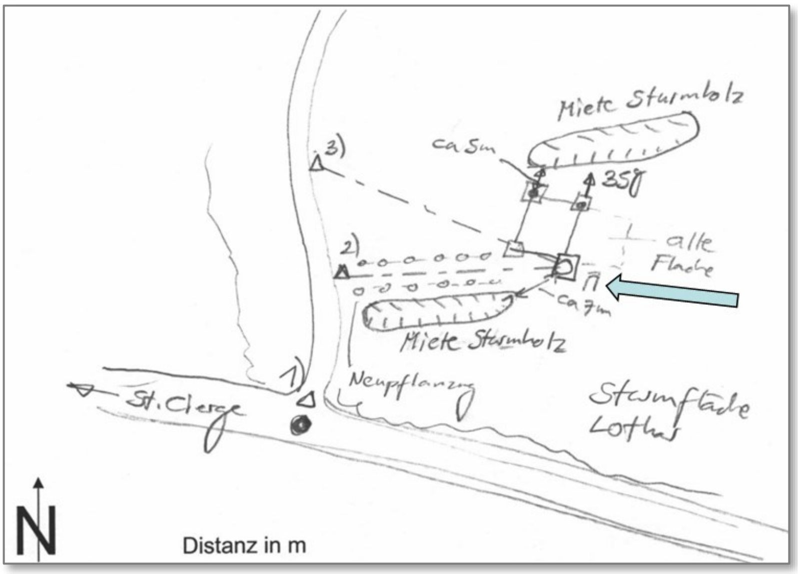
Agroscope Science | No. 216 / 2025



The Development of Carbon Stocks in Topsoil and Subsoil at National Soil Monitoring Sites over 30 Years

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Federal Department of Economic Affairs, Education and Research EAER
Agroscope

Imprint

Publisher	Agroscope Schwarzenburgstrasse 161 3003 Bern www.agroscope.ch
Information	Iris.wollmann@agroscope.admin.ch
Cover Photo	Agroscope
Download	www.agroscope.ch/science
Copyright	© Agroscope 2025
ISSN	2296-729X
DOI	https://doi.org/10.34776/as216e

Content

Abstract

Total organic carbon (TOC) stocks in soil are of central importance for agricultural productivity, climate regulation, and soil ecological functions. They are strongly influenced by environmental conditions and agricultural management practices, yet changes in TOC stocks often only become detectable over decades. Long-term monitoring programs such as the Swiss National Soil Monitoring Network (NABO) enable reliable detection of such changes. While no changes in topsoil (0–20 cm) TOC have been observed at more than 100 NABO sites over the past 30 years, data on subsoil dynamics remain scarce. This gap reflects the later introduction of systematic subsoil sampling and inconsistencies in sampling procedures, depth intervals, TOC analysis, and bulk density determination compared with the first NABO monitoring period (1985–1989). The aims of this study were therefore to (i) harmonize data from the first (1985–1989) and seventh (2015–2019) monitoring period for profile-wide TOC stock calculations, (ii) quantify land use-specific changes in TOC stocks, (iii) assess the influence of pedoclimatic factors on TOC stocks and their temporal dynamics, and (iv) identify data limitations and provide recommendations for future monitoring.

TOC stocks are calculated from measured TOC content and bulk density. Nearly complete datasets on TOC content and bulk density were available for 58 cropland, grassland, orchard/vineyard, and forest sites for both monitoring periods. To ensure comparability, four harmonization steps were implemented: (1) TOC contents determined with different analytical methods were standardized using a generalized linear model; (2) missing bulk density values were estimated with a newly developed pedotransfer function; (3) the depth distributions of the soil parameters were standardized to 60 cm using mass-preserving spline interpolation; and (4) a regression model was developed to correct method-specific differences in bulk density between the monitoring periods. Changes in the harmonized TOC stocks were analyzed in relation to land use and site conditions using linear models. Finally, the minimal detectable difference, pedoclimatic effects, and uncertainties from the harmonization steps were quantified.

Average TOC stocks across the first and seventh monitoring period were 62 and 55 t TOC ha^{-1}, respectively, in the topsoil (0–20 cm), and 57 and 50 t TOC ha^{-1}, respectively, in the subsoil (20–60 cm). Topsoil TOC stocks in croplands declined significantly over time, whereas changes in subsoil and in other land uses were not statistically significant. Depending on land use and soil depth, changes would have needed to be up to 18 times larger to be statistically significant. The topsoil in grassland had 1.5 times higher TOC stocks than cropland—likely due to lower soil disturbance and greater root biomass—while forests and orchards/vineyards showed intermediate values. No significant differences in subsoil TOC stocks were found between land uses.

Topsoil TOC stocks in cropland, grassland, and forest sites were positively correlated with clay content, pointing at greater stabilization of organic matter in fine-textured soils. In the subsoil, TOC stocks correlated positively with soil pH, elevation, or slope, depending on land use. Changes in TOC stocks between monitoring periods were primarily negatively correlated with initial TOC stocks, suggesting gains in soils with initially low carbon and losses in soils with initially high carbon. Uncertainties in data harmonization were 7–9% for gap-filling and method conversions, but only ~1% for depth interpolation.

For future monitoring of TOC stocks, differences in subsoil depth intervals are considered uncritical when spline-based interpolation is applied. However, consistent analytical methods for TOC content and bulk density, as well as quantification of small-scale variability and stone content, are essential for robust, profile-wide estimates of TOC stocks. To better evaluate management effects on cropland TOC and support sustainable soil management in Switzerland, future monitoring should systematically include management data alongside pedoclimatic factors.

Zusammenfassung

Der Gesamtvorrat an organischem Kohlenstoff (total organic carbon − TOC) im Boden ist von zentraler Bedeutung für die landwirtschaftliche Produktivität, die Klimaregulation und die ökologischen Funktionen des Bodens. Er wird massgeblich durch Umweltbedingungen sowie durch landwirtschaftliche Bewirtschaftungspraktiken beeinflusst. Änderungen im TOC-Vorrat lassen sich häufig erst im Verlauf von Jahrzehnten quantifizieren. Langfristige Messprogramme wie die Nationale Bodenbeobachtung (NABO) ermöglichen es, solche Veränderungen zuverlässig zu erfassen. Während im Oberboden (0-20 cm) an über 100 NABO-Standorten in den letzten 30 Jahren keine Veränderungen festgestellt wurden, fehlen bisher

Daten zur langfristigen Entwicklung des TOC-Vorrats im Unterboden. Grund dafür sind die spätere Einführung einer systematischen Tiefenbeprobung und Unterschiede in der Probenahme, Tiefeneinteilung, TOC-Analytik und Bestimmung der Lagerungsdichte im Vergleich zur ersten Erhebungsperiode der NABO (1985–1989). Ziel dieser Studie ist es daher, (i) die Daten der ersten (1985–1989) und siebten (2015–2019) Erhebung zur Berechnung des profilumfassenden TOC-Vorrats zu harmonisieren, (ii) Veränderungen des TOC-Vorrats in Abhängigkeit von der Landnutzung zu quantifizieren, (iii) den Einfluss pedoklimatischer Bedingungen auf den TOC-Vorrat und dessen Entwicklung zu analysieren sowie (iv) bestehende Limitationen der Datengrundlage zu identifizieren und Empfehlungen für künftige Erhebungen abzuleiten.

Der TOC-Vorrat berechnet sich aus dem gemessenen TOC-Gehalt und der Lagerungsdichte des Bodens. Für 58 Standorte der Landnutzungen Ackerbau, Grasland, Obst-/Rebbau und Wald lagen annähernd vollständige Daten zum gemessenen TOC-Gehalt und zur Lagerungsdichte für beide Erhebungen vor. Zur Vergleichbarkeit der TOC-Vorräte wurden vier Harmonisierungsschritte durchgeführt: (1) Die TOC-Gehalte unterschiedlicher Messmethoden wurden mithilfe eines generalisierten linearen Modells vereinheitlicht, (2) fehlende Lagerungsdichten durch eine neu entwickelte Pedotransferfunktion geschätzt, (3) die Tiefenverteilung der Bodenparameter mittels massenerhaltender Spline-Interpolation bis 60 cm standardisiert und (4) ein Regressionsmodell zur Korrektur methodenbedingter Unterschiede in der Lagerungsdichte entwickelt. Die harmonisierten TOC-Vorräte sowie deren Änderungen wurden in Abhängigkeit von Landnutzung und Standortbedingungen mithilfe linearer Modelle ausgewertet. Zudem wurden die minimale nachweisbare Differenz des TOC-Vorrats, pedoklimatische Einflüsse und Unsicherheiten der einzelnen Harmonisierungsschritte quantifiziert.

Der TOC-Vorrat betrug in der ersten und siebten Erhebung durchschnittlich 62 respektive 55 t TOC ha^{-1} im Oberboden (0–20 cm) und 57 respektive 50 t TOC ha^{-1} im Unterboden (20–60 cm). Im Oberboden von Ackerbaustandorten zeigte der TOC-Vorrat eine signifikante Abnahme über die Zeit; im Unterboden und innerhalb der anderen Landnutzungen war der Unterschied zwischen den Erhebungen statistisch nicht signifikant. Hier wären je nach Landnutzung und Bodentiefe 1.0–17.6 mal grössere Abweichungen erforderlich gewesen, um signifikante Veränderungen nachweisen zu können. Grasland wies im Oberboden einen 1.5-fach höheren TOC-Vorrat auf als Ackerland – vermutlich bedingt durch geringere Störungen des Bodens und höhere Wurzelbiomasse – während Wald-, Obst- und Rebbaustandorte dazwischen lagen. Im Unterboden wurden keine signifikanten Unterschiede im TOC-Vorrat zwischen den Landnutzungen festgestellt.

Auf Acker-, Grasland- und Waldstandorten zeigte der TOC-Vorrat im Oberboden einen positiven Zusammenhang mit dem Tongehalt, was auf eine höhere Stabilisierung organischen Materials in feinkörnigen Böden hinweist. Je nach Landnutzung korrelierte der TOC-Vorrat im Unterboden positiv mit dem pH-Wert, der Höhenlage oder der Hangneigung. Die Änderung des TOC-Vorrats zwischen erster und siebter Erhebung stand primär in negativem Zusammenhang mit dem initialen TOC-Vorrat, was auf eine Zunahme bei zunächst niedrigen, und eine Abnahme bei zunächst hohem TOC-Vorrat schliessen lässt. Die Unsicherheiten in der Datenharmonisierung lagen bei jeweils 7–9% für die Schätzung fehlender Werte und Umrechnungen von Werten zwischen verschiedenen Bestimmungsmethoden sowie bei nur etwa 1% für die Tiefeninterpolation.

Für das zukünftige Monitoring des TOC-Vorrats gelten Unterschiede in der Tiefeneinteilung von Unterbodenproben als unkritisch – vorausgesetzt, es kommen Spline-basierte Interpolationsverfahren zum Einsatz. Eine konsistente oder harmonisierte Methodik der Kohlenstoffanalytik und Bodendichtebestimmung sowie die Quantifizierung der kleinräumigen Variabilität und des tatsächlichen Skelettgehalts sind jedoch unerlässlich für belastbare, profilumfassende TOC-Berechnungen. Um den Einfluss von Bewirtschaftungsmassnahmen auf den TOC-Vorrat in Ackerböden und für ein nachhaltiges Bodenmanagement in der Schweiz fundiert bewerten zu können, sollten künftig neben pedoklimatischen Bedingungen auch Informationen zur Bodenbewirtschaftung systematisch in die Datenauswertung einbezogen werden.

Diese Publikation ist auch integral auf Deutsch erschienen: https://doi.org/10.34776/as216g

Résumé

Les réserves de carbone organique total (COT) dans le sol jouent un rôle central pour la productivité agricole, la régulation du climat et les fonctions écologiques du sol. Elles sont fortement influencées par les conditions environnementales ainsi que par les pratiques d'exploitation agricole. Les changements dans les réserves de COT ne peuvent souvent être quantifiés qu'au bout de plusieurs décennies. Des programmes de mesures à long terme, tels que l'Observatoire national

des sols (NABO), permettent de détecter de manière fiable de tels changements. Alors qu'aucune évolution n'a été constatée dans la couche supérieure (0–20 cm) sur plus de 100 sites NABO au cours des 30 dernières années, il n'existe jusqu'à présent aucune donnée sur l'évolution à long terme des réserves de COT dans la couche sous-jacente. Cette lacune s'explique par l'introduction plus tardive d'un échantillonnage systématique en profondeur ainsi que par des différences dans la méthode d'échantillonnage, la répartition en profondeur, les méthodes analytiques du COT et la détermination de la densité apparente par rapport à la première période de mesure du NABO (1985-1989). L'objectif de cette étude est donc d'harmoniser d'un point de vue méthodologique les données de la première (1985–1989) et de la septième (2015–2019) période de relevés afin de calculer les réserves de COT en fonction du profil, (ii) de quantifier l'évolution de ces réserves en fonction de l'utilisation du sol, (iii) d'analyser l'influence des conditions pédoclimatiques sur les réserves de COT et son évolution et enfin (iv) d'identifier les limites existantes de la base de données et de formuler des recommandations pour les relevés futurs.

Les réserves de COT sont calculées à partir de la teneur mesurée en COT et de la densité apparente du sol. Pour 58 sites correspondant à l'utilisation grandes cultures, surfaces herbagères, arboriculture, viticulture et forêts, des données presque complètes sur la teneur en COT et la densité apparente étaient disponibles pour les deux périodes de relevés. Quatre étapes d'harmonisation ont été réalisées afin de comparer les réserves de COT: (1) les teneurs en COT obtenues par différentes méthodes de mesure ont été unifiées à l'aide d'un modèle linéaire généralisé, (2) les densités apparentes manquantes ont été estimées à l'aide d'une nouvelle fonction de pédotransfert, (3) la répartition en profondeur des paramètres du sol a été standardisée jusqu'à 60 cm à l'aide d'une interpolation par splines conservant la masse et (4) un modèle de régression a été développé pour corriger les différences dues à la méthode dans la densité apparente. Les réserves de COT harmonisées ainsi que leur évolution ont été analysés à l'aide de modèles linéaires en fonction de l'utilisation du sol et des conditions du site. Par ailleurs, la différence minimale détectable dans les réserves de COT, les influences pédoclimatiques et les incertitudes associées à chaque étape de l'harmonisation ont été quantifiées.

Les réserves de COT étaient en moyenne de respectivement 62 et 55 t de COT ha^{-1} dans la couche supérieure (0–20 cm) pour la première et la septième période de relevés et de respectivement 57 et 50 t de COT ha^{-1} dans la couche sous-jacente (20–60 cm). Dans la couche supérieure des sites grandes cultures, les réserves de COT ont significativement diminué au fil du temps; dans la couche sous-jacente et pour les autres types d'utilisation des terres, les différences entre les périodes de relevés n'étaient pas significatives du point de vue statistique. Selon l'utilisation du sol et la profondeur, des écarts 1,0 à 17,6 fois plus importants auraient été nécessaires pour détecter des changements significatifs. Dans la couche supérieure des surfaces herbagères, des réserves de COT 1,5 fois plus élevées que pour les grandes cultures – probablement en raison d'une moindre perturbation du sol et d'une biomasse racinaire plus importante – ont été relevées, tandis que les sites forestiers, arboricoles et viticoles affichaient des valeurs intermédiaires. Aucun écart significatif n'a été observé dans la couche sous-jacente entre les différentes utilisations du sol.

Dans les grandes cultures, les surfaces herbagères et les sites forestiers, une corrélation positive a été observée entre la teneur en argile et les réserves de COT dans la couche supérieure, ce qui indique une meilleure stabilisation de la matière organique dans les sols à texture fine. Selon l'utilisation du sol, les réserves de COT dans la couche sous-jacente présentaient une corrélation positive avec le pH, l'altitude ou la déclivité. L'évolution des réserves de COT entre la première et la septième période de relevés était principalement corrélée négativement avec les réserves initiales de COT, ce qui suggère une augmentation là où les valeurs initiales étaient faibles et une diminution là où elles étaient élevées. Les incertitudes liées à l'harmonisation des données étaient de 7 à 9 % pour l'estimation des valeurs manquantes ainsi que la conversion des valeurs entre différentes méthodes de mesure et environ de seulement 1 % pour l'interpolation en profondeur.

Pour le suivi futur des réserves de COT, les différences dans la répartition en profondeur des échantillons de la couche sous-jacente ne sont pas critiques, à condition d'utiliser des méthodes d'interpolation basées sur les splines. Toutefois, une méthodologie cohérente ou harmonisée pour l'analyse du carbone et la détermination de la densité du sol ainsi que la quantification de la variabilité spatiale à petite échelle et de la pierrosité réelle sont essentielles pour des calculs fiables des réserves de COT à l'échelle du profil. Afin d'évaluer de manière fondée l'influence des pratiques d'exploitation agricole sur les réserves de COT sur les sols des grandes cultures et de promouvoir une gestion durable des sols en Suisse, les données relatives à l'exploitation des terres devraient également être intégrées systématiquement dans l'analyse des données, en complément des conditions pédoclimatiques.

Riassunto

Le riserve di carbonio organico totale (TOC) nel suolo sono di fondamentale importanza per la produttività agricola, la regolazione del clima e le funzioni ecologiche del suolo stesso. Esse sono fortemente influenzate dalle condizioni ambientali e dalle pratiche di gestione agricole. I cambiamenti nelle riserve di TOC possono spesso essere quantificati solo nel corso di decenni. Programmi di monitoraggio a lungo termine, come l'Osservatorio nazionale dei suoli (NABO), consentono di rilevare in modo affidabile tali cambiamenti. Nello strato superficiale (0–20 cm) non sono stati osservati cambiamenti in oltre 100 siti NABO negli ultimi 30 anni; tuttavia, mancano ancora dati sull'evoluzione sul lungo periodo delle riserve di TOC negli strati inferiori. Ciò è dovuto alla successiva introduzione di un campionamento sistematico in profondità e a differenze nei metodi per il prelievo dei campioni, nella suddivisione in profondità, nelle analisi del TOC e nella determinazione della densità apparente rispetto al primo periodo di rilevamento NABO. Lo scopo di questo studio è quindi quello di (i) armonizzare i dati del primo (1985–1989) e del settimo (2015–2019) rilevamento al fine di calcolare la riserva di TOC in funzione del profilo, (ii) quantificare i cambiamenti della riserva in funzione dell'uso del suolo, (iii) analizzare l'impatto delle condizioni pedoclimatiche sulle riserve di TOC e sul loro sviluppo, nonché (iv) identificare le limitazioni esistenti della base di dati e formulare raccomandazioni per i rilevamenti futuri.

Le riserve di TOC si calcolano in base al tenore di TOC rilevato e alla densità apparente del suolo. Per 58 siti, il cui suolo è destinato a campicoltura, superfici inerbite, frutticoltura, viticoltura e foreste, erano disponibili dati quasi completi sul tenore di TOC rilevato e sulla densità apparente per entrambi i rilevamenti. Per rendere confrontabili le riserve di TOC, sono state effettuate quattro fasi di armonizzazione: (1) i tenori di TOC ottenuti attraverso diversi metodi di misurazione sono stati uniformati tramite un modello lineare generalizzato; (2) le densità apparenti mancanti sono state stimate tramite una nuova funzione di pedotrasferimento; (3) la distribuzione in profondità dei parametri del suolo è stata standardizzata fino a 60 cm mediante interpolazione spline a conservazione di massa ed (4) è stato sviluppato un modello di regressione per correggere le differenze nella determinazione della densità apparente scaturite dai metodi usati. Le riserve di TOC armonizzate, così come i loro cambiamenti, sono state analizzati mediante modelli lineari in funzione dell'uso del suolo e delle condizioni locali. Sono state inoltre quantificate la differenza minima rilevabile nella riserva di TOC, le influenze pedoclimatiche e le incertezze delle singole fasi di armonizzazione.

Le riserve di TOC erano in media pari a 62 e 55 t TOC ha^{-1} nello strato superficiale (0–20 cm) rispettivamente nel primo e nel settimo rilevamento, e a 57 e 50 t TOC ha^{-1} nello strato profondo (20–60 cm). Nello strato superficiale dei siti a uso agricolo, si è osservata una diminuzione significativa della riserva di TOC nel tempo; nello strato profondo e nel caso di altri usi del suolo, le differenze tra i rilevamenti non risultavano statisticamente significative. A seconda dell'uso del suolo e della profondità, infatti, sarebbero state necessarie deviazioni da 1,0 a 17,6 volte maggiori per rilevare variazioni significative. Nello strato superficiale, le superfici inerbite presentavano una riserva di TOC 1,5 volte superiore rispetto ai terreni agricoli, probabilmente a causa del minore disturbo del suolo e della maggiore biomassa radicale, mentre i siti forestali, frutticoli e viticoli presentavano valori intermedi. Nello strato profondo non sono state riscontrate differenze significative nella riserva di TOC tra i diversi usi del suolo.

Nei siti agricoli, prativi e forestali, la riserva di TOC nello strato superficiale mostrava una correlazione positiva con il contenuto di argilla, indicando una maggiore stabilizzazione della sostanza organica nei suoli a grana fine. A seconda dell'uso del suolo, la riserva di TOC nello strato profondo era positivamente correlata al valore pH, all'altitudine o alla pendenza. Il cambiamento nella riserva di TOC tra il primo e il secondo rilevamento era principalmente correlato negativamente con la riserva di TOC iniziale, il che indica un aumento nei siti con valori iniziali bassi e una diminuzione in quelli con valori iniziali elevati. Le incertezze legate all'armonizzazione dei dati erano del 7–9% per la stima dei valori mancanti e per la conversione dei valori tra metodi analitici differenti, e di circa l'1% per l'interpolazione della profondità.

Per il futuro monitoraggio delle riserve di TOC, le differenze nella suddivisione per profondità dei campioni dello strato profondo non sono considerate critiche, a condizione che si utilizzino metodi di interpolazione basati su spline. Tuttavia, una metodologia coerente o armonizzata per l'analisi del carbonio e la determinazione della densità apparente, così come la quantificazione della variabilità spaziale su piccola scala e del reale contenuto scheletrico sono, a seconda del profilo, essenziali per calcoli affidabili della riserva di TOC. Per valutare in modo fondato l'influenza delle pratiche agricole sulla riserva di TOC nella campicoltura e promuovere una gestione sostenibile del suolo in Svizzera, in futuro dovrebbero essere sistematicamente integrate nell'analisi dei dati anche le informazioni sulla gestione del suolo, oltre alle condizioni pedoclimatiche.

1 Introduction and objectives

The total organic carbon (TOC) stock in soils underpins their regulatory, habitat, and productive functions and represents a key component of the global carbon cycle. TOC stocks are therefore highly relevant both for agricultural production and for climate dynamics. Data on TOC stocks and their temporal development are used in scientific research, agricultural extension (Pfister et al., 2025), climate reporting (FOEN, 2025), and in the implementation of agricultural and environmental policy (Swiss Federal Council, 2025).

Soil TOC dynamics are largely driven by inputs of organic material, microbial decomposition, and carbon losses through soil respiration as CO_2 (Jackson et al., 2017). All three processes are influenced in the short and long term by agricultural management—such as crop choice, fertilization, and tillage—as well as by environmental factors including soil texture, geology, climate, and weather (Funes et al., 2019; Vos et al., 2019; Wiesmeier et al., 2012). Because changes in TOC stocks typically occur over long timescales, they often only become detectable after several decades (Schrumpf et al., 2011). Long-term soil monitoring programs are therefore essential to identify long-term changes in TOC stocks, validate soil carbon models, and develop practice-oriented recommendations (Capriel, 2013; van Wesemael et al., 2011). Over the past decades, many long-term studies in European countries have reported declines in TOC stocks of agricultural soils (Arrouays et al., 2001; Goidts & van Wesemael, 2007; Heikkinen et al., 2013; Kühnel et al., 2019; Lettens et al., 2005; Taghizadeh-Toosi et al., 2014), although some studies have found increases (Dupla et al., 2021; Gubler et al., 2019; Wenzel et al., 2022) or no changes (Moll-Mielewczik et al., 2023).

Most of the soil TOC is stored in the topsoil, since carbon is allocated not only via roots but also through aboveground plant residues and organic fertilizers. For this reason, most studies focus on topsoil (Capriel, 2013; Goidts, Wesemael, & Van Oost, 2009; Gubler et al., 2019). However, other research has shown that subsoil horizons also play an important role in TOC storage and should be included in long-term monitoring programs (Lorenz & Lal, 2005; Skadell et al., 2023). This is especially relevant because roots are the main source of carbon input to the subsoil, where carbon is characterized by longer residence times (Poeplau et al., 2021; Rumpel & Kögel-Knabner, 2011). Global estimates suggest TOC stocks of about 70 t TOC ha^{-1} in topsoil and about 80 t TOC ha^{-1} in subsoil. In Europe, values are slightly higher for topsoil (ca. 75–100 t TOC ha^{-1}) and similar for subsoil (ca. 60–100 t TOC ha^{-1}) (Panagos et al., 2022; Wang et al., 2024). Marked differences are observed between land uses: croplands generally contain lower TOC stocks (around 60 and 70 t TOC ha^{-1} in topsoil and subsoil, respectively) compared with grasslands and forests (90–100 and 100–120 t TOC ha^{-1}, respectively) (Panagos et al., 2022).

Within the Swiss National Soil Monitoring Network (NABO), TOC stocks in topsoil have been measured at more than one hundred sites across Switzerland for nearly 40 years. Previous studies have shown that topsoil TOC stocks have remained stable on average over time (Gross et al., 2024; Gubler et al., 2019; Moll-Mielewczik et al., 2023). In contrast, no comprehensive evaluation has yet been done for subsoils. Subsoil sampling and analysis were carried out systematically only during the initial site characterization in the first monitoring period (1985–1989) and again starting with the seventh monitoring period (2015–2019). Significant methodological differences between these two periods—such as depth intervals used for sampling, TOC analysis, and bulk density determination—complicate assessments of temporal changes in subsoil TOC stocks. As a result, there is not only a lack of information on changes in subsoil TOC stocks at NABO sites over the past decades, but also a gap in understanding the underlying drivers of subsoil carbon dynamics in Switzerland.

The objectives of this study are therefore to:

1. harmonize the depth intervals of soil samples as well as carbon and bulk density data between the first and seventh monitoring period,
2. quantify changes in TOC stocks in topsoil and subsoil between the first and seventh NABO monitoring period with respect to land use,
3. assess the influence of pedoclimatic conditions on TOC stocks in topsoil and subsoil and on their changes between the first and seventh monitoring period, and
4. identify limitations of the current dataset and derive recommendations for robust assessments of TOC stocks in topsoil and subsoil.

2 Data collection

2.1 NABO network and sites

The NABO monitoring network currently comprises 114 sites distributed across Switzerland, where chemical and physical soil properties have been measured since 1985, and biological properties (microbiological and molecular-genetic) for about ten years (Gross et al., 2024). Sampling follows a five-year cycle. Not all sites are sampled in the same year; instead, sampling of the entire network is spread across five years before a new monitoring period begins. Since the launch of the NABO program, eight monitoring periods have been completed. Starting with the seventh period (2015–2019), NABO sites have been divided into main and secondary sites, which differ in sampling intensity (Schwab & Gubler, 2015). At the 89 main sites, composite samples are taken from 0–20 cm depth, along with samples down to 75 cm. For the present analysis, only sites with subsoil sampling during both the first and the seventh monitoring periods were considered.

During the first monitoring period (1985–1989), soil pits were excavated to the C horizon at all NABO sites (then 102 sites; Desaules & Studer, 1993). The exact location of these pits is not precisely documented for every site. In many cases, pit profiles are sketched on the profile data sheets from the first monitoring period, with the distance to the NABO sampling plot noted. For some sites, the distance can only be estimated from schematic sketches. At 30% of the sites, the recorded distance between pit and plot was 2 m; at 41% of sites, it was up to 10 m (estimated); and at 3% it exceeded 10 m. For 26% of sites, the distance is unknown because no pit was drawn on the profile sheets. Soil classification followed the methodology of the Soil Mapping Service of the Swiss Federal Research Station for Agronomy in Zürich-Reckenholz (internal FAP soil classification manual by Erwin Frei, unpublished).

Land use categories in the NABO network include cropland, vegetable production, orchards, vineyards, permanent grassland, forest, urban parks, and protected sites. Protected sites are almost exclusively peat or fen locations and were excluded from this analysis. Some land use categories included very few sites and were therefore merged with related categories: urban parks with grassland, and vegetable production with cropland. Orchards and vineyards were also combined into one category, resulting in four land use categories used in the analysis: cropland, grassland, orchard/vineyard, and forest (Figure 1).

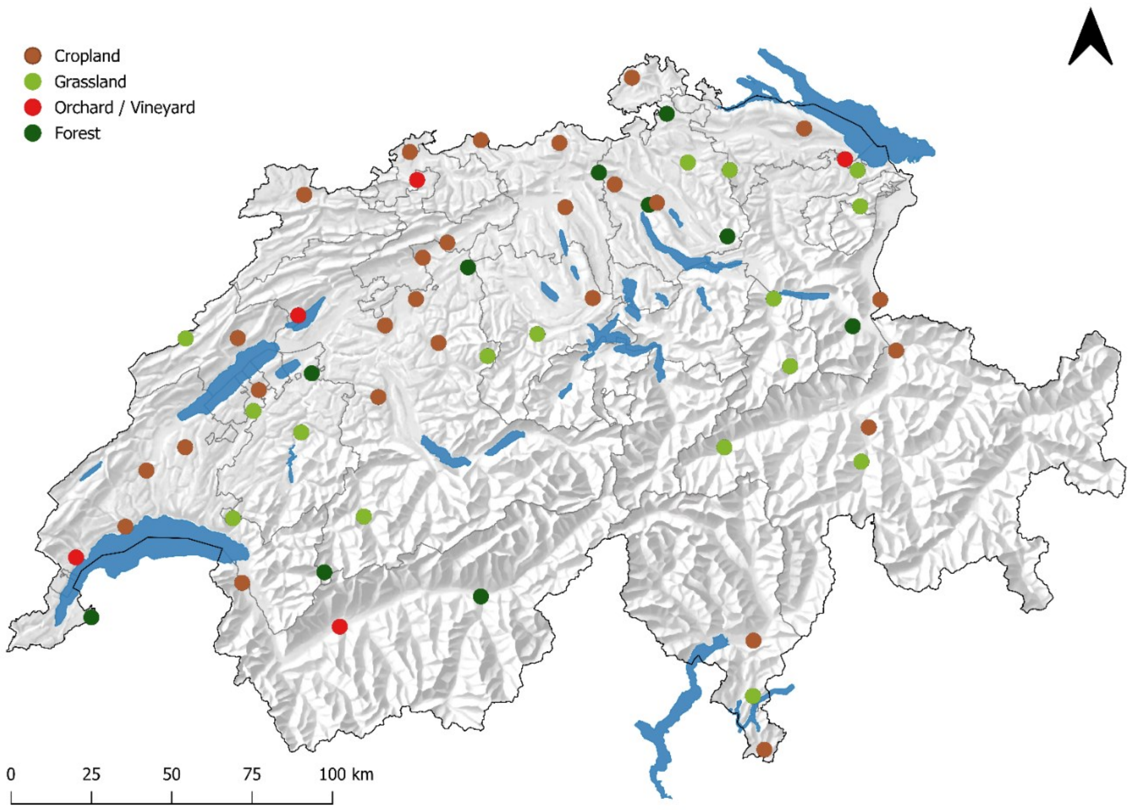

Figure 1: Location and land use of the NABO sites included in this study for TOC stock analysis.

2.2 Soil sampling and sample preparation

In the first monitoring period, at 52 of the initial 102 sites, soil samples were collected from three profile walls in fixed depth intervals of 20 cm, from the surface down to the C horizon. At the remaining 50 sites, samples were collected in a similar manner but by pedological horizon rather than fixed depth intervals. Horizons thicker than 40 cm were subdivided into two depth layers. Organic surface horizons were not sampled at the first 52 sites, but at the remaining 50 sites they were collected and analyzed as separate horizons. To determine the bulk density of the fine earth fraction (BD_{FE}), undisturbed core samples were taken with steel cylinders, three (1000 cm^3) to five (100 cm^3) replicates per horizon, from the middle of each horizon (Desaules & Studer, 1993). The stone content (in vol. %) recorded in the profile sheets was based on visual estimates at the soil pit. Samples for analysis of C were dried at 40 °C, crushed, and sieved to 2 mm. Further details are provided in Desaules and Studer (1993).

In the seventh monitoring period, sampling was carried out with a HUMAX impact probe (75 cm length, 5 cm inner diameter; GreenGround®) directly adjacent to the NABO sampling plot (10 × 10 m). At each site, four cores (up to 14 m apart) were taken to a maximum depth of 75 cm and subdivided into pedological horizons. Horizon boundaries were determined while accounting for core compression. Sampling procedures and the calculation of compression for individual core segments are described in detail in Schwab and Gubler (2016). The samples from the four cores per site and monitoring period were pooled by horizon, and mean horizon depths were calculated. Horizon depths were also averaged across the four cores for the calculation of BD_{FE}. Soil samples were dried at 40 °C for 48 hours and sieved to 2 mm. The stone content in the horizon samples was determined by the mass of the sieved residue.

2.3 Carbon analysis

In the first monitoring period, total carbon content was measured using a Carmhograph (FAC, 1989). The method is based on dry combustion at 1000 °C in an oxygen stream. After the generated CO_2 was absorbed in NaOH, the resulting change in conductivity was determined conductometrically. Combustion at 1000 °C also includes inorganic carbon, which was measured separately on subsamples after treatment with 5% hydrochloric acid (FAC, 1989). The amount of organic carbon, referred to as “orgC” in Desaules and Studer (1993), was calculated as the difference between total and inorganic carbon. As part of data harmonization, samples from soil pits of about 30 sites from the first monitoring period were remeasured by elemental analysis.

In the seventh monitoring period, total carbon content of each pedological horizon was determined by elemental analysis, based on thermal oxidation at 1100 °C (ISO 10694, 1995) using a C/N analyzer (Trumac, Leco). Inorganic carbon was determined by digestion with hydrochloric acid and subsequent volumetric measurement of the released CO_2 following the Scheibler method (Agroscope, 2020). The amount of organic carbon, referred to as “TOC”, was calculated as the difference between total and inorganic carbon.

2.4 Determination of soil bulk density

In the first monitoring period, the undisturbed core samples taken from the soil pits were dried at 105 °C to constant weight and weighed after subtracting the weight of the cylinder (Desaules & Studer, 1993). The cylinder contents were then washed through a 2 mm sieve, and the dried residue retained on the sieve, corresponding to the stone fraction, was weighed. To determine the volume of stones, their mass was divided by an assumed average particle density of 2.65 g cm^{-3}. The oven-dry bulk density of the fine earth was then calculated according to the following equation (Desaules & Studer, 1993):

$$\text{Bulk density of the fine earth } [\text{g cm}^{-3}] = \frac{\text{"Fine earth weight" } [\text{g}]}{\text{Volume of the cylinder } [\text{cm}^3] - \text{Volume of stones } [\text{cm}^3]} \tag{1}$$

The resulting density values do not correspond to the bulk density of the fine earth as defined in the current NABO methodology (BD_{FE} [g cm⁻³] = $mass_{FE}$ / $volume_{sample}$), but rather to the packing density of the fine earth (PD_{FE} [g cm⁻³]), defined as the mass per volume of the fine earth fraction of the sample (PD_{FE} = $mass_{FE}$ / $volume_{FE}$) (Schwab & Gubler, 2016). For the first monitoring period, continuous PD_{FE} values are not available for all soil depths; in particular, the subsoil dataset is incomplete, with 62 missing values out of a total of 127. The raw data originally used for bulk density calculations are no longer available.

In the seventh monitoring period, sample volume was calculated from the internal diameter and sampling depth, and together with the mass of the fine earth ($mass_{sample}$ – $mass_{stones}$) was used to determine BD_{FE} (Schwab & Gubler, 2016). With few exceptions, bulk density data are available continuously down to 75 cm depth.

2.5 Methodological differences between first and seventh monitoring period

Methodological differences in all aspects of sampling and analysis existed between the first and seventh monitoring period (Table 1).

Table 1: Comparison of methodological differences between the first and seventh monitoring period.

	First monitoring period	**Seventh monitoring period**
Type of soil sampling	Composite sample from 3 sides of a soil pit	Composite sample from 4 soil cores (HUMAX impact probe)
Distance between individual samples	< 1 m	up to 14 m
Distance from the NABO plot	2 m (30% of sites) ≤ 10 m (41% of sites) > 10 m (3% of sites) unknown (26% of sites)	≤ 1 m
Sampling depth	down to C horizon	down to 75 cm depth (maximum)
Depth intervals of the samples	defined soil depths (50% of sites) by horizon (50% of sites)	by horizon
Carbon analysis	dry combustion at 1000 °C (Carmhograph)	thermal oxidation at 1100 °C (C/N elemental analysis, Trumac Leco)
Determination of bulk density	PD_{FE} determined from cylinders (dried at 105 °C), assumed density of stones: 2.65 g cm^{-3}	BD_{FE} determined from volumetric samples collected with the Humax impact probe (dried at 40 °C)
Determination of stone content	visual estimation at the soil pit, sieve residues	sieve residues

2.6 Additional data

For the harmonization of bulk density measurements, additional data from the NABO soil physical monitoring program (NABOphys) were used (Supplementary Figure 1). Depth samples were collected with both the HUMAX impact probe and steel cylinders at 25 NABO sites (Schwab et al., 2022), 24 of which were also included in the TOC dataset. At each site, four 75 cm long cores were taken with the impact probe and subdivided into 5 cm segments, accounting for potential compression during sampling. Additionally, at each site, eight steel cylinder samples (5 cm each) were collected from three depths within a 60 cm deep borehole, representing topsoil, transition horizon, and subsoil. To determine BD_{FE}, both the core segments and steel cylinder samples were dried at 105 °C to constant weight. An average density of 2.4 g cm⁻³ was assumed for the stone content of the impact probe samples. For the steel cylinder samples, stones were washed out if visually estimated to exceed 10 vol. %, and the actual stone density was determined by water displacement.

Other data used in this study included soil texture variables (clay, sand, and silt content), pH, and potential cation exchange capacity (CEC), as well as site characteristics including mean annual temperature, mean annual precipitation, elevation, and slope (Table 2; Figures 2 and 3; Supplementary Figure 2). For 46 sites, texture data from the first monitoring period were used because no texture data were available for the seventh period, and texture is assumed to remain stable over long timescales. For the remaining 12 sites, the texture data from the first monitoring period were considered erroneous, and texture data from the sixth monitoring period were used instead. pH values from the first and seventh monitoring periods were averaged.

Table 2: Additional data including units, measurement methods, and references.

Variable	Unit	Method	Reference
Clay, silt, sand	%	pipette method	FAC 1989
pH value	-	0.01 M $CaCl_2$	first monitoring period: FAC 1989 seventh monitoring period: Agroscope 2020
potential CEC	mmolc kg^{-1}	percolation with $BaCl_2$ and atomic absorption spectroscopy	FAC 1989
Temperature	°C	average of annual means for 1985–2019	MeteoSwiss
Precipitation	mm	average of annual sums for 1985–2019	MeteoSwiss
Elevation	m	topographic maps	SwissTopo
Slope	%	Soil slope map	SwissTopo

Changes in temperature and precipitation between the two monitoring periods were also calculated. For this purpose, a linear regression was performed with temperature or precipitation per year as the dependent variable and year as the explanatory variable:

$$\Delta\text{Temperature a}^{-1} = \text{Coefficient of lm(Mean annual temperature} \sim \text{Year)} \tag{2}$$

$$\Delta\text{Precipitation a}^{-1} = \text{Coefficient of lm(Mean annual precipitation} \sim \text{Year)} \tag{3}$$

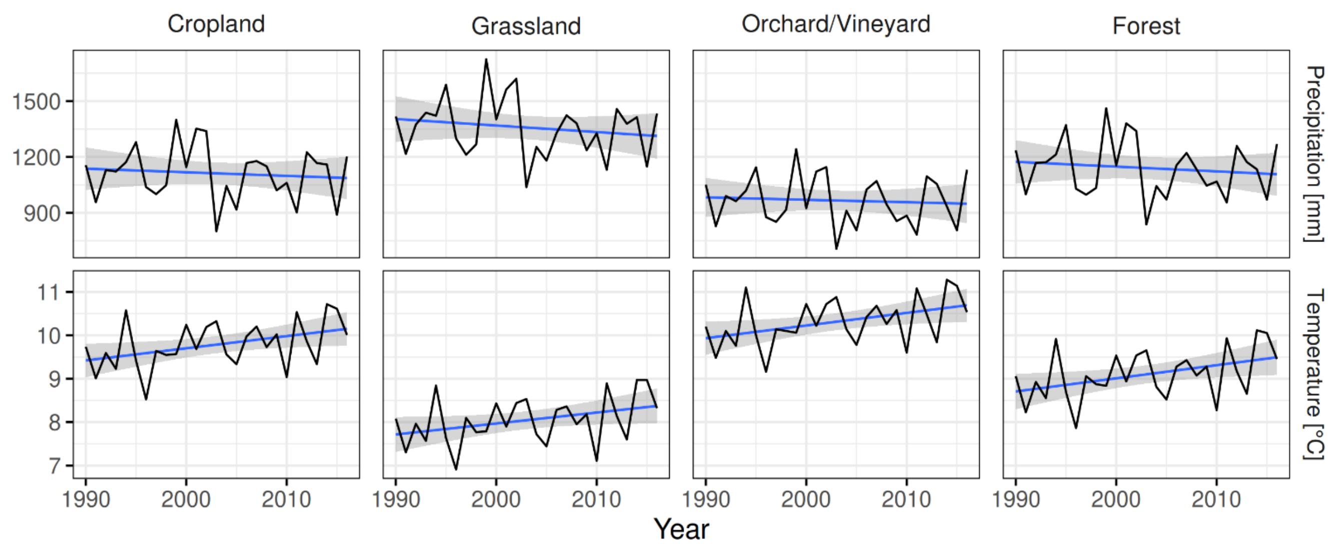

Figure 2: Mean annual precipitation (top) and mean annual temperature (bottom) at sites with different land uses between 1990 and 2016. The black line shows the annual mean across all sites per land use, the blue line indicates the linear trend, and the gray shaded area represents the 95% confidence interval of the linear trend.

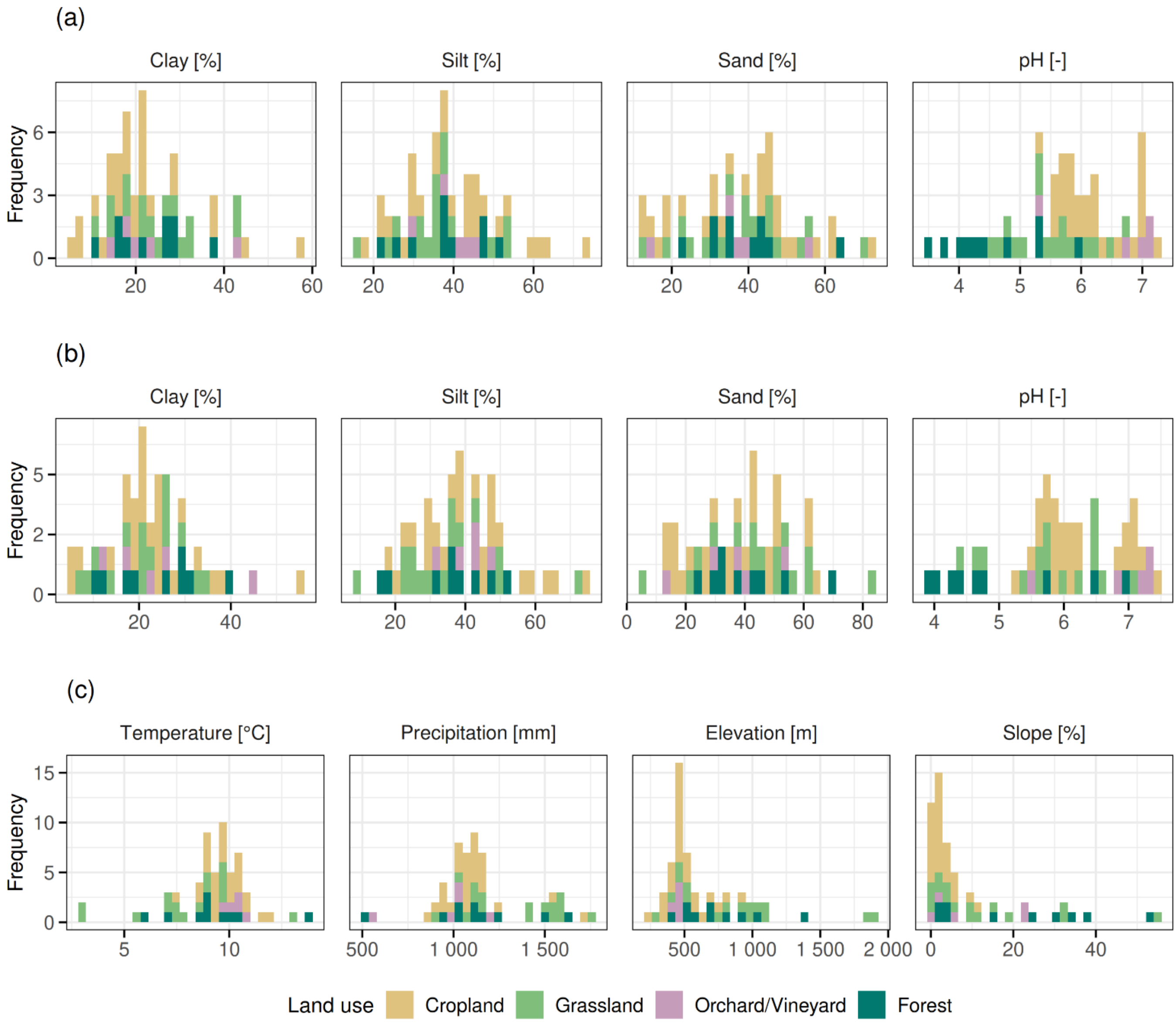

Figure 3: Frequency distributions of the pedoclimatic variables, colored by land use. (a) Pedogenic variables for 0–20 cm soil depth, (b) pedogenic variables for 20–60 cm soil depth, and (c) climatic and topographic variables, independent of soil depth.

3 Data harmonisation

3.1 Criteria for data selection

The number of data points included in the analysis was primarily determined by the overlap of sites that were sampled down to the subsoil in both monitoring periods. To make the soil samples, which had been collected and analyzed in different ways, comparable, several harmonization steps were necessary, which are described below. As a result of this data harmonization, the number of usable data points was substantially reduced (Figure 4). Of the originally sampled 102 sites (first monitoring period) and 90 sites (seventh monitoring period), 58 sites were ultimately included in the analysis, with only topsoil data available for four of them. The representativeness of sites per land use was also affected by data preparation: a small number of cropland and orchard/vineyard sites, but many forest sites in both monitoring periods, were removed. The representativeness of grassland sites varied across the monitoring periods; a larger proportion of sites was included in the first period compared to the seventh period (Supplementary Figure 3).

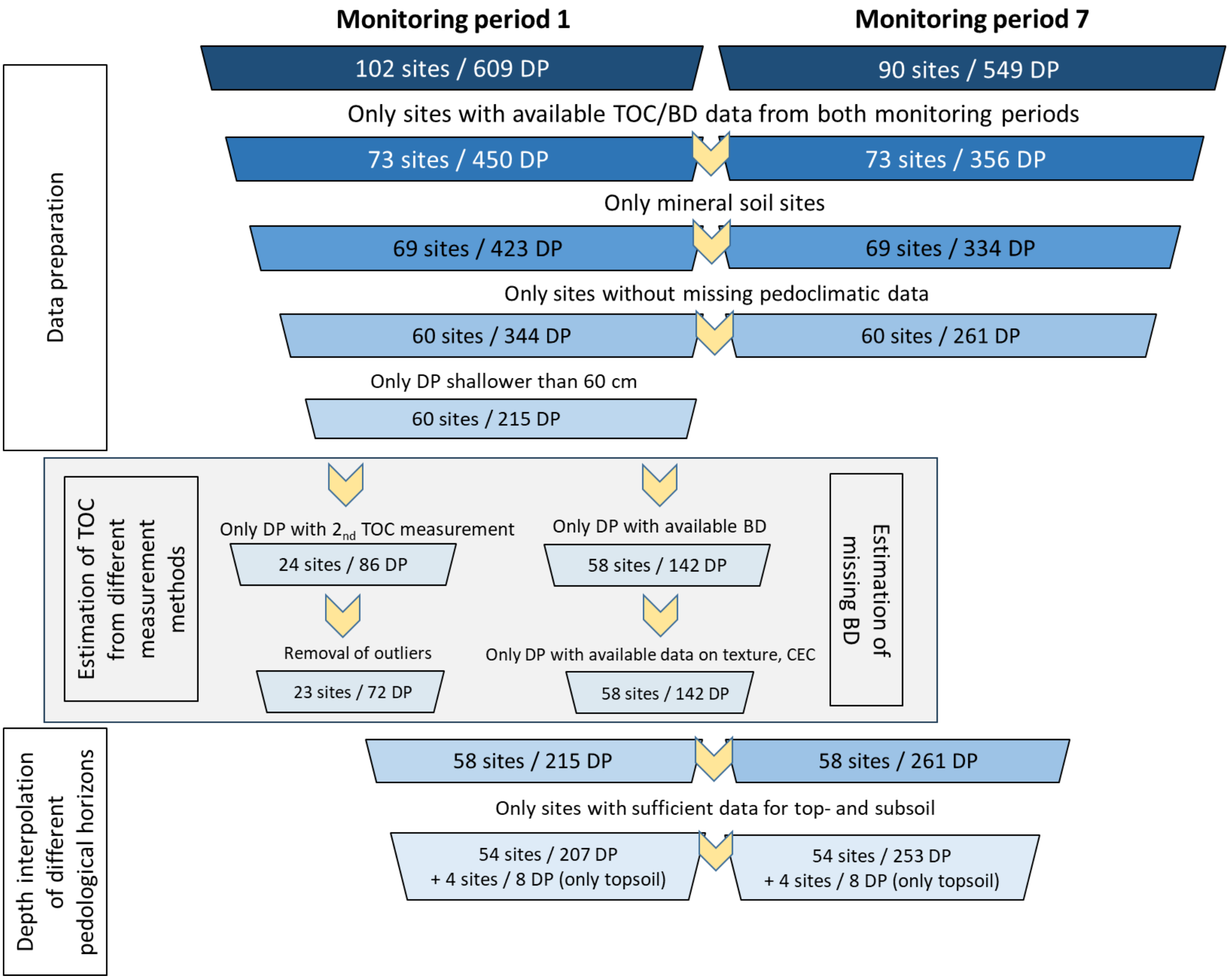

Figure 4: Harmonization steps for the data from the first and seventh monitoring period in chronological order (top to bottom). The reduction in the number of usable sites and data points (DP) per monitoring period results from data preparation and depth interpolation of different pedological horizons. The gray block indicates the number of sites used for estimating total organic carbon (TOC) content and bulk density (BD), reduced by outliers and missing data for texture and potential cation exchange capacity (CEC).

3.2 Harmonization of carbon content from different measurement methods

To enable comparison of carbon contents from both monitoring periods, data from the Carmhograph method (TOC_{carm}) were harmonized with the elemental analysis data (TOC_{EA}) using a conversion factor. For this purpose, the ratio TOC_{EA} / TOC_{carm} was calculated and visualized for 86 samples from 24 sites where both TOC_{EA} and TOC_{carm} values were available (Figure 5a). The ratio ranged from 0.5 to 2.5, so outliers were removed based on interquartile ranges according to Zar (2013). Using the remaining 72 data points from 23 sites, three different predictive models were tested to derive TOC_{EA} values from TOC_{carm} values using classification and regression training (67% training data, 33% test data; 10 repetitions of 5-fold cross-validation):

Linear model without variable transformation:	$\mathrm{lm}(\mathrm{TOC_{EA}} \sim \mathrm{TOC_{carm}})$	(4)
Linear model with variable transformation:	$\mathrm{lm}(\log(\mathrm{TOC_{EA}}) \sim \log(\mathrm{TOC_{carm}}))$	(5)
Generalized linear model (GLM) with gamma-distribution function and identity link:	$\mathrm{glm}(\mathrm{TOC_{EA}} \sim \mathrm{TOC_{carm}})$	(6)

The linear model without transformation (Equation 4) showed a non-normal distribution of residuals and was therefore not further evaluated. The two remaining models (Equations 5 and 6) were compared using a resampling procedure based on the coefficient of determination (R^2) and the root mean square error of the regression (RMSE). The generalized linear model performed best, with R^2 = 0.99 and RMSE = 0.11% for the training data, and R^2 = 0.98 and RMSE = 0.12% for the test data (Figure 5b), and was selected for further use (Figure 6). For the first monitoring period, estimated TOC_{EA} values were only applied to data entries for which measured TOC_{EA} values were not available.

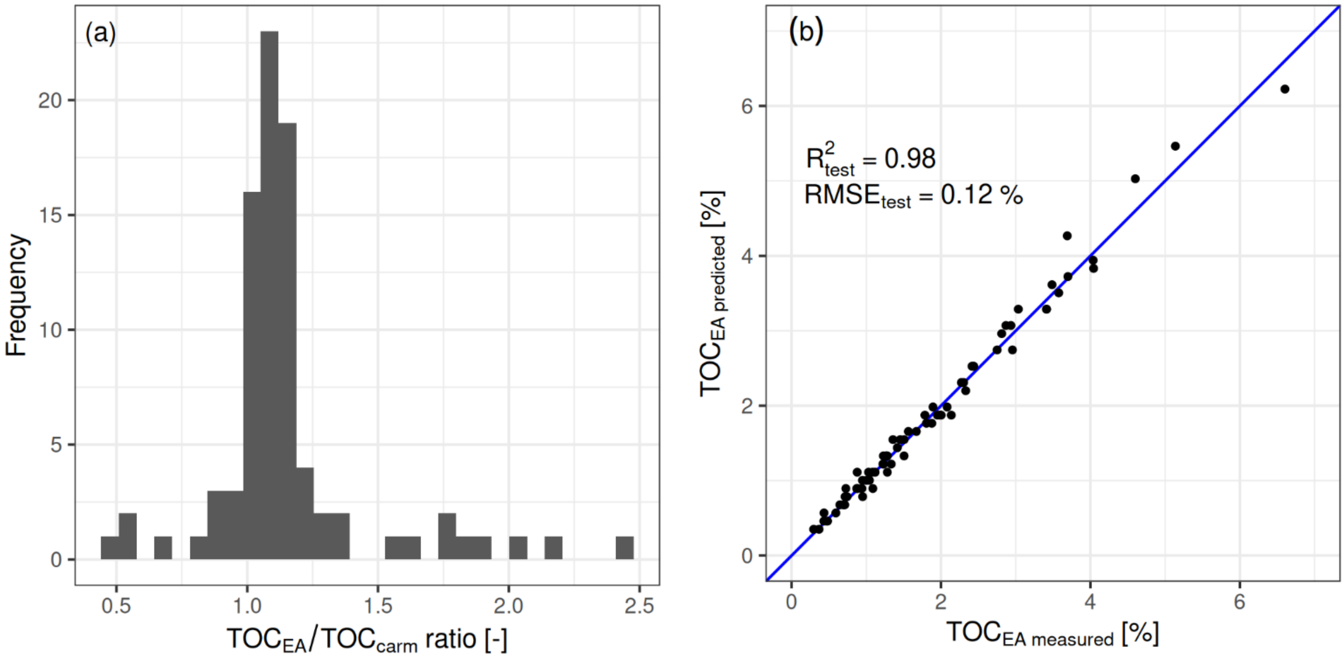

Figure 5: (a) Frequency distribution of the TOC_{EA} / TOC_{carm} ratio and (b) measured TOC_{EA} values versus TOC_{EA} values predicted by the model. The 1:1 line is shown in blue.

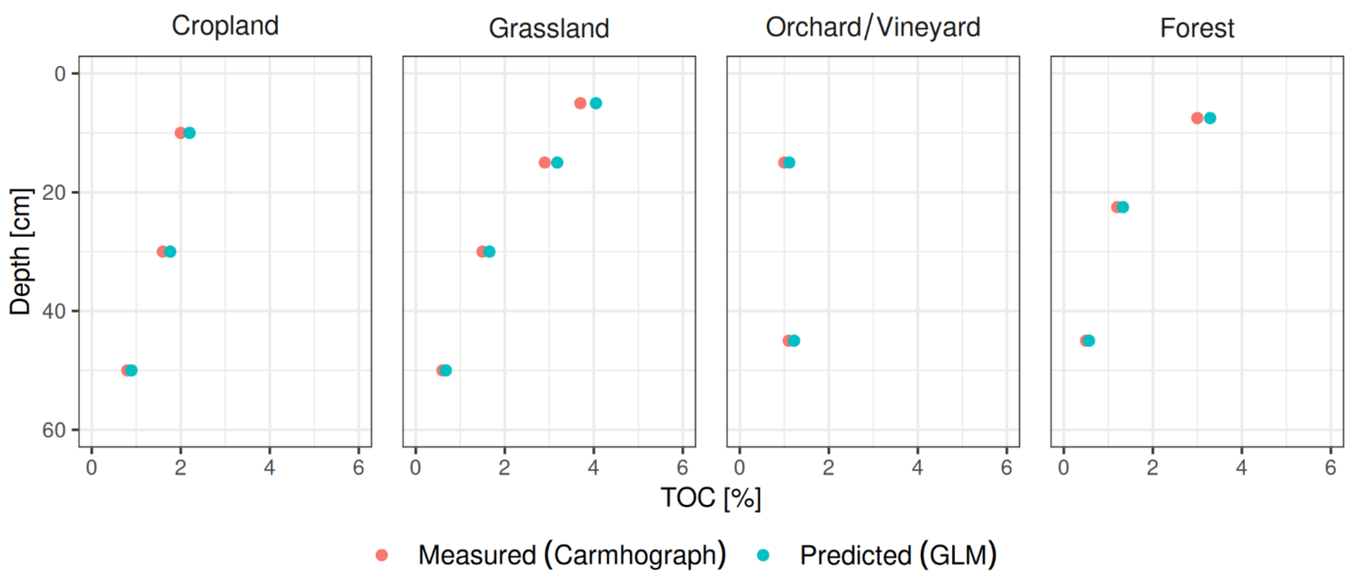

Figure 6: TOC content measured with the Carmhograph and predicted by the model along the soil profile for four selected sites with different land uses.

3.3 Estimation of missing bulk density values

Missing bulk density values from the first monitoring period were estimated using a pedotransfer function (PTF). This approach assumes that a given soil parameter depends on other soil parameters and can thus be derived from them (Van Looy et al., 2017). Using existing PTFs (De Vos et al., 2005; Foldal et al., 2020; Schwab & Gubler, 2016) in preliminary tests produced unrealistic and, in some cases, negative bulk density values, so a PTF based on the present dataset was developed. Complete bulk density and texture data were available for 142 data points from 58 sites.

For sites where the texture data from the first monitoring period were unreliable, the texture data from the sixth monitoring period were interpolated onto the pedological horizons of the first monitoring period using a spline function (see also the subsection on Depth Interpolation). Two different PTFs were tested using classification and regression training (67% training data, 33% test data; 10 repetitions of 5-fold cross-validation):

Linear model with stepwise variable selection:	$\mathrm{lm}(\mathrm{BD} \sim \text{Pedoclimatic variable})$	(7)
Random forest model:	$\mathrm{RF}(\mathrm{BD} \sim \text{Pedoclimatic variable})$	(8)

For the linear model, a forward/backward stepwise selection of the explanatory variables depth, TOC, clay, silt, CEC, temperature, elevation, and slope was performed. For the random forest model, the explanatory variables depth, TOC, clay, silt, sand, CEC, pH, temperature, precipitation, elevation, and slope were used. The number of explanatory variables in each tree (mtry) served as a tuning parameter (final model: mtry = 2). Since the random forest model (training data: $R^2 = 0.70$; RMSE = 0.121 g cm^{-3}, test data: $R^2 = 0.63$; RMSE = 0.146 g cm^{-3}) provided a better fit than the linear model (training data: $R^2 = 0.62$; RMSE = 0.136 g cm^{-3}, test data: $R^2 = 0.55$; RMSE = 0.151 g cm^{-3}) (Figures 7 and 8), it was used for the development of the PTF. For subsequent calculations, the PTF-estimated values were only applied to entries for which bulk density values from the first monitoring period were missing. Existing measured bulk density values were retained.

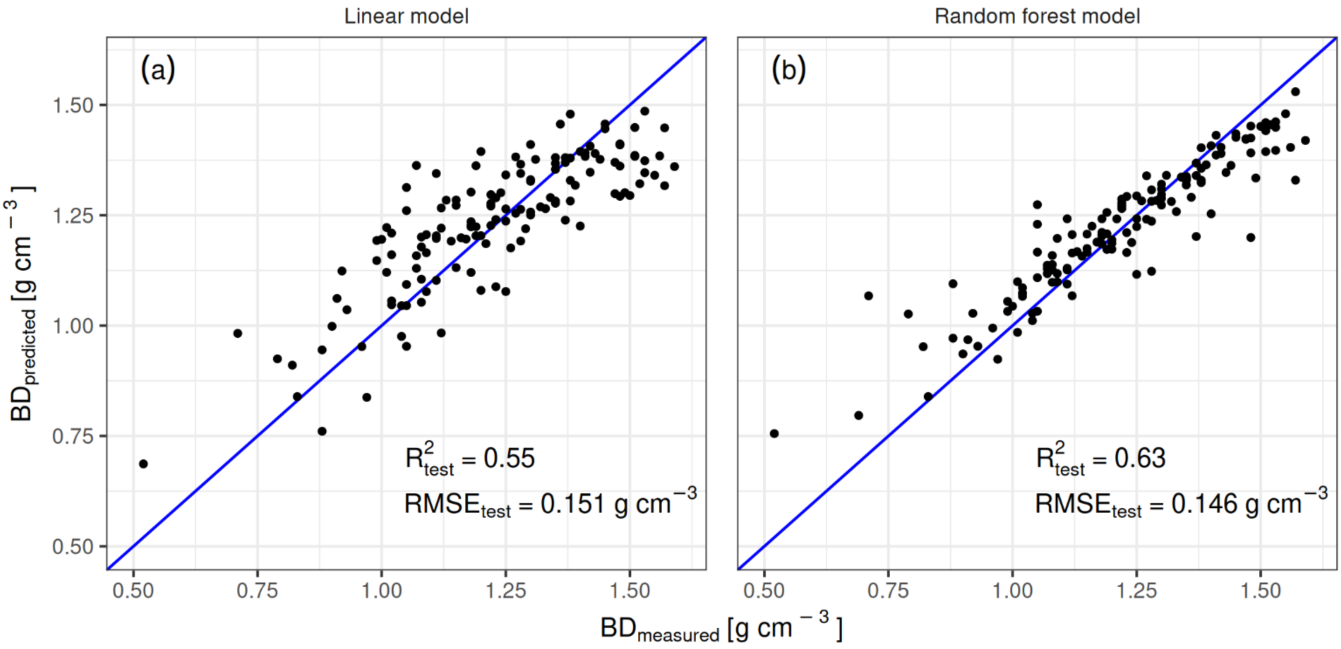

Figure 7: Measured versus PTF-predicted bulk density (BD), (a) for the linear model and (b) for the random forest model. The 1:1 line is shown in blue.

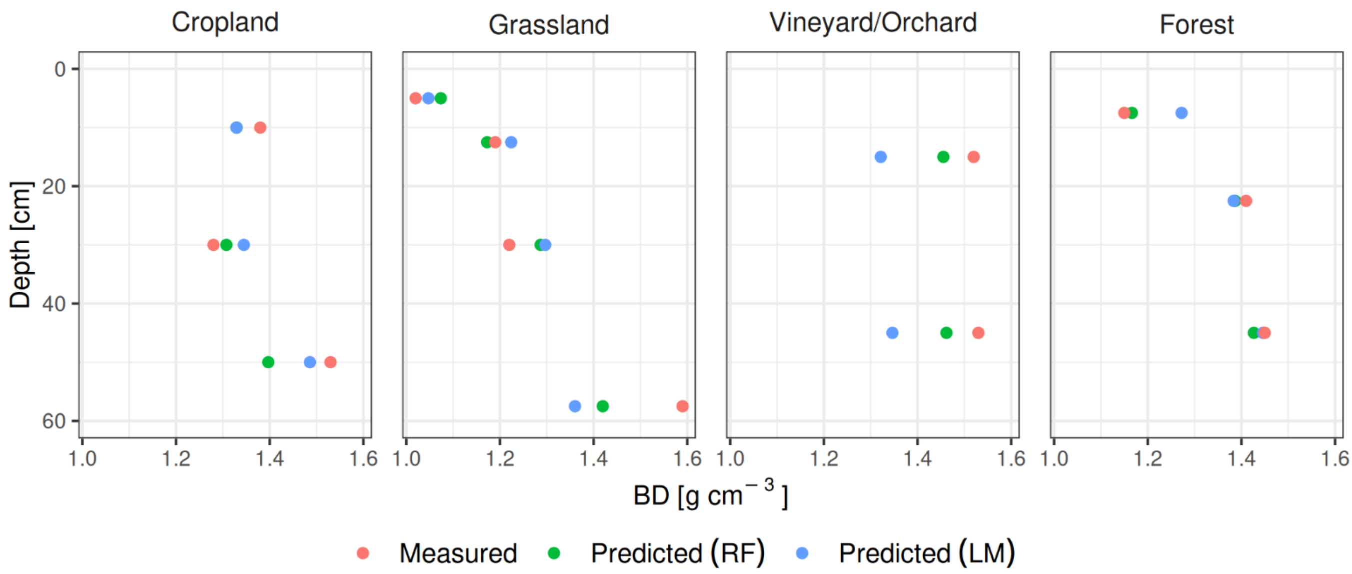

Figure 8: Measured and PTF-predicted bulk densities (BD) along the soil profile for four selected sites with different land uses.

3.4 Depth interpolation of the different pedological horizons

Subsoil samples were collected partially in horizon intervals during the first monitoring period and completely in horizon intervals during the seventh monitoring period (see Section 2.2). To enable depth-specific comparison of TOC stocks between monitoring periods, a mass-preserving spline interpolation was applied. This method connects measurement points with piecewise polygons, allowing interpolation at locations between measured points (Bishop et al., 1999). A maximum depth of 60 cm was chosen for the spline function, and the depth intervals of the interpolated values were set depending on the parameter, either at 1 cm or aggregated to 0–20 and 20–60 cm (Table 3). The smoothing parameter of the interpolation curve, λ, determines how closely the curve follows the measured points: the smaller the λ, the more closely the curve follows the measurements. For all splines, λ = 0.1 was used according to Bishop et al. (1999), which provided the most accurate representation of the actual depth distribution of the soil parameters (Figure 9).

Table 3: Soil parameters for which a spline method was applied for depth interpolation, and the corresponding interpolation intervals.

Soil parameter	**Interpolation interval**
TOC content (first and seventh monitoring period)	1 cm
Bulk density (first and seventh monitoring period)	1 cm
Bulk density (additional data set, see section 3.5.)	1 cm
Stone content (seventh monitoring period)	1 cm
Clay, silt, and sand content (first and seventh monitoring period)	by horizon (PTF), 0–20 cm, 20–60 cm (pedoclimatic analysis)
pH value (first and seventh monitoring period)	0–20 cm, 20–60 cm

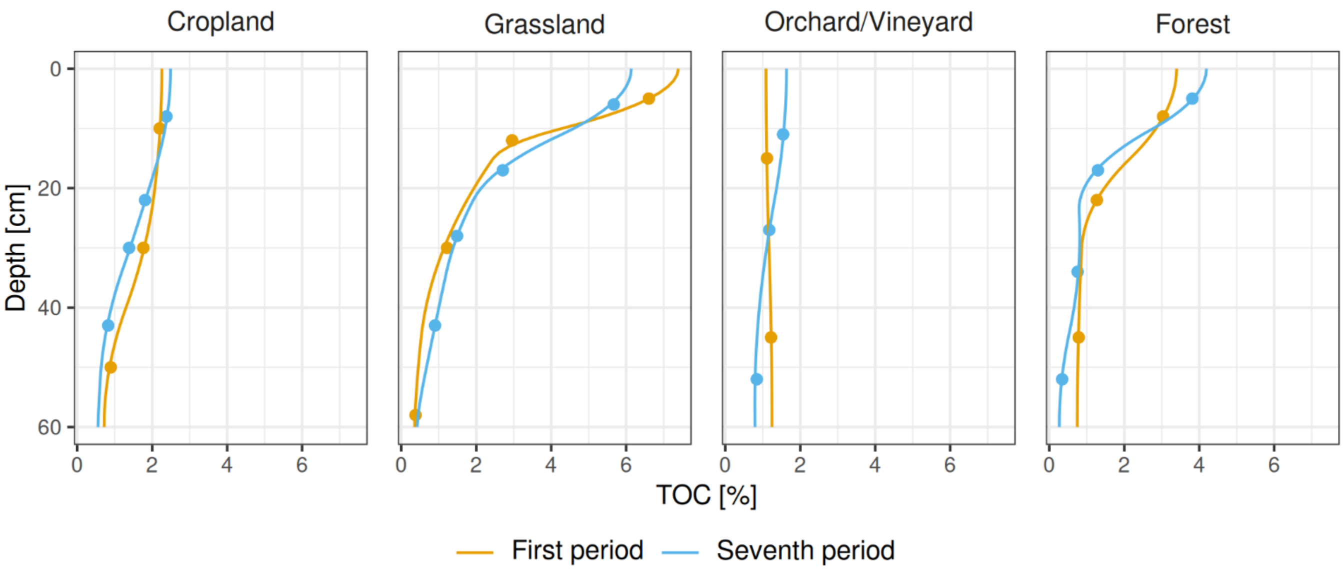

Figure 9: Measured (points) and mass-preserving spline-interpolated (lines) TOC content from the first and seventh monitoring periods for four selected sites with different land uses.

3.5 Harmonization of bulk density from different methods

Bulk density was measured with cylinders in the first monitoring period, whereas in the seventh monitoring period it was determined using impact probes (see Section 2.4). Significant differences in bulk density between the monitoring periods across all land uses (mean difference: 0.25 g cm^{-3}) indicate that methodological differences in bulk density determination would lead to an inaccurate comparison of TOC stocks between periods. To relate bulk densities determined by the different methods, a predictive function was estimated. For this purpose, the NABOphys dataset (see Section 2.6) was used, in which bulk density was measured using both methods at various soil depths for 24 cropland and grassland sites (Figure 10). Since these were unpaired samples, all bulk densities for the same method, depth, and site were first averaged, resulting in 71 data points from 24 sites. A predictive model was then developed to derive bulk density from soil cores based on bulk density measured with the impact probe, using classification and regression training (67% training data, 33% test data; 10 repetitions of 5-fold cross-validation):

$$\mathrm{lm}(\mathrm{BD}_{\mathrm{cylinder}} \sim \mathrm{BD}_{\mathrm{impact\ probe}}) \tag{9}$$

The final predictive model (Equation 9) had an R^2 of 0.70 and an RMSE of 0.09 g cm^{-3} for the training data, and an R^2 of 0.58 and an RMSE of 0.12 g cm^{-3} for the test data (Figures 10 and 11).

Bulk densities from the seventh monitoring period (impact probe) were interpolated at 1 cm intervals using mass-preserving splines. Using the interpolated TOC contents in the predictive model (Equation 9), the adjusted bulk densities (soil cores) were estimated (Figure 10). Finally, the estimated bulk densities (soil cores) were corrected by a factor of 0.937 to account for the use of different stone densities in the first and seventh monitoring periods.

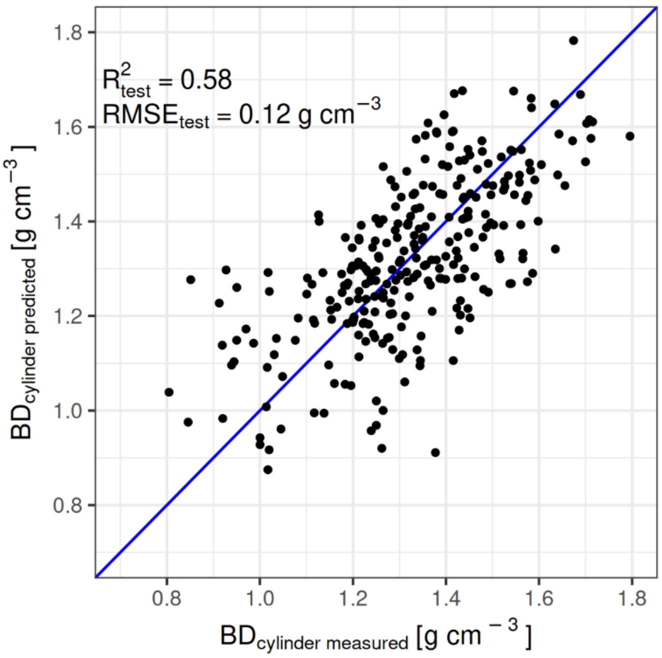

Figure 10: Measured versus predicted bulk density from soil cores based on the NABOphys data. The 1:1 line is shown in blue.

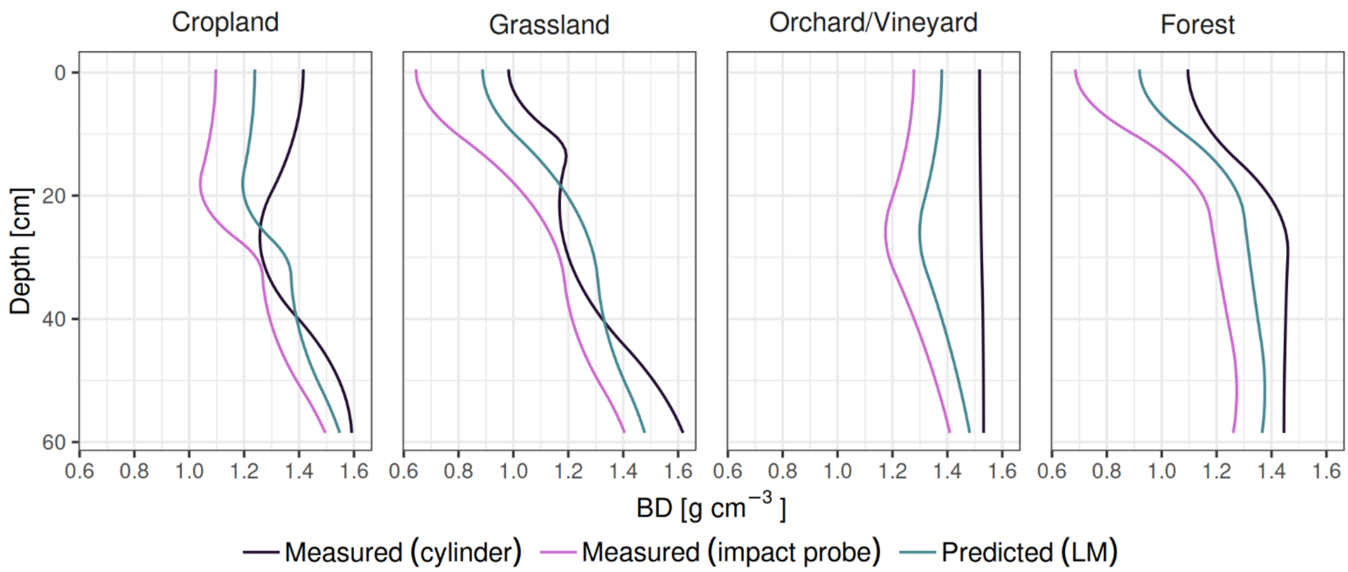

Figure 11: Depth-interpolated bulk density from the first monitoring period measured with soil cores and from the seventh monitoring period measured with the impact probe, as well as bulk density calculated using Equation 9, for four selected sites with different land uses. All bulk densities were interpolated at 1 cm intervals using a spline method.

4 Data analysis

4.1 Calculation of TOC stocks

For the calculation of TOC stocks, the TOC content from the first and seventh monitoring periods, the bulk density from the first period, the adjusted bulk density from the seventh period, and the stone content from the seventh period were interpolated at 1 cm intervals using a spline function. By including the stone content, the calculation of TOC stocks involved the fine earth bulk density (BD_{FE}) instead of the packing density (PD_{FE}). The TOC stock was then calculated for each 1 cm interval as follows:

$$\text{TOC stock } (1\ \mathrm{cm})\ [\mathrm{t\ TOC\ ha^{-1}}] = \mathrm{TOC\ content\ [\%]} * \mathrm{BD\ [g\ cm^{-3}]} * \left(1 - \frac{\mathrm{Stone\ content\ [\%]}}{100}\right) * 1\ \mathrm{cm} \tag{10}$$

For the topsoil and subsoil, the total TOC stock was calculated as the sum of the TOC stock in each 1 cm interval:

$$\text{TOC stock topsoil}\ [\mathrm{t\ TOC\ ha^{-1}}] = \sum_{i=1}^{20} \text{TOC stock } (1\ \mathrm{cm})_i\ [\mathrm{t\ TOC\ ha^{-1}}] \tag{11}$$

$$\text{TOC stock subsoil}\ [\mathrm{t\ TOC\ ha^{-1}}] = \sum_{i=21}^{60} \text{TOC stock } (1\ \mathrm{cm})_i\ [\mathrm{t\ TOC\ ha^{-1}}] \tag{12}$$

Changes in TOC stocks between the first (TOC stock_1) and seventh (TOC stock_7) monitoring periods, as well as the annual changes, were calculated for the topsoil and subsoil as follows:

$$\Delta\text{TOC stock}\ [\mathrm{t\ TOC\ ha^{-1}}] = \text{TOC stock}_7\ [\mathrm{t\ TOC\ ha^{-1}}] - \text{TOC stock}_1\ [\mathrm{t\ TOC\ ha^{-1}}] \tag{13}$$

$$\Delta\text{TOC stock}_{\mathrm{annual}}\ [\mathrm{t\ TOC\ ha^{-1}\ a^{-1}}] = \frac{\Delta\text{TOC stock}\ [\mathrm{t\ TOC\ ha^{-1}}]}{\text{Number of years [a]}} \tag{14}$$

For two cropland sites, one grassland site, and one forest site, only the TOC stock in the topsoil could be calculated due to missing subsoil data.

4.2 Statistical analysis

The analysis of carbon stocks was conducted separately for the topsoil and subsoil. To meet the assumption of normally distributed model residuals, the dependent variable TOC stock was transformed using a Box-Cox function. This method estimates an exponent that results in the residuals best approximating a normal distribution (topsoil: log(TOC stock); subsoil: $\frac{\text{TOC−stock}^{-0.4}-1}{-0.4}$).

Differences in TOC stocks between monitoring periods and land uses

To test for differences in TOC stocks between monitoring periods, a paired t-test was conducted for each land use and soil depth:

$$\text{t-test}(\text{TOC stock}_1 \sim \text{TOC stock}_7) \quad (15)$$

For the land uses orchard/vineyard and forest, a Wilcoxon test was additionally performed due to the small number of data points and the non-normal distribution. The results of both tests differed only slightly, so the t-test was used for further analysis.

To test for differences in TOC stocks between land uses (depending on the monitoring period), a linear mixed-effects model was fitted with Box-Cox transformed TOC stock as the dependent variable, land use in interaction with monitoring period as a categorical fixed effect, and site as a random effect, using restricted maximum likelihood (REML) for variance component estimation:

$$\text{lmer}(\text{BC}(\text{TOC stock}) \sim \text{Land use} * \text{Monitoring period} + (1|\text{Site})) \quad (16)$$

Minimal detectable difference

To quantify the change in TOC stocks required to reach statistical significance, the minimal detectable difference (MDD) was calculated for each land use and soil depth (Saby et al., 2008):

$$\text{MDD}_{\text{TOC stock}} = \sqrt{\left(\text{t}_{\alpha(2),\nu}\right)^2 * \frac{\text{s}_\text{d}^2}{\text{n}}} \quad (17)$$

Here, t_α is the t-statistic for a two-sided t-test with $v = n - 1$ degrees of freedom at a significance level of α, and sd is the standard deviation of ΔTOC stock across all n sites.

Influence of covariates on TOC stocks and their changes

The effects of the pedoclimatic variables (Table 2; excluding CEC) on TOC stocks (Box-Cox transformed; Table 4) were then tested using a linear mixed-effects model, with the pedoclimatic variable as a fixed effect and site as a random effect, for each land use and soil depth:

$$\text{lmer}(\text{BC}(\text{TOC stock}) \sim \text{Pedoclimatic variable} + (1|\text{Site})) \quad (18)$$

For the models of grassland sites with slope as a covariate, the slope was additionally Yeo-Johnson (YJ) power-transformed, which does not require the underlying data to be strictly positive (Yeo, 2000): $\frac{(\text{Slope}+1)^{0.07}-1}{0.07}$. The effects of the initial TOC stock, pedoclimatic variables (Table 2; excluding CEC), and changes in climatic variables on changes in TOC stocks were tested using a simple linear model. The models were initially fitted separately for each land use; however, due to the lower statistical performance of the individual models, a single model across all land uses was ultimately fitted:

$$\text{lm}(\text{YJ}(\Delta\ \text{TOC stock}_{\text{annual}}) \sim \text{Initial TOC stock}) \text{ or} \quad (19)$$

$$\text{lm}(\text{YJ}(\Delta\ \text{TOC stock}_{\text{annual}}) \sim \text{Pedoclimatic variable}) \text{ or}$$

$$\text{lm}(\text{YJ}(\Delta\ \text{TOC stock}_{\text{annual}}) \sim \Delta\ \text{Climate variable})$$

The annual change in TOC stocks was transformed using Yeo-Johnson functions for the 0–20 cm and 20–60 cm soil depths to ensure normality of the residuals. For the 0–20 cm soil depth, the transformation $\frac{(\Delta\text{TOC stock}_{\text{annual}}+1)^2-1}{2}$ for values greater than or equal to 0, and $-\log(-\Delta\text{TOC stock}_{\text{annual}}+1)$ for values less than 0 was used. For the 20–60 cm soil depth, the distribution of the annual change in TOC stocks still did not approximate a normal distribution after the Yeo-Johnson transformation. Two data points outside the interquartile range were identified as outliers and removed. The remaining data were then Yeo-Johnson transformed again, using $\frac{(\Delta\text{TOC stock}_{\text{annual}}+1)^{0.07}-1}{0.07}$ for values greater than or equal to 0, and $\frac{-(-\Delta\text{TOC stock}_{\text{annual}}+1)^{2-0.56}-1}{2-0.56}$ for values less than 0.

Table 4: Box-Cox transformations of the dependent variable TOC stock for Equation 18.

Land use, soil depth	Box-Cox transformation
Cropland, 0–20 cm	$\frac{\text{TOC stock}^{0.3}-1}{0.3}$
Cropland, 20–60 cm	$\log(\text{TOC stock})$
Grassland, 0–20 cm	$\frac{\text{TOC stock}^{0.8}-1}{0.8}$
Grassland, 20–60 cm	$\frac{\text{TOC stock}^{-0.6}-1}{-0.6}$
Forest, 0–20 cm	$\frac{\text{TOC stock}^{1.4}-1}{1.4}$
Forest, 20–60 cm	$\frac{\text{TOC stock}^{0.3}-1}{0.3}$
Orchard/vineyard, 0–20 cm	$\frac{\text{TOC stock}^{-0.9}-1}{-0.9}$
Orchard/vineyard, 20–60 cm	$\log(\text{TOC stock})$

Significance tests and relative importance of explanatory variables

Differences in TOC stocks between monitoring periods (Equation 15) were tested using paired t-tests. Differences in TOC stocks between land uses (Equation 16) were tested using Type III analysis of variance (ANOVA) with the Satterthwaite method and multiple pairwise comparisons of the estimated marginal means (EMMs) with Tukey-adjusted p-values. Significant differences between groups are indicated by different letters. Statistical significance was considered at $p < 0.05$ for all tests.

To identify the main factors influencing TOC stocks and their annual changes, the relative importance of explanatory variables was calculated using variance decomposition for mixed (Equation 18) and simple linear models (Equation 19) (Grömping, 2007; Lai et al., 2022). The dependent variable was again Box-Cox or Yeo-Johnson transformed, with two outliers removed for the annual change in TOC stocks at 20–60 cm soil depth. Silt content was excluded as an explanatory variable due to linear dependence on clay and sand content.

4.3 Quantification of uncertainties

Uncertainties in TOC stocks can arise from sampling, laboratory analysis, and data processing. Due to data gaps and the various harmonization steps, the following focuses only on the uncertainty associated with data processing: conversion of TOC contents between different analytical methods (TOC_{carm} to TOC_{EA}: Equation 6), estimation of missing bulk densities using a PTF (Equation 8), conversion of bulk density between different sampling methods

(Equation 9), and depth interpolation of TOC stocks using mass-preserving splines. As an absolute measure of uncertainty, the deviation between predicted and observed values for each data processing step was calculated for each data point in the test dataset (Taylor, 1997):

$$\text{Uncertainty}_{\text{absolute}} = \sqrt{\left(\text{Value}_{\text{predicted}} - \text{Value}_{\text{abserved}}\right)^2} \tag{20}$$

The uncertainty from converting bulk density refers to the prediction uncertainty of the model (Equation 9) and not to the uncertainty between the estimated and measured bulk density, since no bulk density measurements with cylinders were conducted in the seventh monitoring period.

To allow comparability of uncertainties across the harmonization steps, the absolute uncertainty was normalized by the observed value:

$$\text{Uncertainty}_{\text{relative}} = \frac{\text{Uncertainty}_{\text{absolute}}}{\text{Value}_{\text{observed}}} * 100\% \tag{21}$$

Larger deviations are better accounted for at higher predicted values. Finally, the mean absolute and relative uncertainty was calculated across all data points in the test dataset.

For depth interpolation using spline functions, two types of uncertainty can be distinguished. On the one hand, the continuous value of a soil parameter is unknown and is estimated by the spline value (points and line, Figure 12). On the other hand, discrete values from horizon or interval samples are smoothed by the spline function (rectangles and line, Figure 12). Since the true continuous value of the soil parameter is unknown and this uncertainty cannot be estimated, only the second type of uncertainty was calculated.

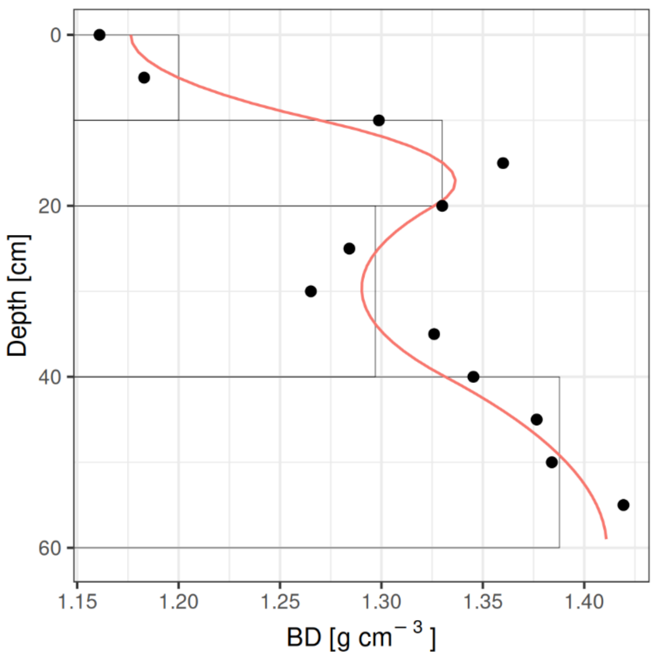

Figure 12: Example illustration of the two types of uncertainty arising from the use of a spline function.

To evaluate how well the spline-based TOC stock agrees with the TOC stock determined from horizon samples, the TOC stock was calculated separately for both monitoring periods, once as the sum of TOC stocks per horizon and once using the spline function. Absolute and relative uncertainty was then calculated per site according to Equations 20 and 21 for the summed TOC stock. Finally, the mean absolute and relative uncertainty across all sites was calculated. As several components of the total uncertainty from the different harmonization steps could not be quantified, uncertainty propagation was not performed.

4.4 Software

All data analyses were performed using R software, version 4.4.2 (R Core Team, 2024). Statistical analyses were carried out using the packages caret (Kuhn, 2008), car (Fox & Weisberg, 2019), emmeans (Lenth et al., 2023), multcomp (Hothorn et al., 2008), lme4 (Bates et al., 2015), relaimpo (Grömping, 2007), and glmm.hp (Lai et al., 2022), and spline functions were implemented with mpsline2 (Malone, 2023; O'Brien et al., 2022). Data visualizations were produced using ggplot2 (Wickham et al., 2016) and ggcorrplot (Kassambara, 2023).

5 TOC stock in the first and seventh monitoring period and its change

5.1 TOC stock in topsoil and subsoil

In the first monitoring period, the cumulative TOC stock over the soil depth of 0–60 cm averaged 113 t TOC ha^{-1} across all land uses, with a coefficient of variation of 45%. At cropland sites, it was 103 t TOC ha^{-1}, at grassland sites 125 t TOC ha^{-1}, at orchard/vineyard sites 167 t TOC ha^{-1}, and at forest sites 96 t TOC ha^{-1}. In the topsoil and subsoil, the mean TOC stock was 62 t TOC ha^{-1} (minimum to maximum: 30 to 161 t TOC ha^{-1}) and 55 t TOC ha^{-1} (22 to 210 t TOC ha^{-1}), respectively, across all land uses; 54 and 53 t TOC ha^{-1} at cropland sites, 76 and 52 t TOC ha^{-1} at grassland sites, 72 and 95 t TOC ha^{-1} at orchard/vineyard sites, and 56 and 45 t TOC ha^{-1} at forest sites (Figure 13; Supplementary Figures 4–7).

In the seventh monitoring period, the summed TOC stock over the soil depth of 0–60 cm averaged 104 t TOC ha^{-1} across all land uses, with a coefficient of variation of 36%. At cropland sites, it was 91 t TOC ha^{-1}, at grassland sites 125 t TOC ha^{-1}, at orchard/vineyard sites 122 t TOC ha^{-1}, and at forest sites 92 t TOC ha^{-1}. In the topsoil and subsoil, the mean TOC stock was 57 t TOC ha^{-1} (18 to 105 t TOC ha^{-1}) and 50 t TOC ha^{-1} (16 to 147 t TOC ha^{-1}), respectively, across all land uses; 46 and 49 t TOC ha^{-1} at cropland sites, 76 and 53 t TOC ha^{-1} at grassland sites, 58 and 64 t TOC ha^{-1} at orchard/vineyard sites, and 55 and 41 t TOC ha^{-1} at forest sites (Figure 13; Supplementary Figures 4–7).

The TOC stocks in this study are within a similar range as those reported in other studies. In soil monitoring programs in Central Europe, mean TOC stocks amount to about 100 t TOC ha^{-1} (0–50 cm and 0–100 cm) in cropland soils (Flessa et al., 2019; Taghizadeh-Toosi et al., 2014), 200 t TOC ha^{-1} (0–100 cm) in grassland soils (Jacobs et al., 2018), and between 65 t ha^{-1} (0–30 cm) and 117 t ha^{-1} (0–90 cm) in forest soils (De Vos et al., 2015; Wellbrock et al., 2017).

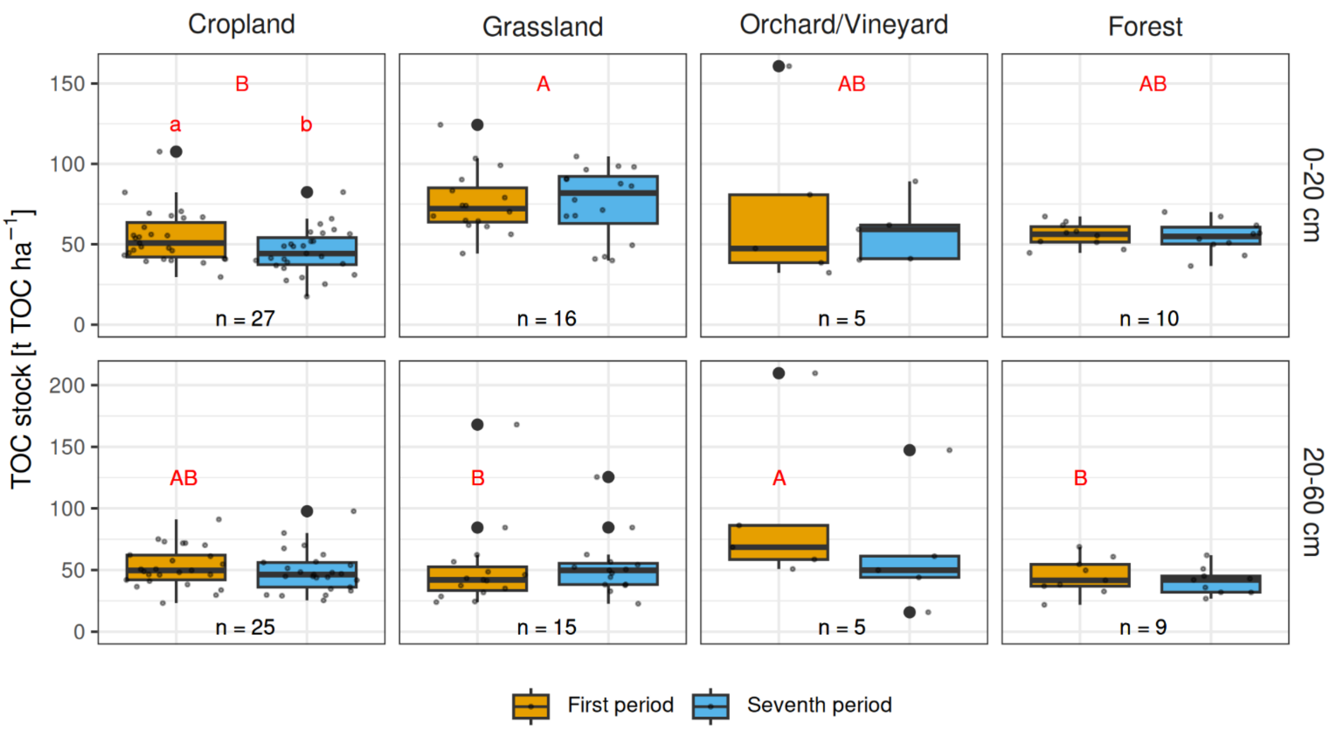

Figure 13: TOC stocks in the first and seventh monitoring period, separated by topsoil and subsoil and by land use. Grey dots represent individual values. Different capital and lowercase letters indicate significant differences in TOC stocks between land uses and monitoring periods, respectively. The number of observations (n) per soil depth and land use is shown below each pair of boxplots.

In the topsoil of cropland sites, the TOC stock was significantly higher in the first compared to the seventh monitoring period ($P = 0.001$), while in the subsoil and within the other land uses no statistically significant differences between monitoring periods were observed (Figure 13). Other studies report different developments depending on land use, soil type, and region. In Austria and Belgium, topsoil TOC stocks increase under grassland, while they partly decrease in cropland (Goidts & van Wesemael, 2007; Lettens et al., 2005; Wenzel et al., 2022). In Germany, TOC stocks tend to increase in topsoil and decrease in subsoil (Steinmann et al., 2016), underlining the importance of subsoils for determining carbon stocks. Studies with a larger number of sites often reveal significant changes (Goidts, van Wesemael, & Van Oost, 2009; Lettens et al., 2005; Wenzel et al., 2022). These allow for a more detailed differentiation not only by land use but also by soil type, making it possible to better capture long-term developments in TOC stocks.

5.2 Change in TOC stocks and minimal detectable difference

The change in TOC stocks between the first and seventh monitoring period across all land uses averaged -5.6 t C ha^{-1} (-72 to +37 t C ha^{-1}) for the topsoil and -4.9 t C ha^{-1} (-148 to +61 t C ha^{-1}) for the subsoil. This corresponds to an average annual change of -0.19 t C ha^{-1} yr^{-1} for the topsoil and -0.17 t C ha^{-1} yr^{-1} for the subsoil. At cropland sites, the change from the first to the seventh monitoring period was -8.7 and -3.9 t C ha^{-1} for topsoil and subsoil, respectively; at grassland sites -0.5 and +1.5 t C ha^{-1}; at orchard/vineyard sites -13.6 and -31.1 t C ha^{-1}; and at forest sites -1.2 and -4.0 t C ha^{-1} (Table 5). The corresponding annual changes were -0.30 and -0.13 t C ha^{-1} yr^{-1} for cropland, -0.03 and +0.05 t C ha^{-1} yr^{-1} for grassland, -0.48 and -1.10 t C ha^{-1} yr^{-1} for orchard/vineyard, and -0.03 and -0.14 t C ha^{-1} yr^{-1} for forest (Figure 14; Supplementary Figures 8–11).

The MDD was 5.5 and 4.0 t C ha^{-1} for cropland, 9.5 and 8.9 t C ha^{-1} for grassland, 51.0 and 94.0 t C ha^{-1} for orchard/vineyard, and 5.1 and 8.0 t C ha^{-1} for forest for topsoil and subsoil, respectively (Table 5). At cropland sites, the change in topsoil TOC between the two monitoring periods was therefore approximately 1.6 times greater than the MDD. In contrast, the change in topsoil TOC for the other three land uses would have needed to be 3.7 to 17.6 times greater to reach statistical significance. In the subsoil, this factor ranged between 1.0 and 5.7 across all land uses. Several studies have also calculated the MDD for TOC content or TOC stocks, but without relating it to actually measured differences (Deluz et al., 2020; Goidts, Van Wesemael, & Crucifix, 2009; Gubler et al., 2019; Saby et al., 2008; Schrumpf et al., 2011), making a direct comparison with our study impossible.

Table 5: Change in TOC stocks and minimal detectable difference (MDD) between the first and seventh monitoring period, separated by soil depth and land use.

Soil depth	Land use	Change in TOC stock [t TOC ha^{-1}]	MDD of TOC stock [t TOC ha^{-1}]
0–20 cm	Cropland	-8.7	±5.5
	Grassland	-0.5	±9.5
	Orchard/vineyard	-13.6	±51.0
	Forest	-4.0	±5.1
20–60 cm	Cropland	-3.9	±4.0
	Grassland	+1.5	±8.9
	Orchard/vineyard	-31.1	±94.0
	Forest	-1.2	±8.0

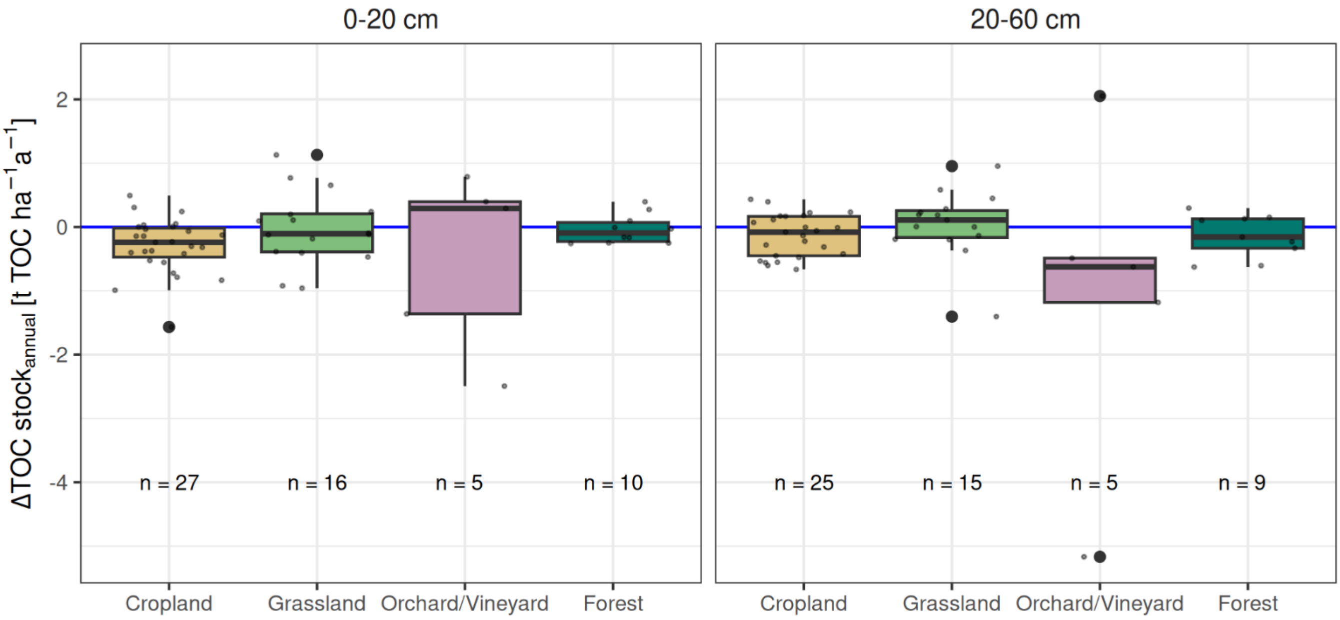

Figure 14: Annual change in TOC stocks, separated by topsoil and subsoil. Grey points represent individual values. The number of observations (n) per soil depth and land use is shown below each boxplot. The blue horizontal line represents zero change.

5.3 TOC stocks in different land uses

The comparison between land uses also reveals significant differences in TOC stocks (Figure 13; Table 6): Regardless of the monitoring period, TOC stocks in the topsoil of grassland sites are 1.5 times higher than in cropland sites (Figure 13). Differences between the other land uses are not significant. In the subsoil, TOC stocks differ significantly between the first and seventh monitoring periods, with significant interactions with land use (Table 6). In the first monitoring period, TOC stocks at orchard/vineyard sites are significantly higher than at grassland and forest sites, whereas differences between other land uses in the first monitoring period and between all land uses in the seventh monitoring period are not significant (Figure 13; Table 6). The difference for orchard/vineyard sites is due to a high outlier in the first monitoring period. The model of Equation 16 was therefore refitted for the subsoil with the outlier removed, and a repeated ANOVA showed neither a significant difference between monitoring periods nor a significant interaction term.

Numerous studies show that land use strongly influences TOC stocks (Jacobs et al., 2018; Wenzel et al., 2022; Wiesmeier et al., 2012). Grassland generally exhibits higher topsoil TOC stocks than cropland (Lettens et al., 2005; Wenzel et al., 2022; Wiesmeier et al., 2012), which can be attributed to reduced disturbance from tillage (Six et al., 1999), higher root biomass, and continuous carbon inputs via root exudates (Kätterer et al., 2011; Poeplau et al., 2021). Long-term studies in different regions show site-dependent TOC dynamics: grassland typically promotes long-term topsoil carbon accumulation, whereas management practices on cropland often lead to carbon losses or a redistribution of TOC between topsoil and subsoil (Kühnel et al., 2019; Skadell et al., 2023; Wenzel et al., 2022). Soil texture and water balance are key factors, influencing whether carbon is stored long-term or mineralized more quickly (Flessa et al., 2019; Jacobs et al., 2018). Detailed information on management and site conditions is therefore essential to better understand TOC stock changes and to develop targeted carbon storage measures in agroecosystems (Lettens et al., 2005; Wiesmeier et al., 2012).

High variability in TOC stocks within grassland and orchard/vineyard sites highlights the diversity of these land uses (Figure 13). Variability among grassland sites is likely related to elevation differences (273–1880 m) and varying management intensity, while orchard/vineyard variability reflects heterogeneous crops and management practices. Steep slopes and high stone content at vineyard sites complicate representative sampling and may explain subsoil TOC variability. In such heterogeneous land uses, expanding the number of study sites is essential for robust assessments of TOC stock changes.

At forest sites, TOC stocks in this study fall between those of cropland and grassland sites. Other studies report higher TOC stocks in forest soils compared to grassland (Jackson et al., 2017; Lettens et al., 2005), mainly due to the organic layer. While the mineral soil under forest often has similar TOC stocks to grassland, the organic layer represents an additional carbon pool that is often not systematically assessed. Differentiated sampling of the organic layer is therefore crucial for accurately determining TOC stocks in forests and for comparisons with other land uses.

The necessary data harmonization reduced the number of data points and increased uncertainty, likely masking actual differences in TOC stocks. Upscaling the results to the landscape level would further increase uncertainty (Goidts, Van Wesemael, & Crucifix, 2009) and is therefore not appropriate with the current dataset. However, future NABO monitoring periods conducted with consistent methodology will improve confidence in interpreting changes in TOC stocks over time.

Table 6: P-values from an ANOVA based on a linear model with TOC stock as the dependent variable and monitoring period in interaction with land use as explanatory variables.

Dependent variable	**Land use**	**Monitoring period**	**Land use * Monitoring period**
TOC stock 0–20 cm [t TOC ha^{-1}]	< 0.001	0.08	0.23
TOC stock 20–60 cm [t TOC ha^{-1}]	0.31	0.008	0.005

6 Pedoclimatic effects on the TOC stock and its change

6.1 Pedoclimatic effects on the TOC stock

Within individual land uses and soil depths, the TOC stock shows a significant positive relationship with clay content, pH, elevation, and slope, and a negative relationship with sand content and temperature (Table 7; Supplementary Figures 12–19). The positive relationship between fine-textured soils or pH and TOC stock is well documented in the literature. Clay minerals bind organic matter and promote the formation of microaggregates (Six et al., 2002), thereby protecting carbon from microbial decomposition (Lützow et al., 2006). Soil inventory data from France, Germany, and Belgium confirm this relationship, particularly for arable topsoils (Arrouays et al., 2006; Goidts & van Wesemael, 2007; Poeplau et al., 2020). Positive correlations between clay content and TOC stock have also been reported in forest soils in Germany (Grüneberg et al., 2019). The positive effect of pH on TOC stock is attributed to pH-dependent sorption of organic matter and the associated stabilization mechanisms (Lützow et al., 2006). At low pH, Fe^{3+} and Al^{3+} predominantly stabilize organic matter, whereas at higher pH values (>6), typical of cropland soils in our study, Ca^{2+} plays a key role (Rowley et al., 2017). Studies from Bavaria and other parts of Germany also report a positive relationship between pH and TOC stock for mineral forest soils (Grüneberg et al., 2019; Wiesmeier et al., 2013) and grasslands (Kühnel et al., 2019).

The observed relationship between elevation and TOC stock in forest soils may be related to decreasing temperatures with increasing altitude (Supplementary Figure 2). Although the relationship between temperature and TOC stock is not statistically significant, a negative trend is apparent (Supplementary Figure 19). Reduced decomposition rates at lower temperatures often lead to longer residence times of TOC in the soil and correspondingly higher TOC stocks (Kühnel et al., 2019; Leifeld et al., 2005), a pattern also observed at grassland sites in our study (Supplementary Figure 14). The positive relationship between slope and TOC stock in grassland and forest soils in our study contrasts with another study in which slope was identified as a key factor for decreasing TOC (Kühnel et al., 2019). This discrepancy may be explained by the strong correlations in our dataset between slope and elevation (positive) and slope and temperature (negative) (Supplementary Figure 2). Therefore, the observed positive effect of slope on TOC stock likely does not reflect a true causal effect.

Table 7: Direction (and p-value) of the relationship between each covariate and TOC stock for all land uses and soil depths. Non-significant effects are not shown (this also applies to silt content and precipitation).

Soil depth	Land use	Clay [%]	Sand [%]	pH [-]	Elevation [m]	Temperature [°C]	Slope [%]
0–20 cm	Cropland	+ (0.003)					
	Grassland	+ (0.005)	- (0.042)			- (0.029)	+ (0.001)
	Orchard/Vineyard						
	Forest	+ (0.029)					
20–60 cm	Cropland			+ (0.005)			
	Grassland						+ (0.038)
	Orchard/Vineyard						
	Forest				+ (0.005)		+ (0.009)

For the topsoil and subsoil, the analysis of the relative importance of explanatory variables reveals different key drivers (Figure 15). In the topsoil, the two most important factors are clay content and land use, which together explain over 55% of the variability in TOC stocks. In the subsoil, pH is the most influential factor, with a relative importance of nearly 30%, followed by clay content and slope (both 18%) (Figure 15). Other studies confirm the importance of land use for topsoil TOC stocks and show that pedological factors become increasingly important with depth (Flessa et al., 2019; Vos et al., 2019). In our study, climatic variables are assigned a relatively low importance for TOC stocks in both soil layers, which contrasts with findings from other studies (Vos et al., 2019; Wiesmeier et al., 2014). The narrower range of mean annual precipitation in our dataset (530–1800 mm vs. 490–3300 mm in other studies) may explain why less variation is captured compared to previous studies.

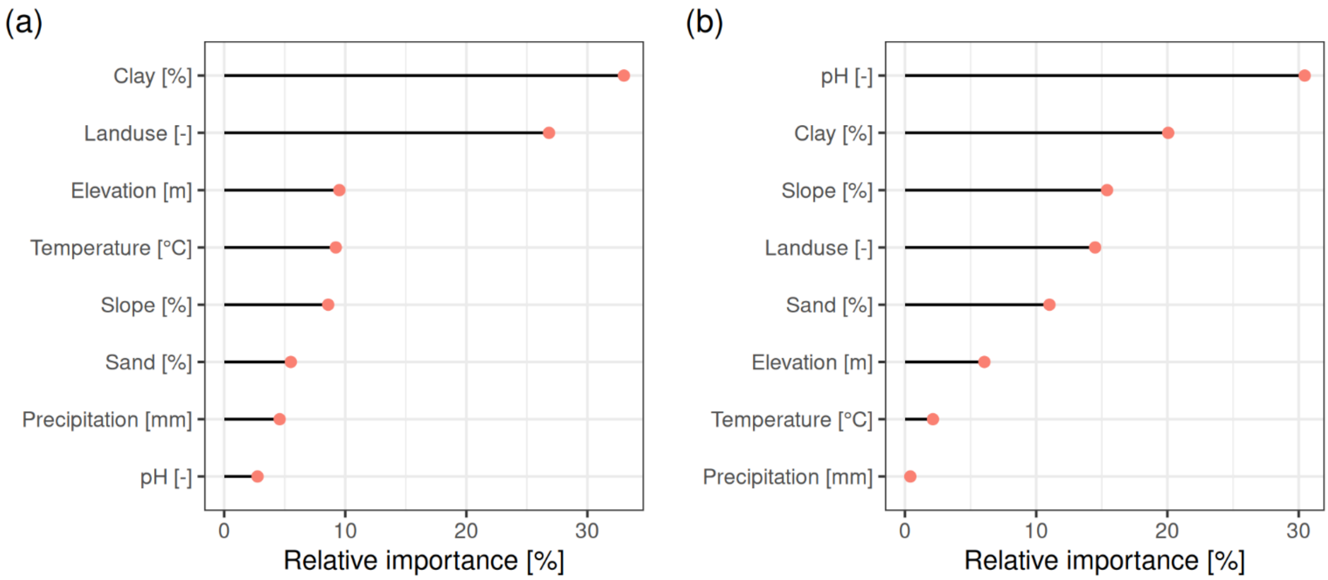

Figure 15: Relative importance of explanatory variables for TOC stocks in (a) 0–20 cm and (b) 20–60 cm soil depth.

6.2 Pedoclimatic effects on the change in TOC stocks

The annual change in TOC stocks in the topsoil shows a negative relationship with the initial TOC stock, which is by far the most important explanatory variable (Figures 16 and 18). In the topsoil, pH and temperature also have a negative effect on the annual change in TOC stocks, while elevation and precipitation have a positive effect (Figure 16). For all other explanatory variables, the relationship with the annual change in TOC stocks is not significant (Figures 16 and 17). In the subsoil, land use is the most important explanatory variable (Figure 18).

The negative relationship between initial TOC stocks and TOC change has been observed in various studies (Bellamy et al., 2005; Goidts & van Wesemael, 2007; Hanegraaf et al., 2009). One possible explanation is that soils tend toward a long-term equilibrium, where soils with higher initial TOC stocks experience greater losses than soils with lower starting values (Goidts & van Wesemael, 2007). A similar explanation is the biophysical saturation limit, according to which TOC-poor soils accumulate carbon more quickly, while TOC-rich soils may lose carbon faster until the saturation limit is reached (Slessarev et al., 2023). This also explains the positive relationship between TOC change and elevation, and the negative relationship with temperature and pH, because these variables are associated with higher TOC stocks in certain land uses (Table 7). Finally, a statistical explanation may also be relevant: regression to the mean. Initial TOC values that are unusually high or low due to random variation during sampling or processing are more likely to be followed by moderate measurements, producing a negative change for higher initial TOC and vice versa, thus explaining the observed negative relationship between TOC stocks and their change (Slessarev et al., 2023).

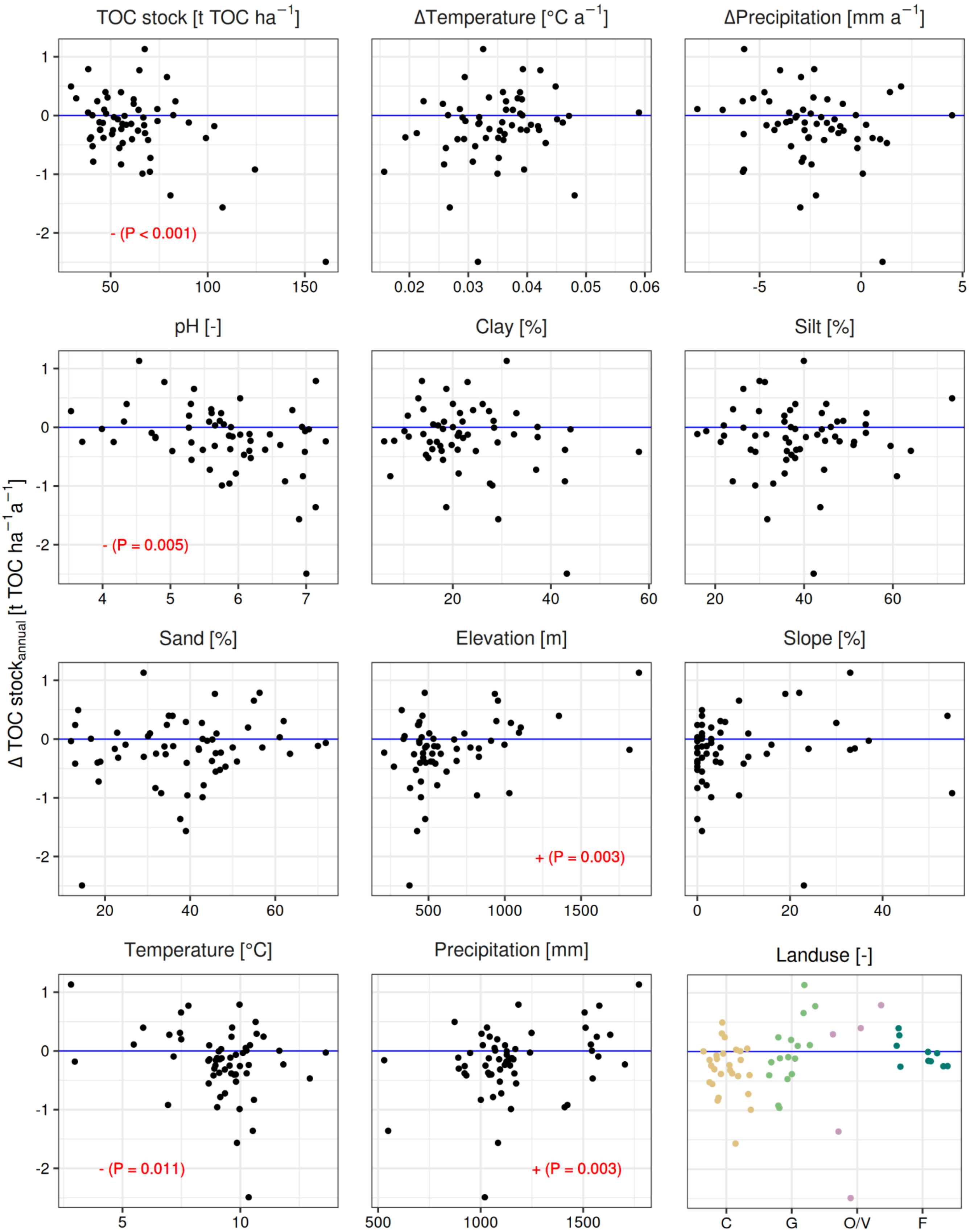

Figure 16: Relationship between initial TOC stock, pedoclimatic variables, and land use, and the annual change in TOC stocks in 0–20 cm soil depth. The blue horizontal line indicates zero change. The direction of the effect and the corresponding P-value are shown for significant relationships. A regression line is not displayed due to prior data transformations. Land use: C, cropland; G, grassland; O/V, orchard/vineyard; F, forest.

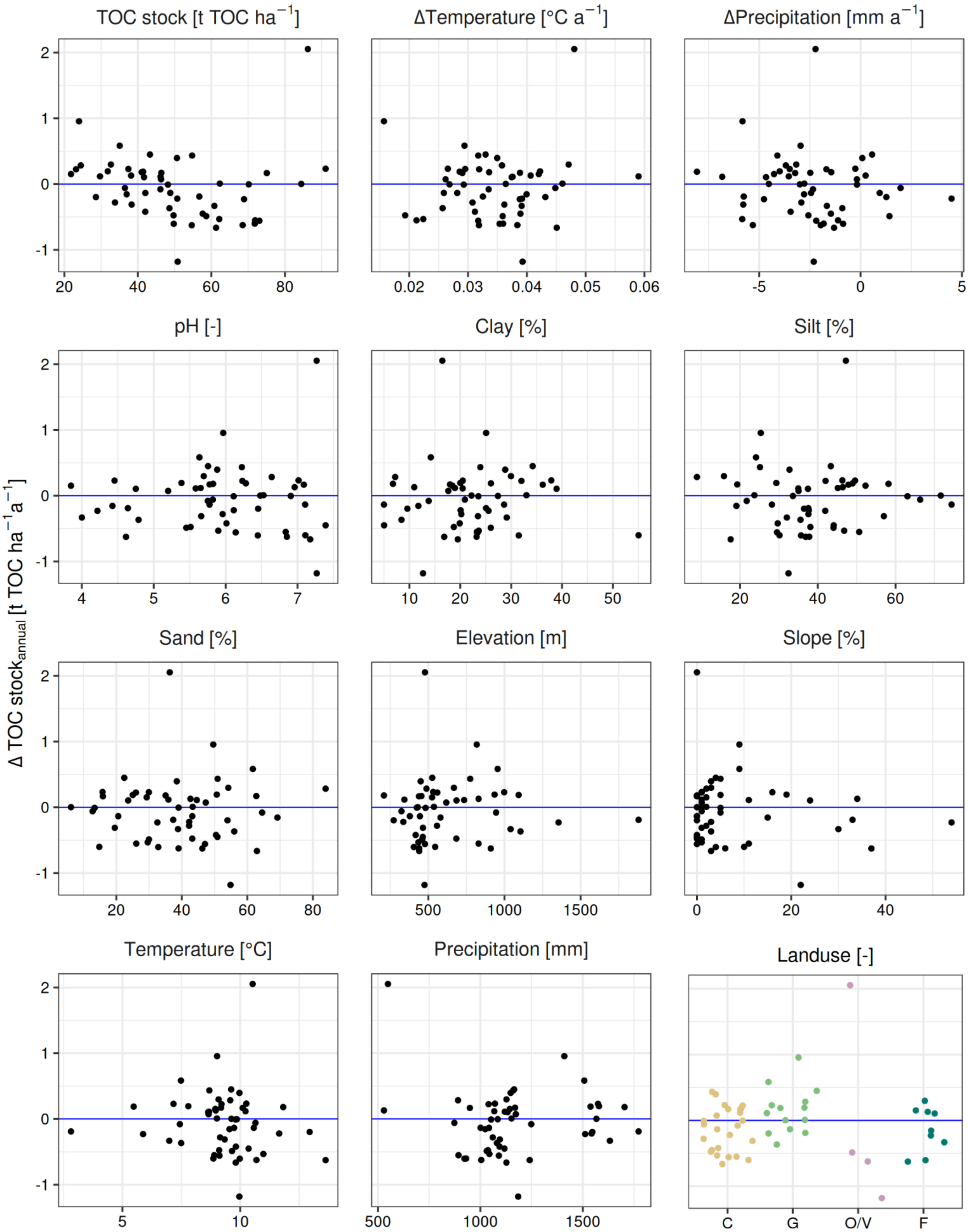

Figure 17: Relationship between initial TOC stock, pedoclimatic variables, and land use, and the annual change in TOC stocks in 20–60 cm soil depth. The blue horizontal line indicates zero change. Land use: C, cropland; G, grassland; O/V, orchard/vineyard; F, forest.

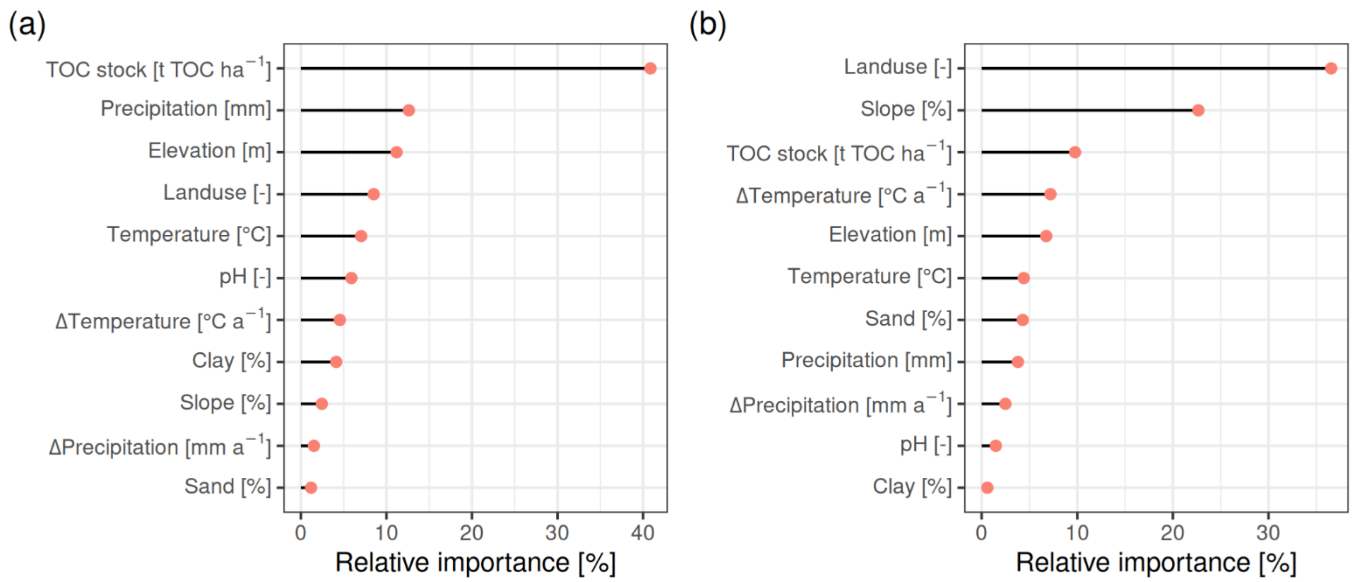

Figure 18: Relative importance of the explanatory variables for the annual change in TOC stocks in (a) 0–20 cm and (b) 20–60 cm soil depth.

7 Limitations of the data and recommendations for soil monitoring

The uncertainties in the TOC stock data from the first monitoring period are 7% for the conversion of TOC contents between the two analytical methods, 9% for estimating missing bulk density using the PTF, and 1% for depth interpolation using the spline function (Table 8). For the seventh monitoring period, uncertainties are 8% for the conversion of bulk density between the two sampling methods and also 1% for depth interpolation using the spline function (Table 8). However, since the uncertainty between the calculated and actual bulk density for the seventh monitoring period could not be quantified, the overall uncertainty is likely highest for the conversion of bulk density between the two sampling methods.

Table 8: Absolute and relative uncertainties of the data harmonization steps.

Monitoring period	Data harmonization step	Equation	Mean deviation (absolute uncertainty)	Normalized mean deviation (relative uncertainty)
1	conversion of TOC_{carm} to TOC_{EA}	6	0.09 mass-%	7%
1	estimation of missing bulk density values using a PTF	8	0.11 g cm^{-3}	9%
1	depth interpolation using a spline function	-	1.7 t TOC ha^{-1}	1%
7	conversion of bulk density from impact probe to bulk density from cylinders	9	0.10 g cm^{-3}	8%
7	depth interpolation using a spline function	-	1.4 t TOC ha^{-1}	1%

The effect of the sampling method on TOC stocks has been documented in several studies (Dold et al., 2018; Sharma et al., 2020). Both the type of sampling (cylinders vs. impact probe) and the diameter of the device significantly influence bulk density (Walter et al., 2016), and this effect can vary across soil depths (Dold et al., 2018). On average, higher bulk densities are measured with cylinders than with probes in the topsoil, while the opposite is often true in the subsoil (Poeplau & Gregorich, 2022). In the NABOphys dataset, bulk density measured with the impact probe is consistently lower than that measured with cylinders, although the values converge with increasing soil depth, showing the same depth-dependent effect (Supplementary Figure 1). To minimize uncertainty in TOC stocks due to the sampling method in long-term monitoring, the same method should be applied consistently across monitoring periods. Since bulk density determination using probes is efficient and can be flexibly combined with other soil analyses, probes are generally preferred (Poeplau & Gregorich, 2022). Among probe types, the closed sheet probe shows the smallest deviation from bulk densities measured with cylinders (Walter et al., 2016).

Laboratory analysis also significantly affects TOC stock estimates. Many studies compare dry combustion with wet oxidation (Bisutti et al., 2004; Tivet et al., 2012; Vitti et al., 2016), but few provide information on how dry combustion affects total carbon content. Differences between methods are attributed to combustion temperature (900–1300 °C) in calcareous samples (Wright & Bailey, 2011), the type and quality of organic material in the sample (Grahmann et al., 2023), and sample mass (Brinton et al., 2025). In our study, the presence of lime and the type and quality of organic material added to the soil (e.g., roots, aboveground plant material, organic fertilizers) may have influenced uncertainty in converting TOC contents between analytical methods. The temperature-gradient method provides high precision and reproducibility and does not require additional analysis to account for inorganic carbon in calcareous samples (Bisutti et al., 2004).

The estimation of missing values contributes similarly to uncertainty in TOC stocks as the conversion between measurement methods. PTFs are commonly used to estimate bulk density when direct measurements are unavailable, but their precision often depends on regional soil properties (Chen et al., 2024; Makovníková et al., 2017). Due to the limited dataset, we could not derive PTFs specific to different soil types. In contrast, the contribution of depth interpolation to TOC uncertainty is negligible. Several studies report good agreement when using spline functions for interpolated TOC stocks (Lacoste et al., 2014; Malone et al., 2009), making this approach suitable and reliable for comparing TOC stocks across different soil depths.

Other sources of uncertainty not quantified in this study include small-scale spatial variability of TOC (Poeplau et al., 2022) and the estimation of the stone content (Poeplau & Gregorich, 2022). In the first monitoring period, replicate sampling points at a site were located close together (same pit profile), whereas in the seventh period they could be up to 14 m apart. Additionally, pit profiles were located at varying distances from the current NABO plot (<2 m to >10 m). As a result, small-scale variability differs both between monitoring periods and between sites. Pooling field replicates after sampling prevents quantification of this variability. Using three field replicates per sampling event can reduce uncertainty compared to single measurements by about 50% (Poeplau et al., 2022). Stone content is now considered when calculating bulk density according to the definition of fine-earth bulk density (BD_{FE}), but due to the small volume of the impact probe, it is systematically underestimated (Schwab & Gubler, 2016). In the first monitoring period, stone content was not systematically recorded and, due to missing raw data, cannot be used to convert bulk density to BD_{FE}. Both factors likely contribute significantly to uncertainty in the dataset.

In summary, the conversion between different measurement methods and the estimation of missing values are the main contributors to measurable uncertainty in our dataset, while small-scale spatial variability and the determination of the stone content contribute to non-measurable uncertainty in the harmonized data. For the first monitoring period, the total measurable uncertainty of approximately 15% represents about one-third of the variation in summed TOC stocks across sites (coefficient of variation: 45%).

To minimize uncertainties in estimating subsoil TOC stocks in future soil monitoring, we recommend to:

- measure bulk density using probes
- determine TOC contents using the temperature-gradient method (with the same temperature step as used in elemental analysis)
- assess TOC stocks with multiple field replicates per sampling event and site
- determine the stone content for each sample

We do not consider harmonization of the sampling depth necessary when mass-preserving spline methods are used for depth interpolation of the TOC stock.

8 Conclusion

In the present study, significant decreases in TOC stocks between the first and seventh monitoring periods were only observed in the topsoil of cropland sites, while differences in the subsoil and within the other land uses were not significant. Differences between land uses were generally small, except in the topsoil, where grassland sites had higher TOC stocks than cropland sites. Depending on land use, clay content, pH, and temperature were the main factors influencing TOC stocks, while the initial TOC stock was the strongest driver of changes in TOC.

Data gaps and the necessary data harmonization resulted in a reduced dataset with increased variability, potentially masking existing differences in TOC stocks. Spline-based depth interpolation proved to be a robust method with relatively low uncertainty for comparing TOC stocks across soil depths. This makes it a suitable tool for long-term monitoring and cross-site comparisons of TOC stocks, and it also allows for the integration of additional datasets in the future. For future studies, it is particularly important to quantify uncertainties related to small-scale variability in TOC stocks in the field and to stone content of the soil.

A deeper understanding of the factors driving TOC stock changes will require incorporating management information into data analyses, as neither site-specific soil and climate conditions nor climate changes between the two monitoring periods showed a significant effect on TOC stock changes. To specifically explain decreases in topsoil TOC at cropland sites, detailed data on crop rotation, tillage, fertilization, and carbon return via crop residues are needed. Since the soil monitoring of NABO is conducted on Swiss commercial farms, these data are particularly valuable for identifying practices that either increase or deplete soil organic carbon under real-world conditions and for providing recommendations for sustainable soil management in Switzerland.

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Table of abbreviations

Abbreviation	Explanation
a	Year
Al	Aluminium
ANOVA	Analysis of Variance
$BaCl_2$	Barium chloride
BC	Box-Cox transformation function
BD_{FE}	Bulk density of the fine earth
°C	Degrees Celsius
C	Carbon
Ca	Calcium
C-Horizont	pedological horizon with parent material
$CaCl_2$	Calcium chloride
CEC	Cation exchange capacity
CO_2	Carbon dioxide
C/N	Carbon/nitrogen
DP	Data points
EA	Elemental analysis
EMM	Estimated marginal mean
FAC	Research Institute for Agricultural Chemistry and Environmental Hygiene; predecessor (1900–1996) of Agroscope
FAP	Federal Research Station for Agricultural Crop Production
FE	Fine earth
Fe	Iron
GLM	generalized linear model

ha	Hectare
ISO	International Organization for Standardization
LM / lm	Linear model
lmer	Linear mixed-effects model
log	Natural logarithm
MDD	Minimal detectable difference
mtry	Statistical parameter in the random forest model
NABO	Nationale Bodenbeobachtung (National Soil Monitoring)
NABOphys	Soil physical monitoring of the National Soil Monitoring
org.C	Organic carbon
P-Wert	Measure of statistical significance of a test result
PD_{FE}	Packing density of the fine earth
pH value	negative base-10 logarithm of the hydrogen ion concentration
PTF	Pedotransfer function
R	Programming language and environment for statistics and data analysis
R^2	Coefficient of determination
RF	Random forest model
RMSE	Root Mean Squared Error
t	Ton
TOC	Total organic carbon
TOC_{Carm}	Total organic carbon content determined using a Carmhograph
TOC_{EA}	Total organic carbon content determined using elemental analysis

Acknowledgement

We thank all NABO staff involved in data collection and provision, as well as the Environmental Analytics team of Agroscope for the laboratory analyses. We are grateful to Janine Moll-Mielewczik and John Köstel for their professional exchange and support. Our thanks also go to the (former) farm managers of the NABO monitoring for their long-term collaboration and provision of site-specific information. Meteorological and topographical data were provided by MeteoSwiss and swisstopo. The National Soil Monitoring program is conducted on behalf of the Federal Office for the Environment, the Federal Office for Agriculture, and the Federal Office for Spatial Development.

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Use of artificial intelligence

Parts of the text were translated and linguistically edited using AI-assisted tools (ChatGPT by OpenAI and DeepL). The authors have reviewed and approved all content.

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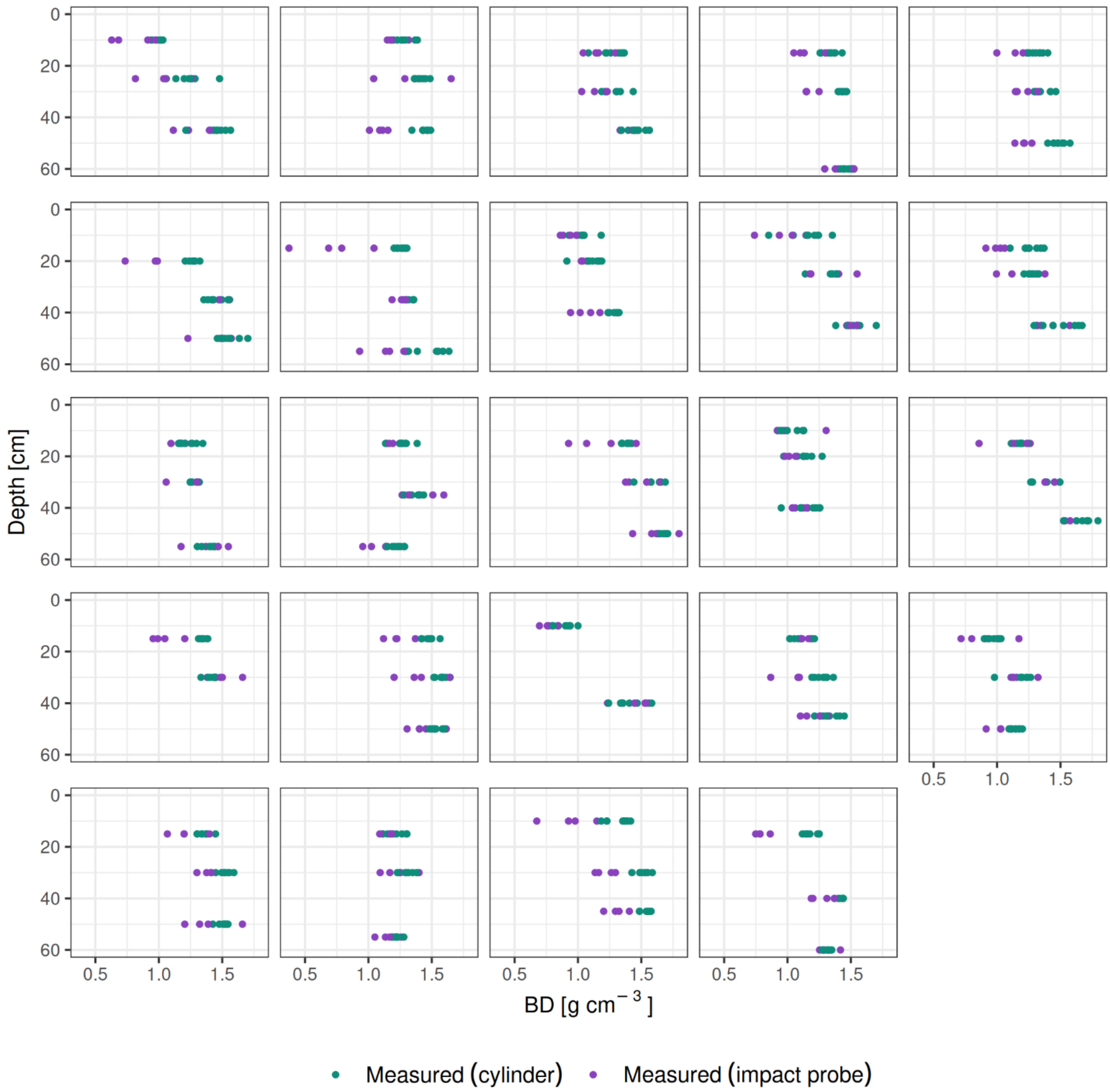
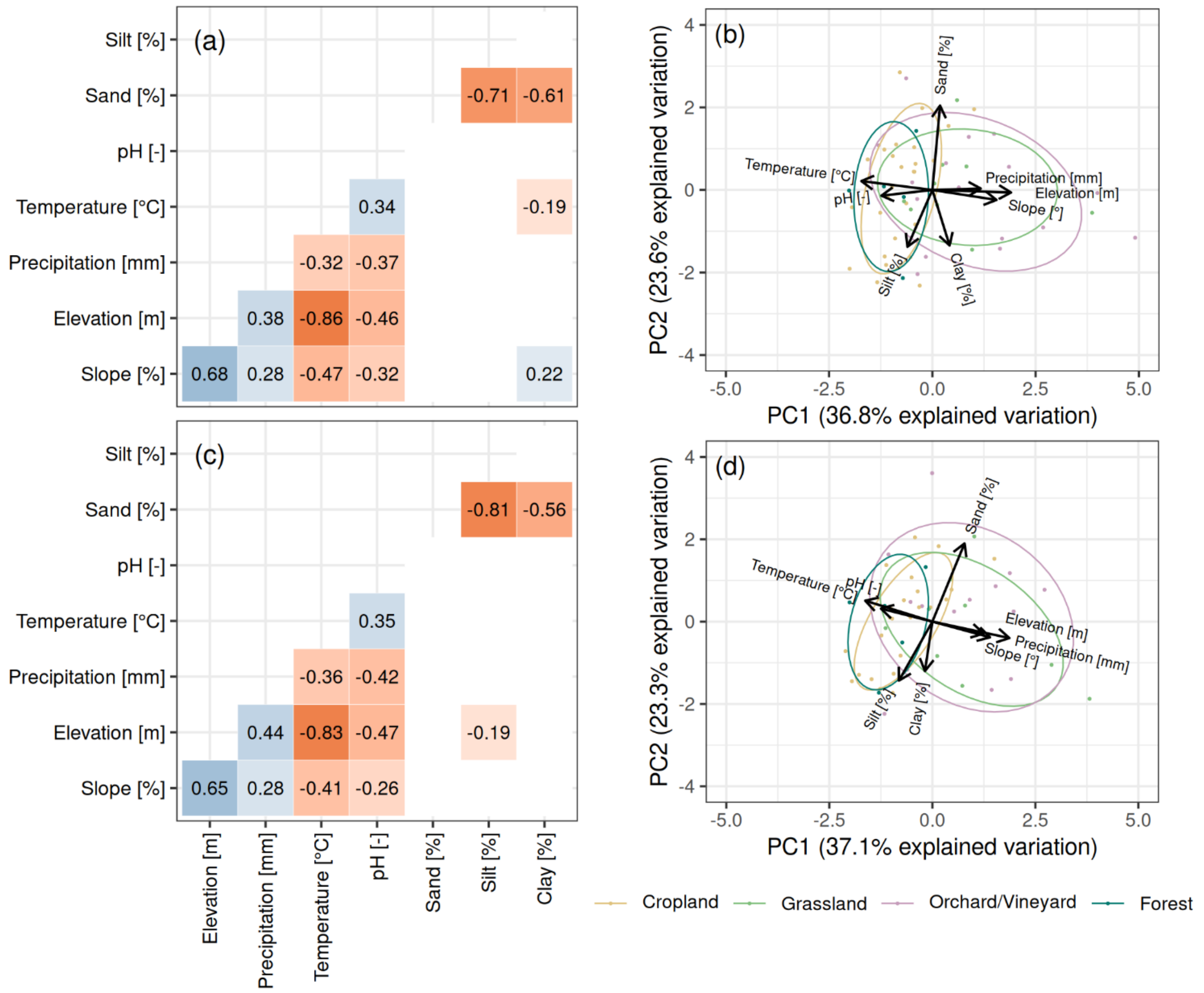
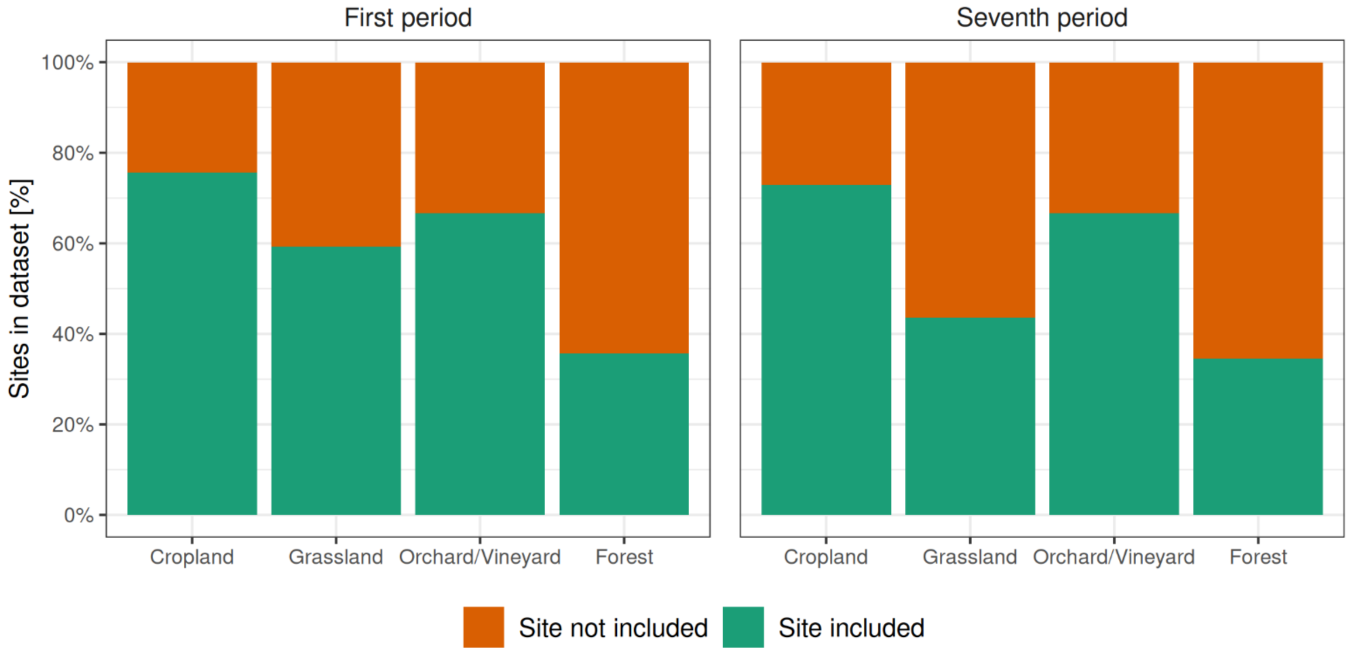
Appendix



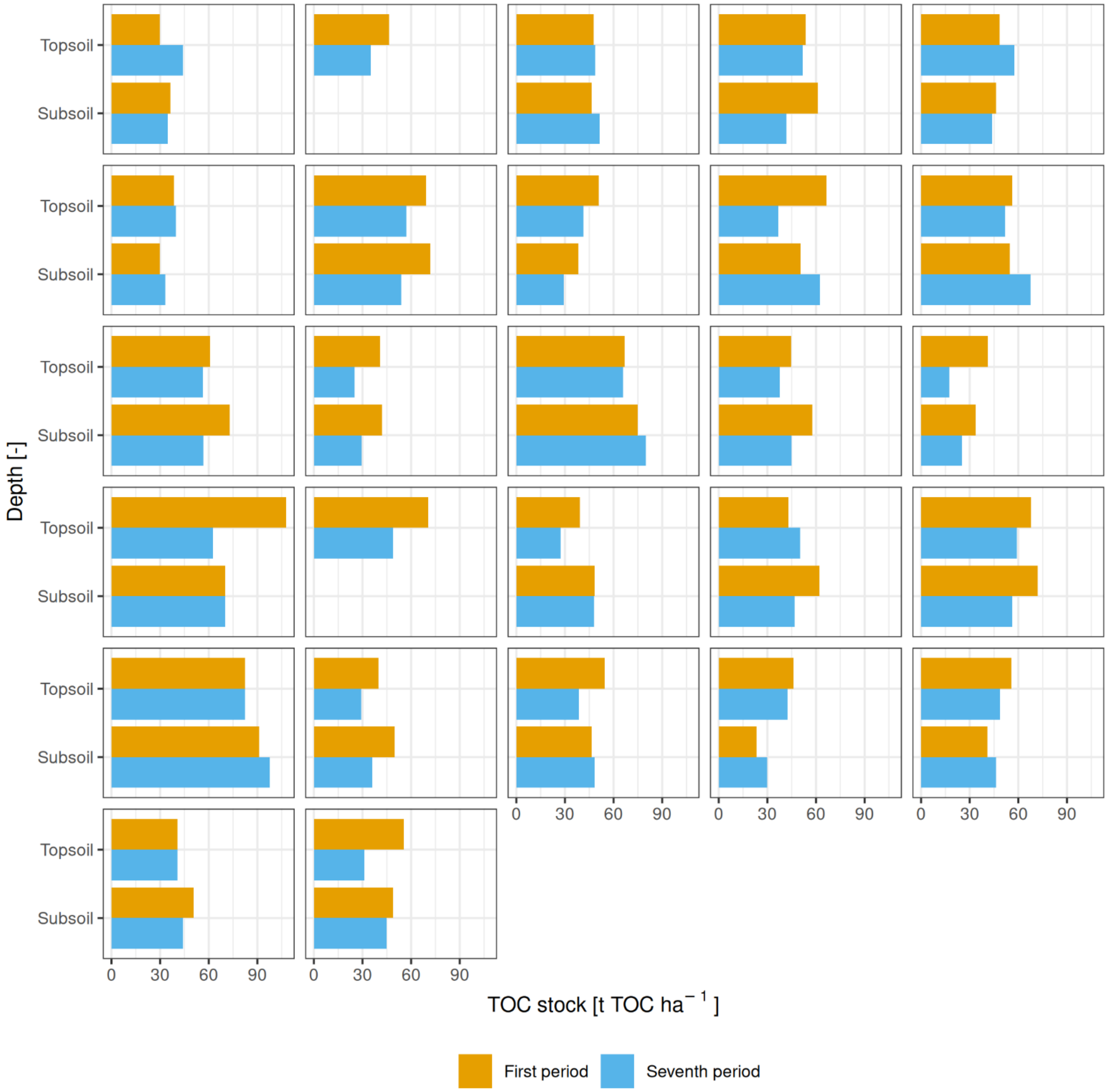
Supplementary figure 1: Bulk densities measured with cylinders and an impact probe at different soil depths across 25 NABO grassland and arable sites (NABOphys). Each point represents a single measurement.



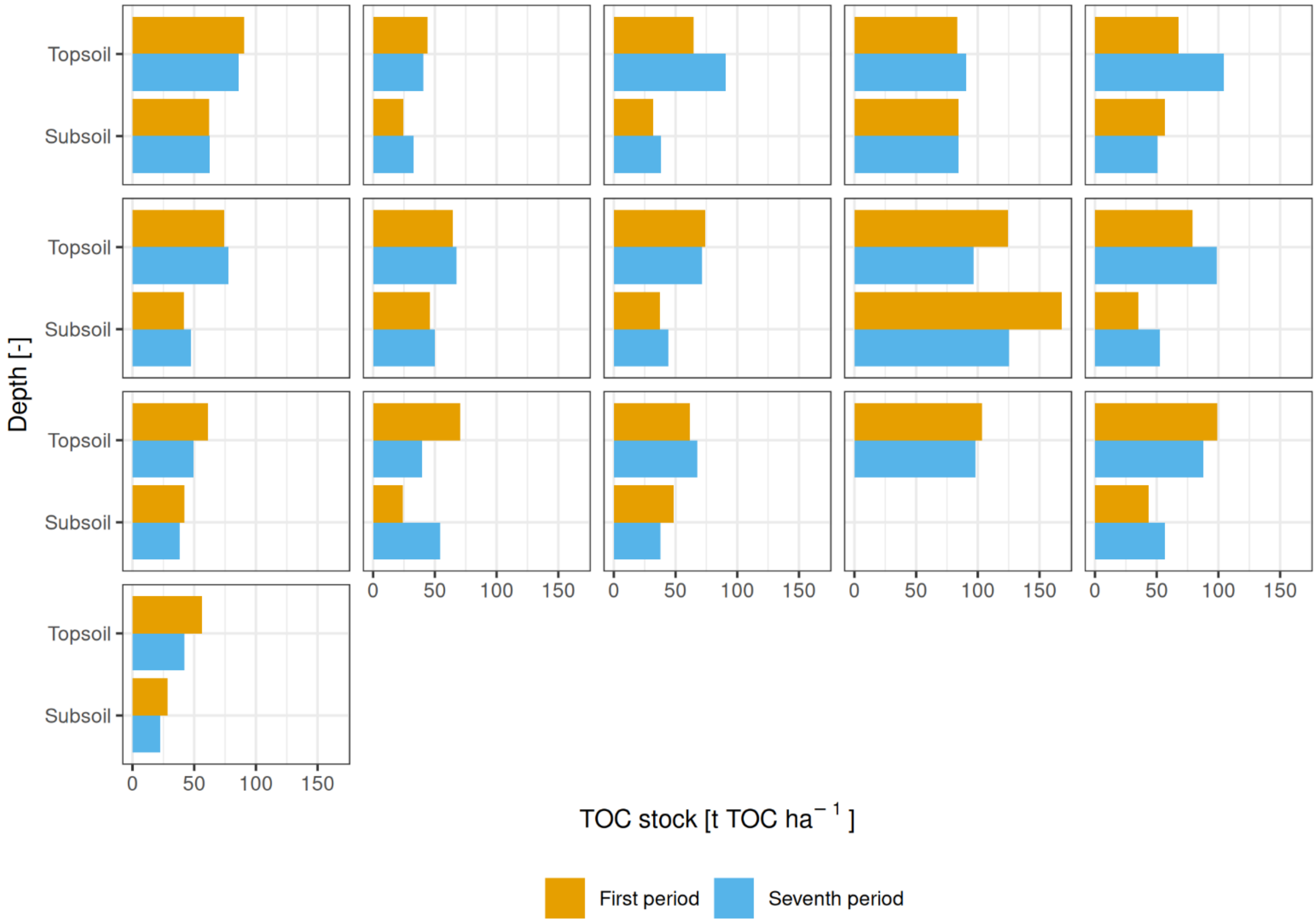
Supplementary figure 2: Correlation and principal component analyses (PCA) of the pedoclimatic variables. (a, c) Correlation plots for (a) 0–20 cm and (c) 20–60 cm soil depth, showing correlation coefficients for significant correlations; non-significant correlations are shown in white. (b, d) PCA biplots for (b) 0–20 cm and (d) 20–60 cm soil depth, with the first two principal components on the x- and y-axes. Individual sites are shown as points, and ellipses represent the 68% confidence intervals for the four land use types.



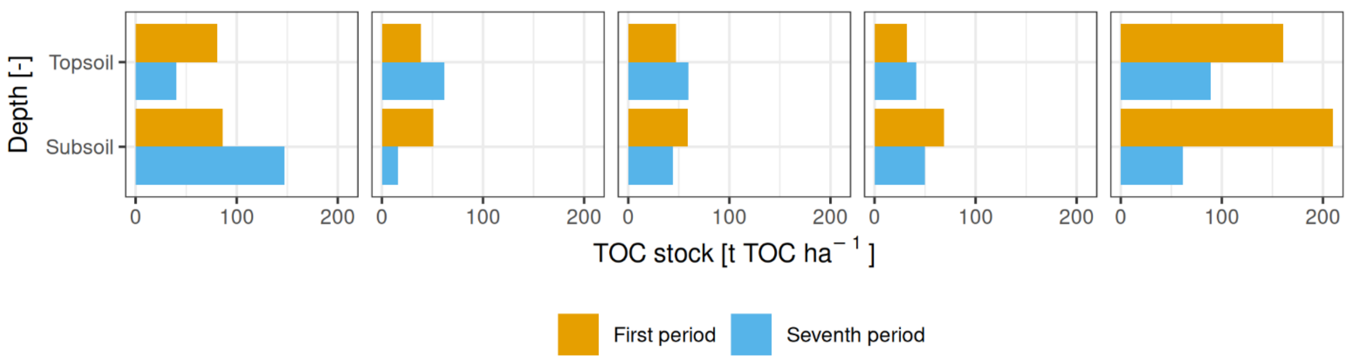
Supplementary figure 3: Proportion of sites in the NABO monitoring network (first and seventh monitoring periods shown separately) included in the analysis after data processing, separated by land use.



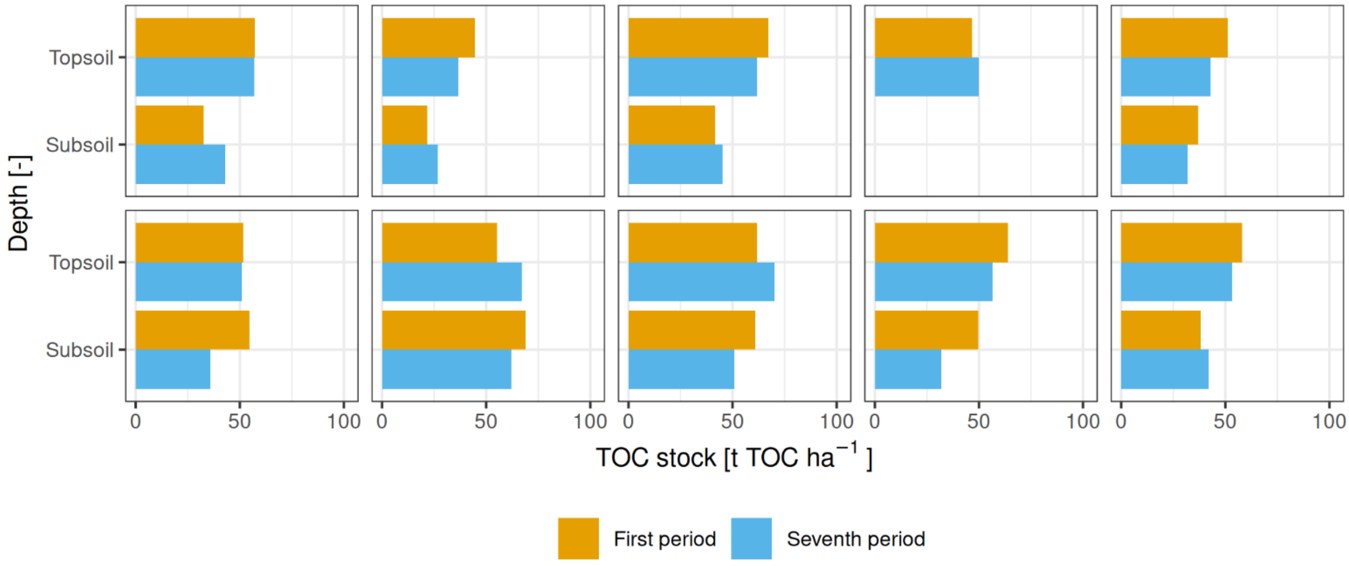
Supplementary figure 4: TOC stock per cropland site, divided by soil depth and color-coded by monitoring period.



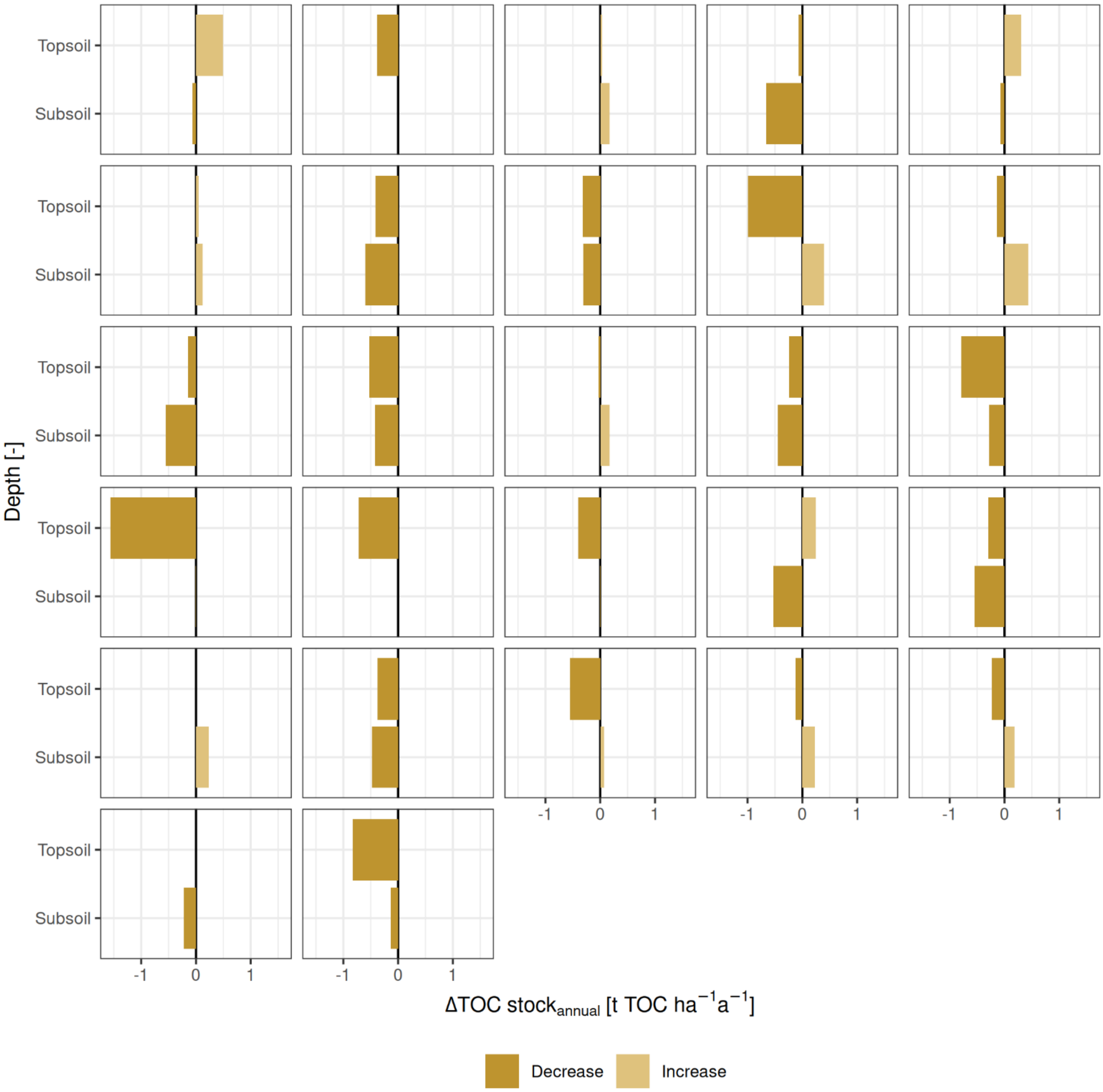
Supplementary figure 5: TOC stock per grassland site, divided by soil depth and color-coded by monitoring period.



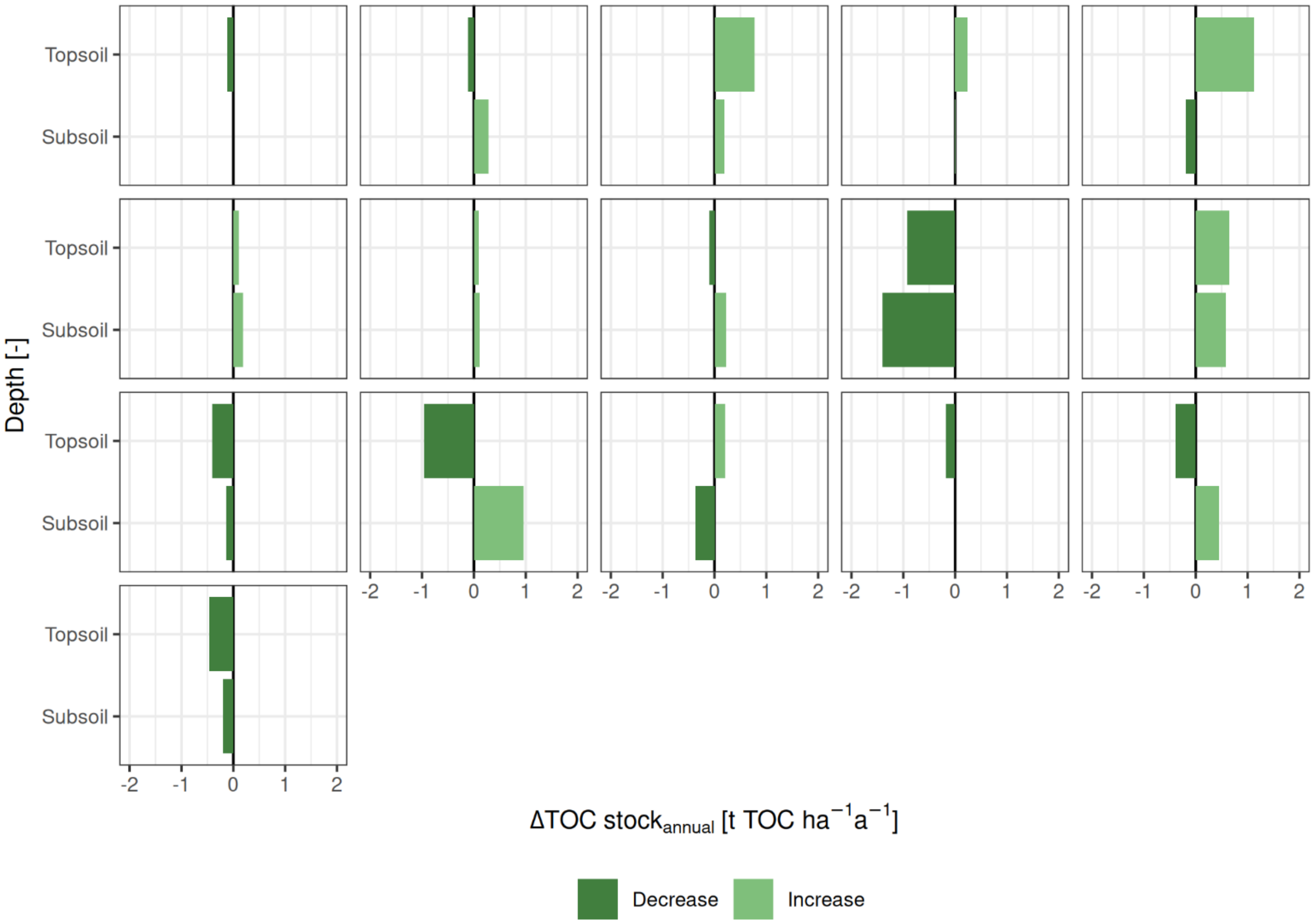
Supplementary figure 6: TOC stock per orchard/vineyard site, divided by soil depth and color-coded by monitoring period.



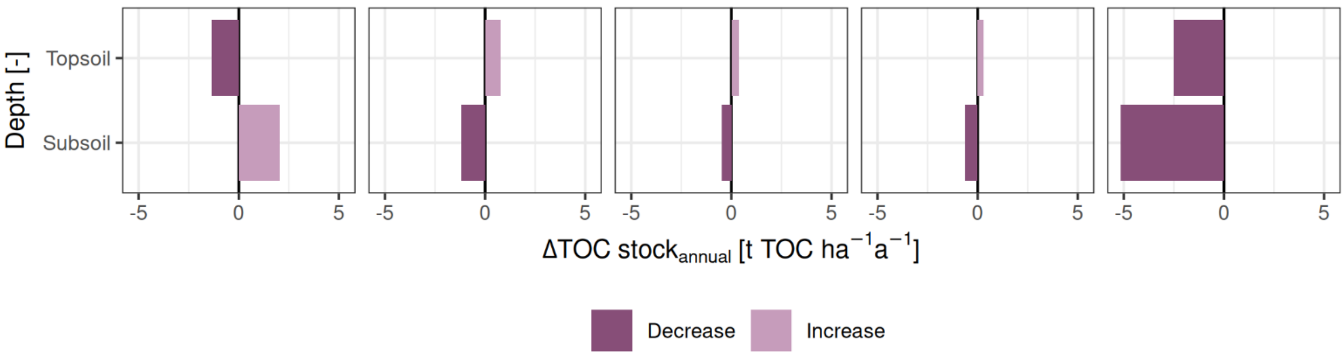
Supplementary figure 7: TOC stock per forest site, divided by soil depth and color-coded by monitoring period.



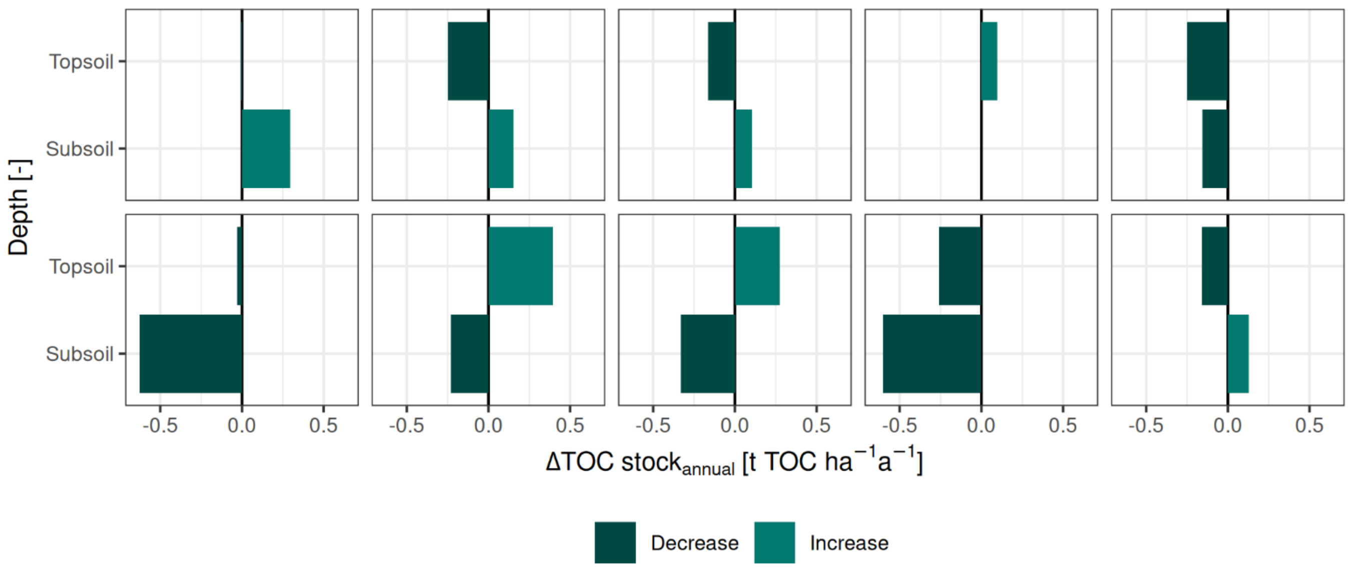
Supplementary figure 8: ΔTOC stock per cropland site, divided by soil depth and color-coded by direction of change.



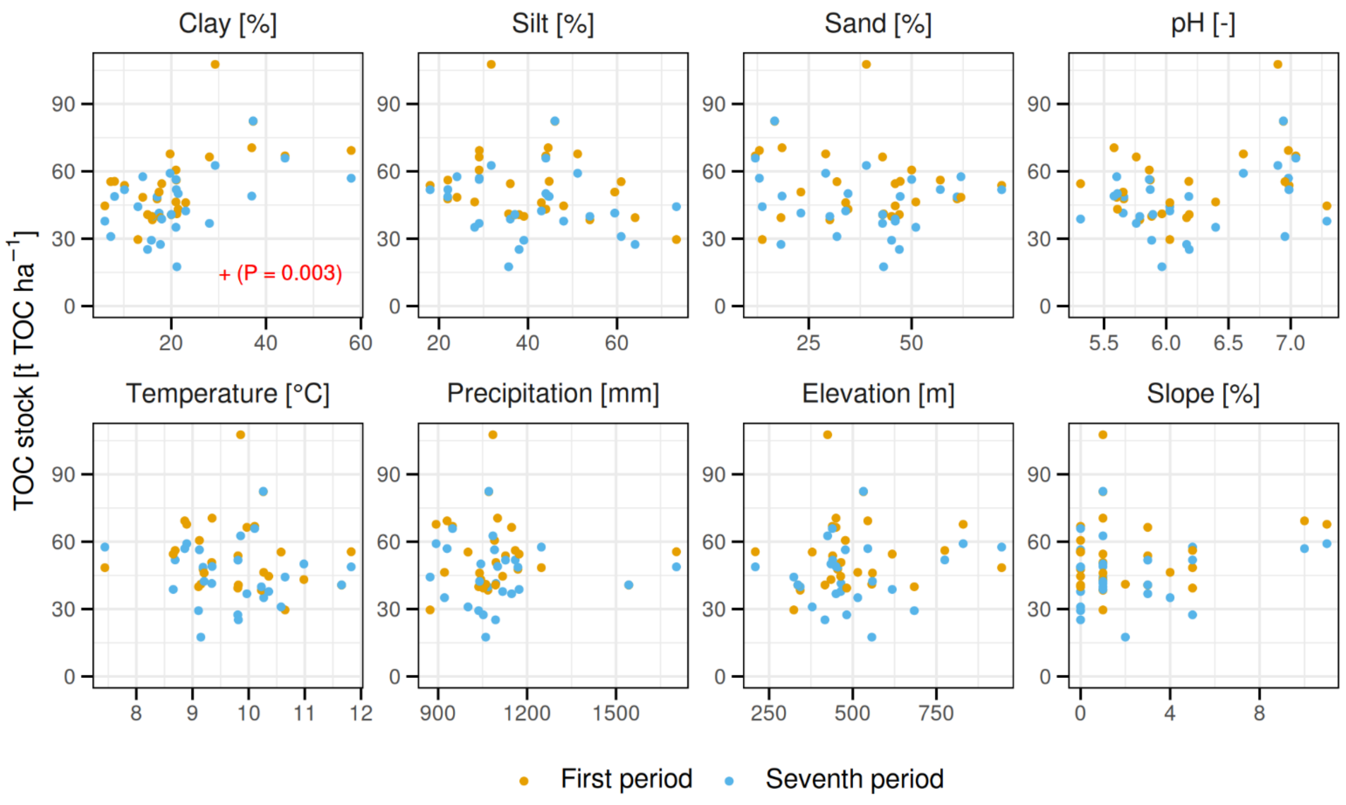
Supplementary figure 9: ∆TOC stock per grassland site, divided by soil depth and color-coded by direction of change.



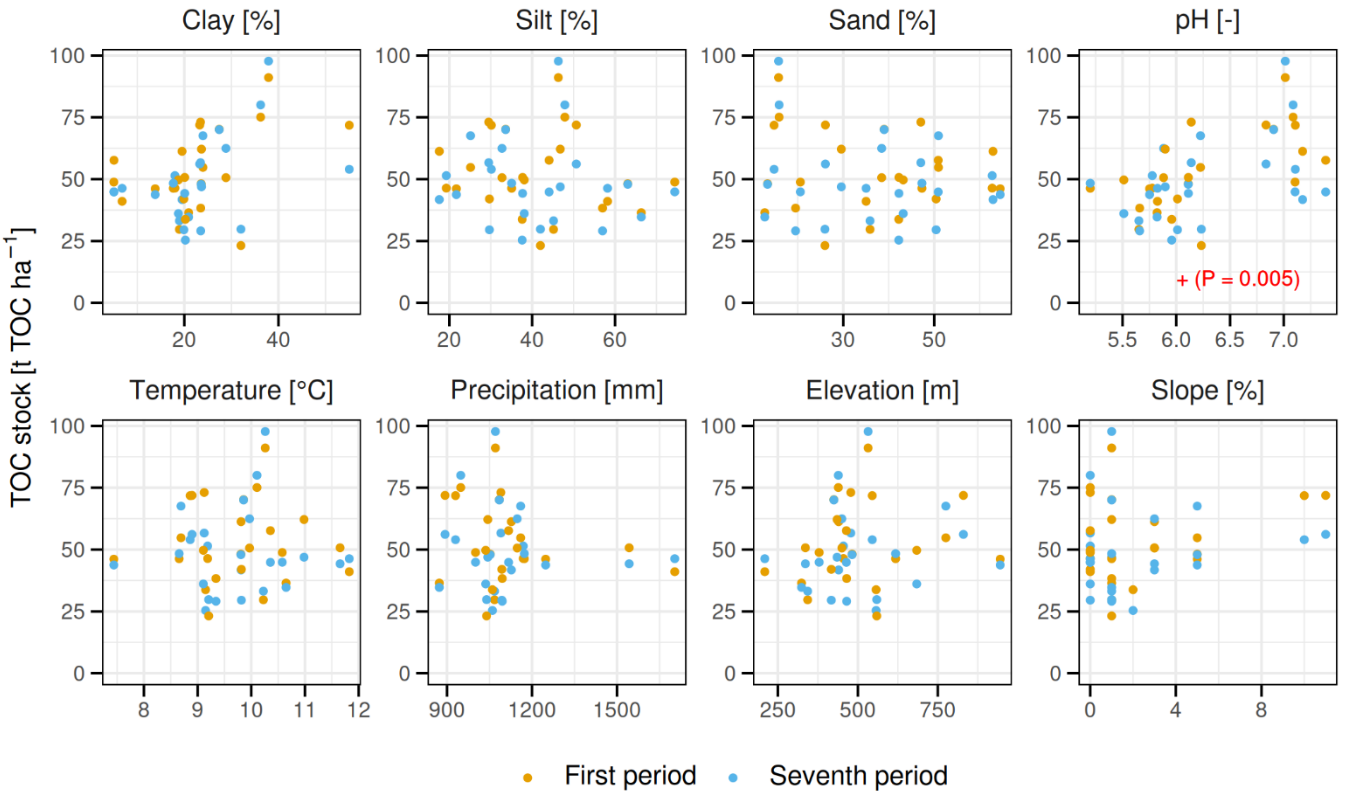
Supplementary figure 10: ∆TOC stock per orchard/vineyard site, divided by soil depth and color-coded by direction of change.



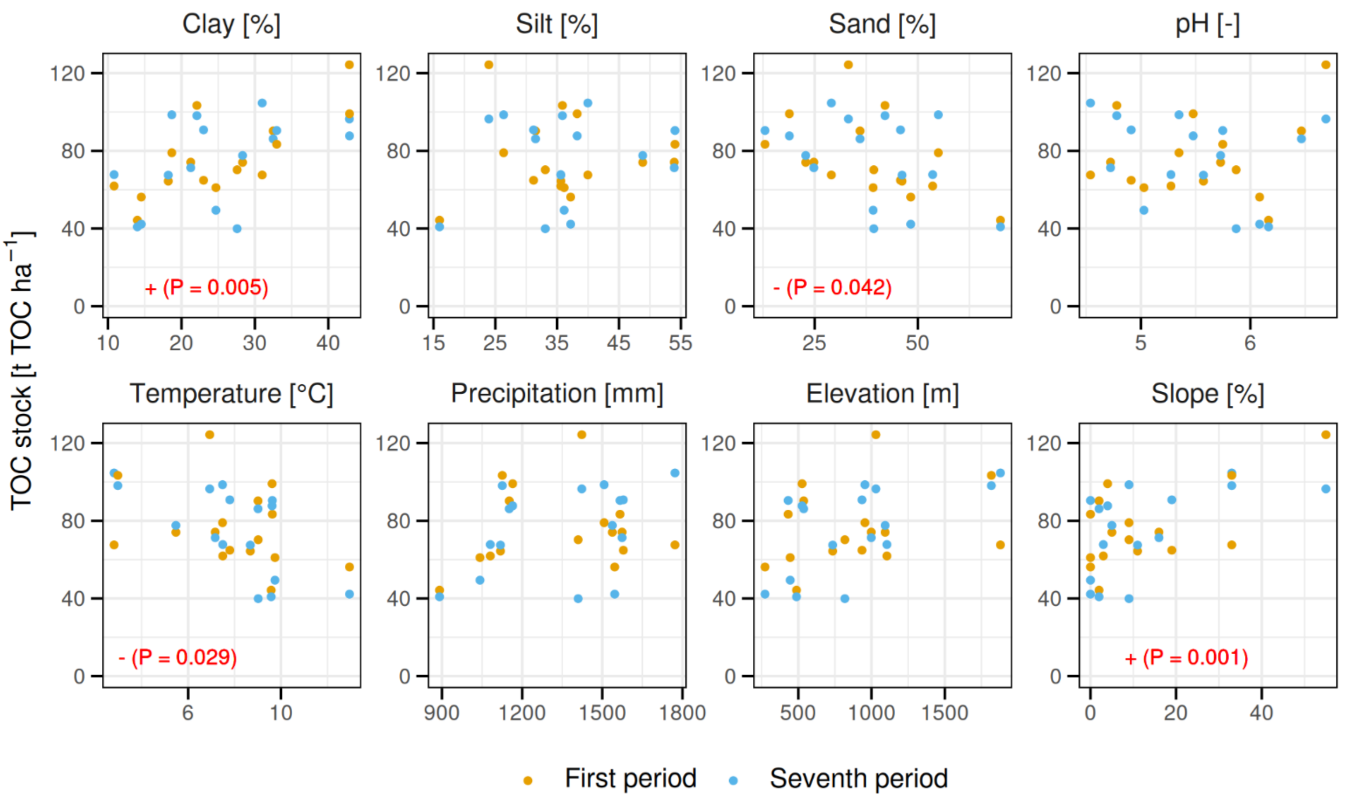
Supplementary figure 11: ΔTOC stock per forest site, divided by soil depth and color-coded by direction of change.



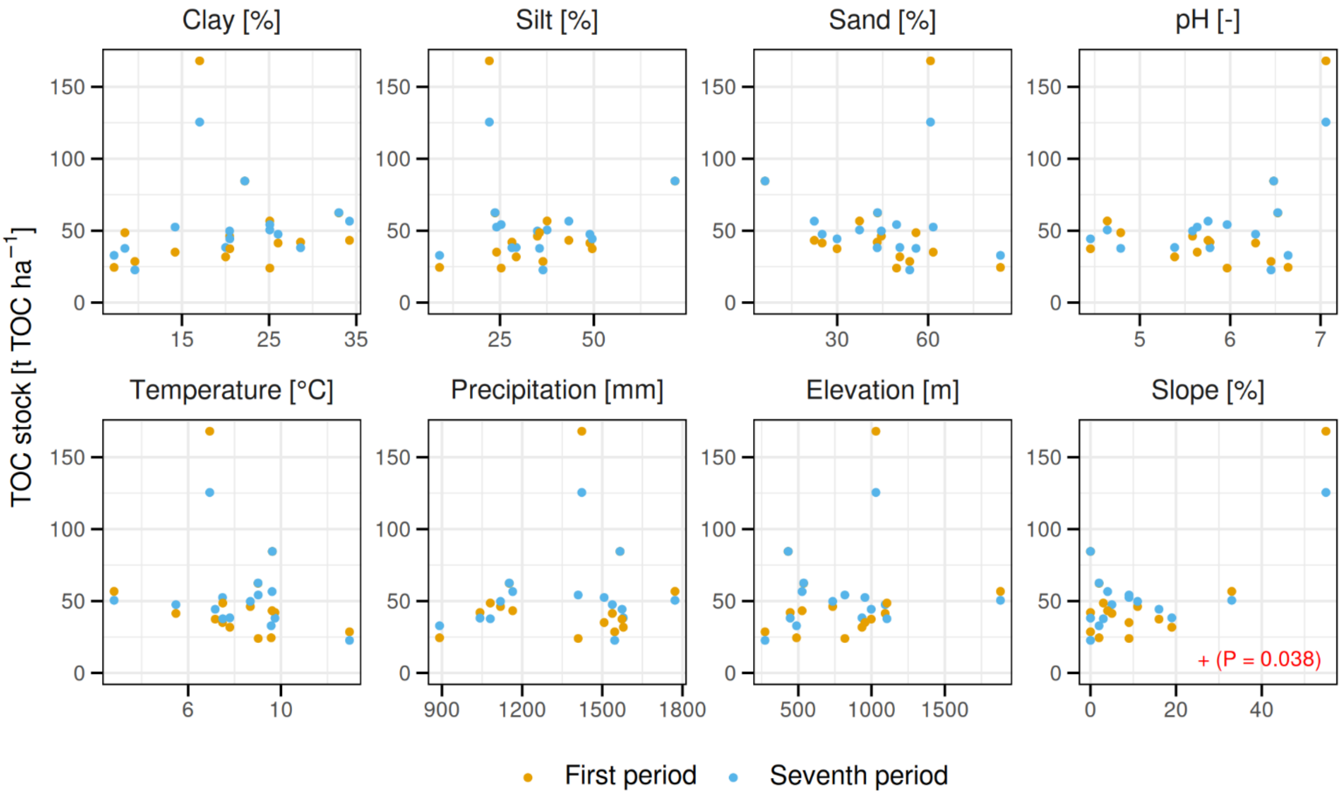
Supplementary figure 12: Effect of pedoclimatic variables on TOC stock at cropland sites in 0–20 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.



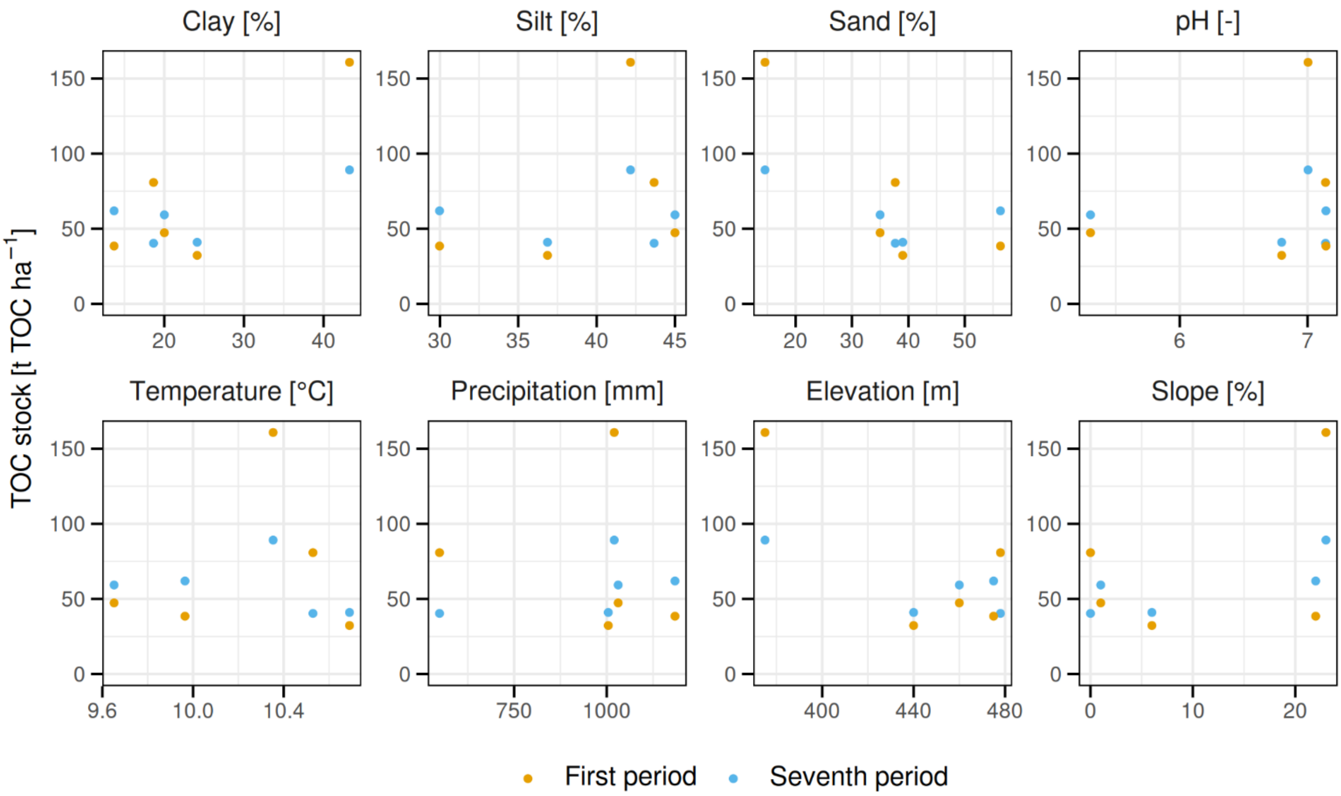
Supplementary figure 13: Effect of pedoclimatic variables on TOC stock at cropland sites in 20–60 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.



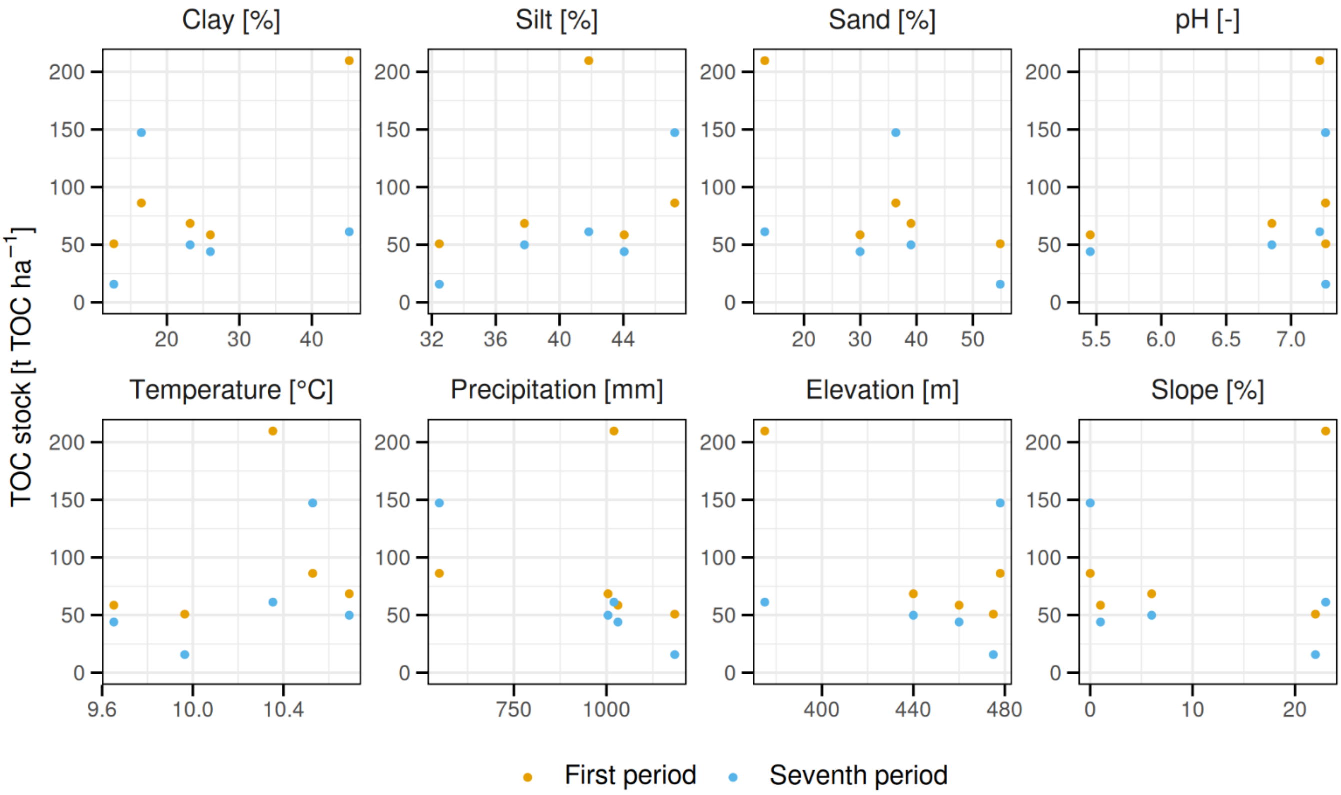
Supplementary figure 14: Effect of pedoclimatic variables on TOC stock at grassland sites in 0–20 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.



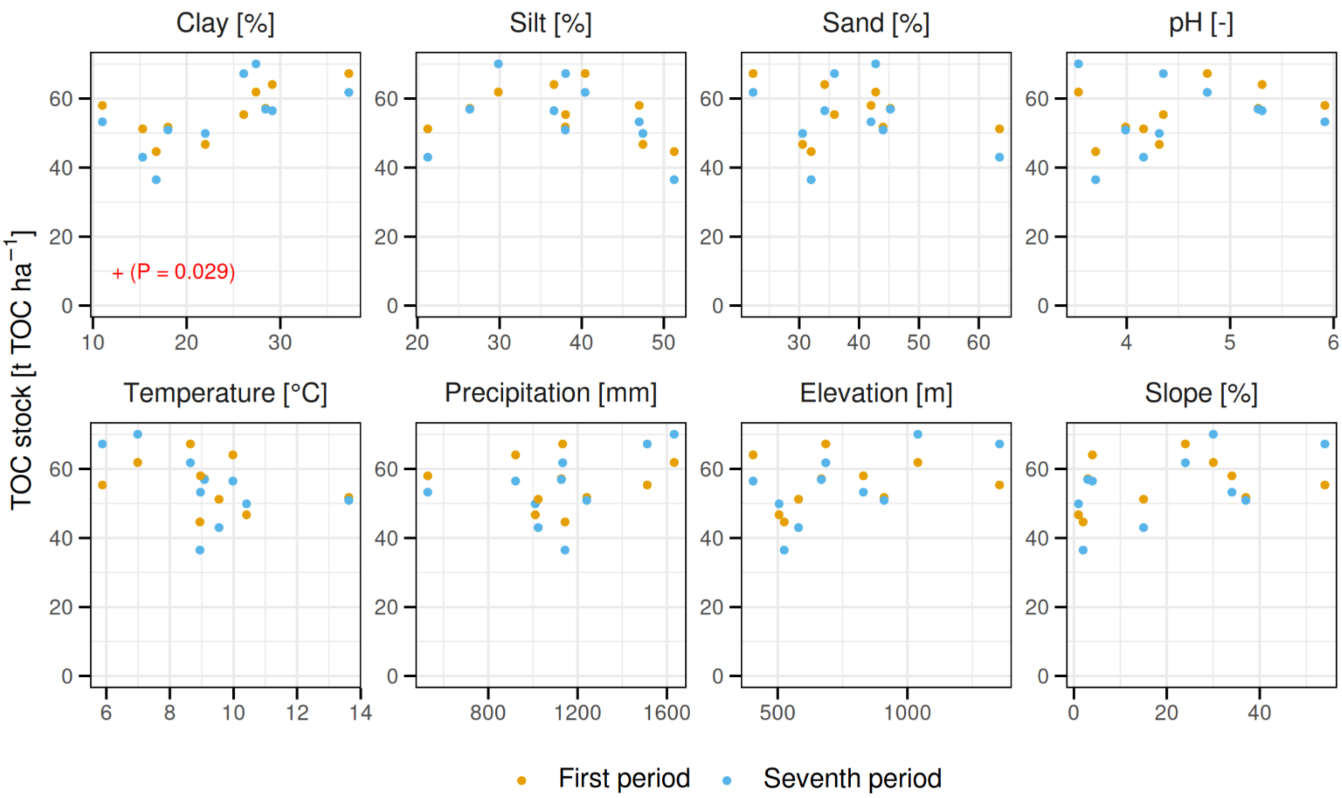
Supplementary figure 15: Effect of pedoclimatic variables on TOC stock at grassland sites in 20–60 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.



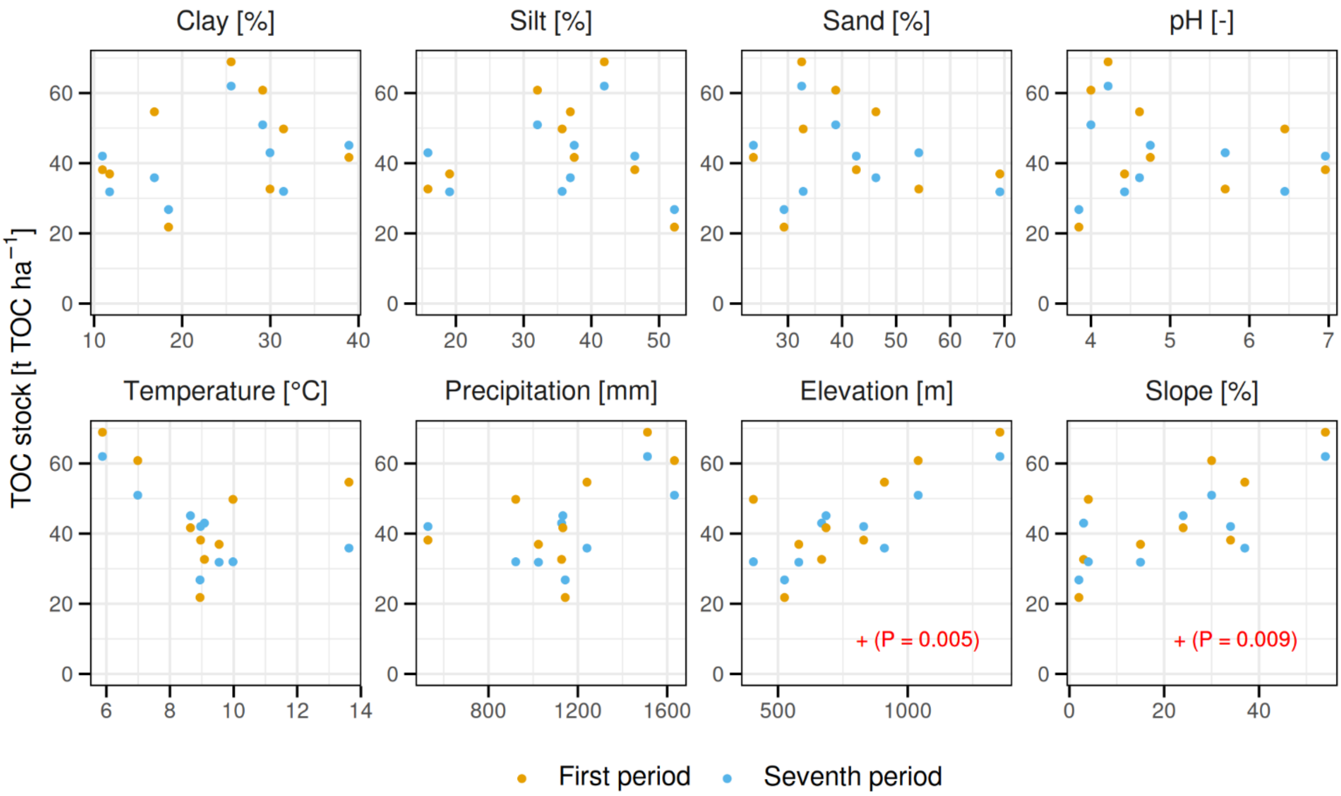
Supplementary figure 16: Effect of pedoclimatic variables on TOC stock at orchard/vineyard sites in 0–20 cm soil depth.



Supplementary figure 17: Effect of pedoclimatic variables on TOC stock at orchard/vineyard sites in 20–60 cm soil depth.



Supplementary figure 18: Effect of pedoclimatic variables on TOC stock at forest sites in 0–20 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.



Supplementary figure 19: Effect of pedoclimatic variables on TOC stock at forest sites in 20–60 cm soil depth. The direction and p-value of each covariate's effect on TOC stock are shown if significant. A regression line is not shown due to prior data transformation.