relative importance among the predictor groups. This relationship, however, varies with short-term precipitation and temperature, with nonlinear models revealing clear climatic thresholds, whereas management responses are generally smoother. Climate and management are closely intertwined, with climatic conditions being associated with differences in the strength and

direction of observed management relationships.

These findings suggest that management is more strongly associated with short-term soil property changes and soil degradation risks than with long-term soil property states. While pedoclimatic conditions largely define baseline soil property states, management is associated with the potential for change, with climatic conditions modulating the magnitude and direction of these changes. These patterns suggest that soil management may benefit from focusing on site-adapted practices that stabilize soil functions, reduce loss pathways, and buffer soils against adverse climatic conditions, while also enabling site-specific improvements rather than aiming for uniform increases in soil property levels (Blanchy et al., 2023; Davis et al., 2023; Lal, 2015; Paustian et al., 2016). This perspective is also reflected in policy frameworks and national initiatives such as the EU Soil Strategy for 2030 and the EU Soil Monitoring Law, which promote flexible, locally appropriate approaches to soil protection and sustainable use, and the Swiss Soil Strategy (European Commission, 2021; European Parliament and Council, 2025; Swiss Federal Council, 2020).

Among the management indicators considered in our study, soil cover days was most consistently associated with multiple soil properties. Continuous soil cover can be achieved through practices such as cover crops, temporary leys, residue retention, reduced fallow periods, and diversified rotations (Blanchy et al., 2023). In Switzerland, soil cover is an established agri-environmental indicator (Büchi et al., 2016; Gilgen et al., 2023), and a federal subsidy scheme promoting continuous soil cover has been in place since 2023 (FOAG, 2025). Based on farm-level data, 73% of Swiss wheat farms participated in this scheme in the 2022/2023 season; 32% applied mulching, 6% used undersowing, and 44% established cover crops (Rees et al., 2025). In addition, temporary leys occupy roughly one third of arable land in Switzerland and are a common component of crop rotations (Guillaume et al., 2022; Swiss Federal Statistical Office, 2025). Both cover crops and temporary leys provide multiple agronomic and environmental benefits, including reduced soil erosion and nitrate leaching, improved greenhouse-gas balance, lower mineral fertilizer requirements, and enhanced carbon sequestration, biodiversity, and soil structure (Büchi et al., 2018; Coolidge et al., 2022; Guillaume et al., 2022; Keel et al., 2019; Rivière et al., 2022). Consequently, practices that increase continuous soil cover may contribute to further improvements in soil protection in Swiss agricultural systems.

Our results indicate that the manageability of soil properties differs fundamentally among properties, with important implications for soil-related policy instruments (Table 3). Changes in SOC and TN show meaningful sensitivity to management, indicating that practice-based incentives can plausibly deliver measurable effects over policy-relevant time horizons. This is consistent with the current Swiss direct payments ordinance (Swiss Federal Council, 2025), which explicitly promotes measures such as soil cover, erosion risk reduction, and efficient nutrient use (Suisse-Bilanz). While long-term SOC levels are strongly constrained by soil and climate conditions, incentives can help protect existing stocks and prevent losses by supporting continuous soil cover, residue retention, and reduced disturbance. In contrast, the stronger responsiveness of short-term TN dynamics highlights the importance of policies that enable adaptive management, including flexible fertilization timing, cover crop establishment, and crop rotations that enhance N uptake and retention.

By contrast, the manageability of PTP and BD is more limited. For PTP, the observed associations are consistent with strong soil buffering and legacy effects, suggesting that policy approaches focusing on efficient nutrient use and regular monitoring of soil P concentrations are more appropriate than incentives aimed at altering soil P stocks. Accordingly, measures should prioritize limiting P mobilisation and losses through erosion control, soil cover, avoidance of surface runoff, and careful timing of manure and fertilizer applications (Frossard et al., 2004). Similarly, BD is primarily associated with climate and, to a minor extent, inherent soil characteristics, making uniform improvement

Table 3

Dominant controls and qualitative manageability of key soil properties at arable sites in the Swiss soil monitoring network, distinguished between long-term soil states and short-term changes. Dominant controls are inferred from variance partitioning and indicate the predictor group explaining the largest proportion of variance. Manageability is based on a qualitative synthesis of the relative importance and consistency of management predictors across the LME and MARS analyses and reflects the relative scope for management to influence outcomes within typical agricultural time frames.

Soil property	Long-term state		Short-term change		Implications
	Dominant controls	Manageability	Dominant controls	Manageability	
SOC	Soil, climate	Low	Climate, management	Moderate	Long-term maintenance strategies; incentives should reward loss prevention and continuity
TN	Soil	Low–moderate	Management, climate	High	Support adaptive, responsive management; allow flexibility in timing and implementation
PTP	Soil	Very low	Soil	Low	Avoid further accumulation; focus on minimizing losses
BD	Climate	Low	Climate, management	Low	Emphasize compaction prevention and risk avoidance, especially under wet conditions

across sites unrealistic. In contrast to SOC or nutrient management, current policy instruments provide few direct incentives to address soil compaction, although practices promoted under broader soil protection measures—such as maintaining soil cover or reducing disturbance—may indirectly reduce compaction risk. Taken together, these findings underline that soil policy should be aligned with the biophysical limits of manageability and support site-adapted management strategies, rewarding continuity and persistence of protective practices, focusing on risk reduction, and allowing flexibility in timing and implementation.

4.5. Suitability of monitoring network and gaps in data collection

The Swiss Soil Monitoring Network currently comprises 45 sites with long-term management data. Although permanent grassland accounts for 58% (71% including alpine summer pastures) of Switzerland's agricultural area (Stettler & Probst, 2023; Swiss Federal Statistical Office, 2025), the 19 permanent grassland sites were excluded from this study because their management regimes and soil dynamics differ fundamentally from those of arable systems. The remaining 26 arable sites represent a relatively small sample size compared to similar analyses, such as the Bavarian soil monitoring study with 80 cropland sites (Wiesmeier et al., 2025). In addition, organically managed (Bio Suisse) farms account for 27% of the study sites, exceeding the national average of 12% organically managed arable land (Swiss Federal Statistical Office, 2025), which may bias the representation of management intensity toward more extensive systems. Because the monitoring network is observational rather than factorial, interactions among indicators were not modelled to avoid overfitting and spurious inference. While these constraints limit causal attribution, they allow a focused evaluation of predictor importance and soil-property-specific responses under realistic agricultural conditions.

Several limitations in soil and management data further constrain inference, particularly for short-term change variables. The timing of soil sampling strongly influences short-term climatic conditions and, in turn, the inferred drivers of change, highlighting the sensitivity of temporal analyses to weather variability. Bulk density measurements are currently available for only three sampling periods, and their high short-term variability may mask longer-term trends (Wuest, 2015). In addition, the available soil P data only cover pseudo-total (HNO_3 -extractable) P rather than more labile P fractions. Consequently, PTP is likely to be less sensitive to short-term management than more labile P fractions, which respond more rapidly to changes in fertilization (Farhan et al., 2021). Management data rely on farmer-reported information, resulting in variable data quality among sites and necessitating gap-filling procedures. In addition, detailed information on machinery use, the nutrient composition of organic fertilizers, and crop-derived C and N inputs is limited, requiring standardized assumptions across sites.

Future soil monitoring would benefit from expanding the number of

intensively monitored sites, increasing sampling frequency for soil properties, and maintaining consistent, reproducible analytical methods. Further gains could be achieved by extending, harmonizing, and increasingly automating management data collection, including more detailed information on field traffic and organic fertilizer composition. Such improvements would strengthen the capacity of monitoring networks to disentangle soil, climate, and management effects and to support more robust assessments of soil change and manageability under evolving agricultural and climatic conditions.

5. Conclusion

This study shows that understanding soil dynamics requires a clear separation between long-term soil states and short-term changes, as these are related to fundamentally different combinations of soil, climate, and management controls. While inherent soil characteristics and climate set constraints on baseline levels of SOC, TN, PTP, and BD, management is more strongly associated with the direction, magnitude, and risk of short-term change within these constraints. This distinction has important implications for both interpretation and application: apparent weak management relationships with soil states do not indicate ineffectiveness, but rather reflect buffering, legacy effects, and nonlinear damping that limit responsiveness at long time scales. By combining linear and nonlinear modelling approaches, our analysis shows that robust ranking of dominant predictors and identification of context-dependent thresholds are complementary rather than competing objectives. Linear models provide stable inference on driver hierarchies across heterogeneous monitoring data, whereas nonlinear models reveal when and under which conditions management-soil property relationships are stronger or weaker across climatic and soil contexts. These insights highlight that soil manageability is property-specific. Soil organic C and TN show meaningful sensitivity to management at shorter time scales, whereas PTP remains strongly constrained by soil chemical buffering and legacy pools, and BD is primarily associated with climatic conditions and shows limited responsiveness to management. Consequently, soil management and policy should prioritize continuity of protective measures and site-adapted management that reduces soil degradation risks and aligns practices with local soil and climate conditions. Incentives should therefore be aligned with the properties and time scales over which management can plausibly exert influence. More broadly, this work illustrates the value of observational soil monitoring networks for diagnosing dominant controls, context dependence, and limits of intervention under real-world conditions, while underscoring the need for improved temporal resolution and management data to better capture soil dynamics under ongoing climatic and agricultural change.

CRediT authorship contribution statement

Fabien Durand-Maniclas: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Olivier Heller:** Writing – review & editing, Validation, Software, Methodology. **Michael Müller:** Writing – review & editing, Validation, Investigation, Data curation. **Ramon Zimmermann:** Writing – review & editing, Visualization, Investigation. **Daniel Suter:** Writing – review & editing, Investigation. **Florian Walder:** Writing – review & editing. **Juliane Hirte:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.geoderma.2026.118066>.

Data availability

Data will be made available on request.

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