

Article

Does Small-Scale Spatial Heterogeneity Influence Carbon Dioxide Emissions from Agricultural Sandy Soil? A Case Study

Eszter Tóth ¹, Imre Cseresnyés ^{1,*}, Márton Dencső ^{1,†} and Marianna Magyar ²

¹ Department of Soil Physics and Water Management, HUN–REN Centre for Agricultural Research, Institute for Soil Sciences, Fehérvári út 132–144, H-1116 Budapest, Hungary; toth.eszter@atk.hun-ren.hu (E.T.)

² Department of Soil Chemistry and Material Turnover, HUN–REN Centre for Agricultural Research, Institute for Soil Sciences, Fehérvári út 132–144, H-1116 Budapest, Hungary; magyar.marianna@atk.hun-ren.hu

* Correspondence: cseresnyes.imre@atk.hun-ren.hu

† This author died in 2026.

Abstract

The sequestration and release of carbon in soil is a crucial aspect of agricultural production studies, involving numerous small-plot trials and modelling processes. Small-scale heterogeneity in soil properties can influence measured carbon dioxide (CO₂) fluxes. This study aimed (i) to compare CO₂ emission from two neighbouring sandy soil plots managed with identical agricultural practices; (ii) to identify the key factors influencing soil CO₂ emissions; and (iii) to examine the effect of soil water content (SWC) and soil temperature (Ts) on the results. Two plots located approximately 30 m apart and differing in terms of their humus depths and contents were selected for investigation. Continuous SWC and Ts measurements were taken. Portable devices were used to determine CO₂ emissions, penetration resistance (PR) and vegetation cover. The humus layer in plot A was 55 cm thicker than in plot B, while the soil organic carbon (SOC) content was 18% and 163% higher in the 0–30 cm and 30–90 cm soil layers, respectively. Vegetation cover was nearly twice as high in plot A, and the mean soil CO₂ emissions were 36% higher than those measured in plot B. SWC showed an opposite trend, with plot B exhibiting values that were 9.7% and 17.7% higher than those of plot A in both the top and deepest soil layers, respectively. These findings emphasize the importance of including small-scale spatial heterogeneity when parameterizing or interpreting biogeochemical models, particularly when model inputs are based on limited soil measurements from specific locations.

Keywords: carbon cycling; cover crops; greenhouse gas emissions; in situ measurements; penetration resistance; soil organic carbon; soil respiration; soil water content; spatial variability



Academic Editor: Xianjin Zhu

Received: 27 July 2026

Revised: 27 August 2026

Accepted: 31 August 2026

Published: 3 September 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Prior to human intervention, the rates of carbon sequestration and carbon loss in natural ecosystems were balanced. However, since the Industrial Revolution, the concentration of CO₂ in the atmosphere has steadily increased from 280 ppm to 410 ppm, primarily due to growing anthropogenic activity [1].

As soil is the largest terrestrial carbon reservoir, soil respiration represents a major component of ecosystem respiration [2,3], and emissions of carbon dioxide (CO₂) from soil play a crucial role in the global carbon cycle [4,5]. Soil CO₂ emissions originate from two main sources: autotrophic respiration by plant roots and their associated mycorrhizal symbionts and heterotrophic respiration driven by microbial activity and the decomposition

of organic matter [6]. These components are controlled by different biological processes and environmental drivers, and determining the extent to which they contribute to soil respiration is challenging [7,8].

Numerous studies have confirmed that soil moisture content and temperature are the primary environmental factors governing CO₂ emissions from soils, influencing microbial activity and the rate of root respiration [9–11]. The relationship between these environmental variables and soil CO₂ emissions is non-linear: within a certain range, increases in either factor lead to higher emissions; however, values outside specific thresholds of emissions may decrease.

Soil organic matter (SOM), soil compaction, pH and vegetation cover density are also key parameters influencing soil CO₂ emissions [12,13]. SOM serves as a substrate for microbial activity, so higher organic matter content generally increases CO₂ emissions [14]. In denser or compacted soil, gas diffusion is limited due to reduced pore space for oxygen, which suppresses the rate of aerobic decomposition. Several studies have confirmed that when soil bulk density exceeds 1.7 g m^{−3}, it has a negative impact on soil microorganisms, hinders carbon mineralization, and thus reduces CO₂ emissions from the soil [15]. At the same time, minor soil compaction can have a positive effect on soil moisture content and increase microbial activity, resulting in higher CO₂ emissions typically being observed in looser or well-aerated soils [16–18].

Soil CO₂ emissions are influenced by numerous interacting factors, and sometimes the impact of one factor can overshadow another. These factors exhibit temporal and spatial variability, often demonstrating significant variation on a small scale; their effects can manifest as small-scale heterogeneity in soil respiration [19–23]. Many small-plot studies overlook this small-scale heterogeneity, and data for the same treatments at this scale is limited. Furthermore, individual soil properties are frequently determined from composite samples at the plot level, which can potentially mask small-scale spatial heterogeneity [24]. Consequently, identifying the dominant drivers under specific environmental conditions remains challenging. The variability in emission measurements is well-documented. Eliminating this variability requires a large number of repetitions, which is challenging to achieve. This can typically only be achieved using automated systems with multiple chambers. In an average-sized agricultural field, measurements must be taken approximately 20 times to reduce measurement uncertainty to 5% [25]. While the importance of measurements taken with portable, handheld instruments is clear, these are usually conducted in 3–10 repetitions due to time and labour constraints. Nevertheless, such field observations contribute to a better understanding of the subject. Uncertainties also arise from measurements during predictive modelling for a given area, since models usually assume homogeneous input parameters based on point-source data. However, the results of the model are area-based and are upscaled to at least the field level. These results are usually calibrated using a limited number of parameters, primarily soil moisture and soil temperature data, due to the ease with which these can be continuously measured. Other parameters that also influence soil CO₂ emissions must be entered as one-time input data [26,27].

The small-scale spatial heterogeneity of soil properties is a well-known phenomenon, yet it is frequently overlooked when evaluating small-plot experiments. Even areas that appear homogeneous and have undergone identical land management practices for years can exhibit variability in key soil properties, resulting in functionally different soil states. This variability is rarely considered in experimental design or data interpretation, which can lead to biased estimates of soil CO₂ emissions and soil water content (SWC). This reduces the reliability of upscaling approaches and model-based predictions at the plot or regional scale.

The main aim of this study is therefore to assess the influence of natural small-scale spatial heterogeneity on soil CO₂ emissions and SWC under comparable conditions, by comparing two plots that differ in humus depth and soil organic carbon (SOC) content. The primary criterion for selecting these plots was the variation in humus horizon depth. In total, two plots were chosen. While this limits the generalizability of the study results, as the investigation was conducted at only two locations, selecting these two extreme cases enabled significant differences between the plots to be demonstrated, even over a short study period.

The primary objectives of our study were to: (i) compare soil CO₂ emissions between two neighbouring plots that have been managed using the same agricultural practices for several years; (ii) identify the key factors influencing soil CO₂ emissions in this specific case; and (iii) examine the effect of traditional controlling parameters, such as soil moisture content and soil temperature, on the results. The following questions were addressed: (i) Can distinct differences in CO₂ emissions be detected between two nearby plots that differ in organic carbon content and humus layer thickness? (ii) Can these differences be demonstrated through continuous measurements? (iii) Do emissions in this heterogeneous environment depend primarily on soil moisture content or other local factors?

Based on the initial, comprehensive survey conducted at the start of the study period, we formulated the following hypotheses: (i) Small-scale soil heterogeneity results in distinct variations in carbon flux intensity. (ii) Soil temperature and moisture content are not always the dominant drivers of soil CO₂ emissions. (iii) The degree of vegetation can contribute the effects of these primary environmental factors.

2. Materials and Methods

2.1. Site Description

The study area is located at the experimental site of the HUN-REN Centre for Agricultural Research, Institute for Soil Sciences, in Órbottyán, Hungary (47°40′22.6″ N; 19°14′56.2″ E), on humic sandy soil, i.e., Calcaric Arenosol [28]. According to the Köppen–Geiger climate classification, this region of Hungary is characterized by a Cfb climate type, with a long-term average annual precipitation of 560 mm and featuring warm summers [29]. However, the study year was extremely dry, with only 247 mm of total rainfall, 109 mm of which occurred during the growing period from May to October.

A 0.7 ha study area was established in Autumn 2024. This area was dedicated to a long-term regenerative agriculture trial designed to examine the effect of tillage methods, fertilization, and cover cropping on soil characteristics, crop productivity and greenhouse gas emissions. There are no noticeable differences in elevation in the area. In April 2025, before the different treatments were established, 36 plots were designated, each with a net area of 108 m². Soil core drilling was then conducted to a depth of 1 m in all plots. Due to visible differences in the thickness of the humus layer between the plots, two plots (designated A and B) located approximately 30 m apart with different humus depths and contents were selected for further analyses. Land use in the area has remained uniform in recent years. All agricultural practices were performed consistently across the site, as detailed in Table 1.

We used a homemade seed mixture as a cover crop. This included grass pea (*Lathyrus sativus* L.), crimson clover (*Trifolium incarnatum* L.), Pannonian vetch (*Vicia pannonica* Crantz), linseed (*Linum usitatissimum* L.), and phacelia (*Phacelia tanacetifolia* Benth). The proportions of each seed were 23%, 24%, 15%, 23% and 15%, respectively.

Table 1. Agricultural practices in the study area.

Date	Crop	Agrotechnical Practices
2019–2022	fallow	disk harrowing (several times)
2 May 2022 26 August 2022	<i>Zea mays</i> L.	fertilization with 300 kg N ha ^{−1} and sowing stalk chopping, leaving on surface
12 April 2023 20 April 2023 14 August 2023	<i>Panicum miliaceum</i> L.	disk harrowing sowing harvesting
2024	fallow	
21 May 2024 23 June 2024		stalk cutting fertilization with 200 kg N ha ^{−1}
25 April 2025 28 April 2025 8 May 2025 9 May 2025 29 July 2025 12 September 2025	cover crop mix	disk harrowing ring rolling sowing rolling with a smooth roller shredding crop residues non-selective weed control

2.2. In Situ Measurements

An SWC and Ts monitoring system was installed in the two selected plots using Teros 12 soil probes (Meter Group, Pullmann, WA, USA). According to Meter Group's recommendations, the probes do not require calibration [30]. Data were collected at 10 min intervals from soil depths of 5–10 cm, 15–20 cm and 30–35 cm using ZL6 data loggers (Meter Group). One probe was installed at each of these depths in each plot. Ts was measured in °C and SWC in m³ m^{−3}, with an accuracy of ±0.03 m³ m^{−3}. For presentation purposes, SWC values were later converted to percentages. Both SWC and Ts data were averaged daily. The dataset was subject to data quality checks. Water-filled pore space (WFPS, %) was calculated as the ratio of volumetric water content to total porosity (plot A: 0.429%, plot B: 0.421%) expressed as a percentage, following the approach of Linn and Doran [31].

Soil CO₂ emission measurements were carried out using a portable infrared gas analyzer (EGM5; PP Systems, Amesbury, MA, USA). Seven collars were established on both plots on the bare soil before the first measurement, with their tops aligned with the soil surface. This enabled us to take measurements at the same points each time. Measurements were conducted in the morning between 9 and 11 a.m., as this best reflects the average daily CO₂ emissions [32]. Sampling time was two minutes using the soil respiration chamber (A = 77.6 cm², V = 1171 cm³) supplied by the manufacturer. Measurements were performed from May to October, typically on a weekly basis, with seven replicates per plot. Since our goal was to compare the seasonal CO₂ emissions of two neighbouring plots, rather than capturing short-lived emission peaks, we deemed this consistent, weekly sampling scheme suitable for characterizing temporal trends. Soil CO₂ emission data were calculated by the EGM5 analyser software (v. 01.23) using a quadratic regression model, defined by the following equation:

$$C = a + bT + cT^2 \quad (1)$$

where C represents the CO₂ concentration measurements made over time and T denotes the corresponding time variable. The coefficients a, b and c are calculated from a least squares fit of the data. Soil CO₂ emission is calculated from the rate of change in CO₂ concentration at time zero, or dC/dT at T = 0. We measure dC/dT = b in ppm/second, V in cm³, and A in cm². CO₂ flux is expressed as g m^{−2} h^{−1}.

Soil penetrometer resistance (PR) was measured at twenty randomly selected points on both plots on 9 October 2026, using an Eijkelkamp penetrometer (Royal Eijkelkamp Co., Ltd., Giesbeek, The Netherlands). A cone with a top angle of 60° and a base area of 1 cm^2 was screwed onto an 80 cm probing rod with an 8 mm diameter. Measurements were taken up by inserting the probing rod vertically into the soil to a depth of 22 cm with 1 cm resolution. The measurement depth was restricted because the long-term summer drought had drastically increased the PR in the subsoil, meaning that inserting the instrument into deeper layers would risk breaking the probing rod. The PR data (in MPa units) were logged using PenetroWiever 6.08 software.

Vegetation cover was assessed non-destructively using the Canopy Cover smartphone app [33]. Downward-facing nadir photographs of the canopy were captured at a uniform height of 1.2 m directly above the crop using the camera on a Samsung Galaxy A21 smartphone (Samsung Electronics, Suwon, South Korea). To avoid artefacts caused by shadows, measurements were conducted at the end of the study period under uniform lighting conditions. Five spatial replicates per plot were recorded along a representative diagonal across each plot, and the software calculated fractional green canopy cover by automatically segmenting green pixels.

2.3. Soil Analyses

Soil samples were taken by drilling and separated into layers according to depth: 0–30 cm, 30–60 cm, and 60–90 cm. As this information is provided for background purposes only, no replicates were processed. Soil plasticity index according to Arany (KA), total soluble salt (TSS) content and sulphur (S) content showed no variation across the different plots or depths. Nitrite- and nitrate-N concentrations were below the detection limit ($<1\text{ mg kg}^{-1}$) and are therefore omitted. Additional soil samples were taken from the top 0–30 cm layer of both plots at the beginning and end of the study period to determine humus content and pH, as these are key factors influencing CO_2 emissions, alongside SWC and Ts. Particulate organic matter (POM) content was determined from the 0–10 cm depth using the Zimmermann method, as this soil layer plays a crucial role in CO_2 emissions [34]. SOC content was determined by titration with 0.2 N Mohr's salt, after digestion with potassium dichromate and sulfuric acid, in accordance with the Hungarian Standard (MSZ-08-0210-2:1977 2.1.6.). Humus content was estimated from SOC content using the van Bemmelen conversion factor [35]. At the end of the study period, undisturbed soil samples were taken from the top 5–10 cm of soil in five replicates in order to determine the bulk density and the soil water retention (pF) curves. The results of the analysis of the two selected plots (A and B) are shown in Tables 2 and 3.

2.4. Calculations and Data Analyses

Cumulative CO_2 fluxes were determined by numerically integrating the flux measurements over time using the trapezoidal rule. The dataset comprised paired observations of time (days) and flux ($\text{g m}^{-2}\text{ day}^{-1}$). The cumulative flux was calculated by approximating the integral of the flux–time relationship as the sum of trapezoidal areas between successive observations. For each time interval, the area was computed as the product of the mean of two consecutive flux values multiplied by the corresponding time increment. The cumulative flux over the entire measurement period was obtained by summing these interval-specific contributions.

Table 2. Soil texture and chemical properties data in plots A and B.

Measured Parameters	Plot A				Plot B			
Soil Depth (cm)	0–10	0–30	30–60	60–90	0–10	0–30	30–60	60–90
POM (mg g ^{−1})	0.800				0.367			
KA		26	26	26		26	26	26
Texture (according to KA)		sand	sand	sand		sand	sand	sand
pH _{KCl}		7.49	7.60	7.6		7.86	8.02	8.25
humus (%)		0.61	0.49	0.47		0.48	0.34	0.20
SOC (%)		0.35	0.28	0.27		0.28	0.19	0.11
TSS (%)		<0.02	<0.02	<0.02		<0.02	<0.02	<0.02
CaCO ₃ (%)		0.80	0.70	<0.1		7.60	14.5	14.1
NO ₂ + NO ₃ -N (mg kg ^{−1})		<1.00	<1.00	<1.00		<1.00	<1.00	<1.00
Mg (mg kg ^{−1})		50.6	42.7	35.7		20.4	15.9	10.7
S (mg kg ^{−1})		<2.5	<2.5	<2.5		<2.5	<2.5	<2.5
AL-P ₂ O ₅ (mg kg ^{−1})		100	51.4	30.8		147	74.7	<25
AL-K ₂ O (mg kg ^{−1})		63.2	39.9	28.5		44.3	30.5	<25

n = 1.

Table 3. Soil water retention data in plots A and B.

	Plot A		Plot B	
	Mean ± SD	CV%	Mean ± SD	CV%
Bulk density (g cm ^{−3})	1.58 ± 0.02	1	1.58 ± 0.04	2.67
Water content (v/v%)				
pF0	42.89 ± 0.6	1.39	42.05 ± 1.86	4.41
pF2.0	13.23 ± 1.45	10.94	14.73 ± 2.69	18.27
pF2.5	8.12 ± 0.22	2.76	8.46 ± 1.08	12.74
pF4.2	2.78 ± 0.06	2.04	2.66 ± 0.07	2.66
pF6.2	0.60 ± 0.02	3.18	0.56 ± 0.01	1.98

n = 5.

All statistical analyses were performed using R version 4.5.3 [36]. The Shapiro–Wilk test was applied to the daily mean SWC and the PR data to assess normality. As the SWC data were not normally distributed, differences between the two plots were evaluated using the Mann–Whitney test. Differences in PR (on a per-centimetre basis), SOC content and pH were assessed using a two-sample *t*-test. For pH and SOC, homogeneity of variances was first evaluated using an *F*-test, and based on its results the two-sample test was applied. Statistically significant differences were accepted at $p < 0.05$ in each case. The difference in soil CO₂ emissions between the two plots was evaluated using Hedges' *g* with 95% confidence intervals to enhance the analyses of statistical significance. For each sampling day, differences in CO₂ emissions between the two plots were evaluated using a non-parametric permutation test based on 10,000 random reassignments of observations between groups. The resulting *p*-values were corrected for multiple testing using the Benjamini–Hochberg method. Data visualization was performed in Excel and R version 4.5.3 using the ggplot2 package.

3. Results

3.1. Soil Temperature and Moisture Conditions

Figure 1 illustrates the dynamics of SWC and Ts over the period from May to October. During the first two months of the study, both plots exhibited a similar trend in SWC at all three depths. The effects of rainfall events were comparable at both plots, with only slight

differences in the subsequent increase in SWC. However, a notable difference emerged in the top 5–10 cm layer, where plot A experienced more rapid and severe desiccation during this period. Following the long drought that started in mid-July, the moisture trends diverged between the two plots. Higher SWC values were recorded in the top layer of plot A over a short period, whereas SWC in the deeper layer showed minimal response to precipitation. In contrast, the influence of precipitation on the increase in SWC was more pronounced in the deeper layer at plot B (Figure 1a). Regarding soil temperature trends, no significant differences were detected between the two plots. However, plot A exhibited slightly higher soil temperatures in the top layer at the beginning of the study period. No distinct variations in soil temperature were observed in the deeper layers between plots A and B (Figure 1b).



Figure 1. Dynamics of soil water content (a) and soil temperature (b) at the studied soil depths in plots A and B. The blue dots in the first figure represent precipitation events.

The mean SWC in the upper soil layer was significantly lower in plot A ($8.15 \pm 2.25\%$) than in plot B ($8.99 \pm 1.82\%$). At a depth of 15–20 cm, slightly higher mean SWC values were observed in plot A ($9.20 \pm 2.09\%$) than in plot B ($9.04 \pm 2.40\%$). In the deepest layer (30–35 cm), the SWC was significantly higher in plot B ($10.50 \pm 2.47\%$) than in plot A ($9.03 \pm 1.79\%$) (Figure 2). No statistically significant differences were detected in Ts values between the two plots.

3.2. CO₂ Emission Trends

Figure 3 illustrates the differences in CO₂ emission trends between plots A and B. CO₂ emissions were consistently higher at plot A than at plot B throughout the monitoring period (Figure 3). The CO₂ emissions difference between the two plots exhibited a large standardized effect size (Hedges' $g = 0.91$ CI: 0.59–1.22).

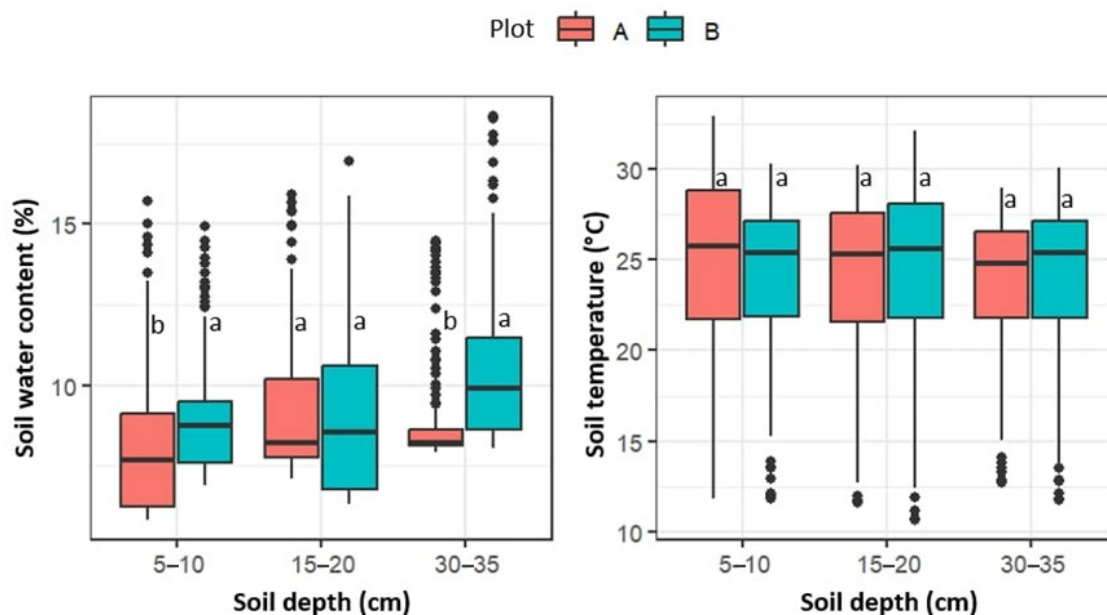


Figure 2. Mean soil water content and soil temperature in plots A and B at various soil depths. Lowercase letters a and b indicate significant differences ($p < 0.05$).

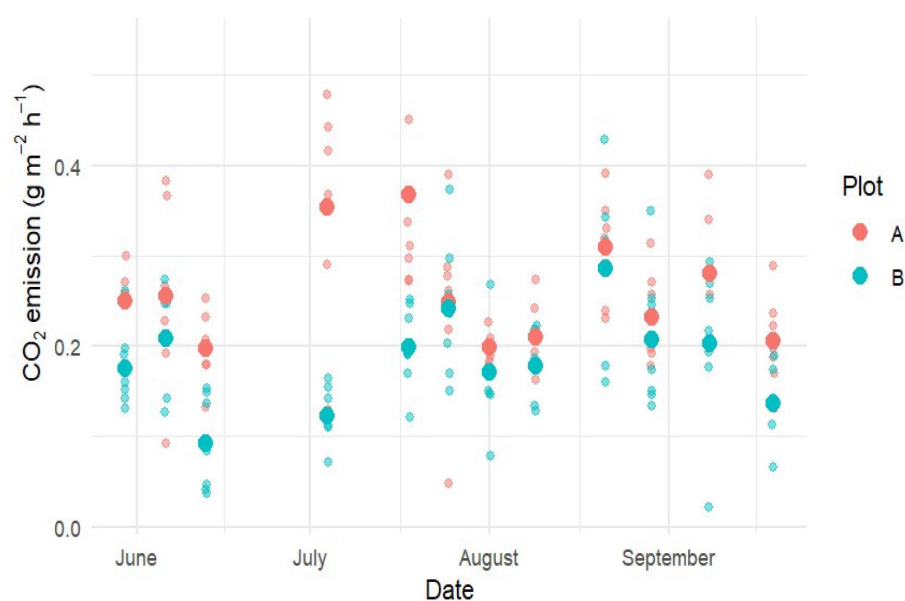


Figure 3. CO₂ emission trends in plots A and B during the study period. The large dots show the average of the seven daily measurements. $n = 84$ for plot A and 83 for plot B.

CO₂ emissions are usually affected by moisture levels in the period before the measurement is taken. Therefore, we investigated the relationship between the cumulative CO₂ emissions over the interval between two measurements and average SWC over the same period. We also examined the relationship between average soil moisture levels over three and seven days prior to CO₂ measurements and the measured CO₂ emissions. However, we were unable to demonstrate a statistical relationship in either plot A or plot B.

Throughout the study, plot A emitted more CO₂ than plot B on every measurement date. However, a non-parametric permutation test revealed that statistically significant differences were only observed on five of the twelve measurement days. These significant differences occurred at the beginning and end of the study period, whereas no significant differences were observed in daily mean CO₂ emissions between June and early September. The mean CO₂ emission values and the detailed results of the permutation test are presented

in Table 4. The coefficient of variation values indicate that the variability of the CO₂ emission data was higher in plot B. In fact, for every measurement in plot B, the CV value was above 20%; values below this threshold define low variability. In contrast, plot A displayed low variability in nearly half of the measurement points.

Table 4. Results of non-parametric permutation tests for differences in CO₂ emissions between plots A and B. Reported values include mean emissions for each plot, and the mean difference (A–B), as well as the raw *p*-values and adjusted *p*-values.

Date	CO ₂ Emission (g m ^{−2} h ^{−1})			<i>p</i>	<i>p</i> adj	CV-Plot A (%)	CV-Plot B (%)
	Mean—Plot A	Mean—Plot B	Δ (A–B)				
2025-05-30	0.251 ± 0.039	0.174 ± 0.044	0.074	0.012	0.036	15.6	25.5
2025-06-06	0.257 ± 0.100	0.209 ± 0.056	0.047	0.308	0.420	39.1	26.9
2025-06-13	0.196 ± 0.038	0.093 ± 0.052	0.104	0.003	0.014	18.5	55.7
2025-07-04	0.353 ± 0.117	0.123 ± 0.031	0.231	0.002	0.010	33.0	25.3
2025-07-18	0.367 ± 0.132	0.199 ± 0.046	0.168	0.000	0.005	35.9	23.2
2025-07-25	0.248 ± 0.104	0.240 ± 0.076	0.007	0.906	0.906	41.8	31.7
2025-08-01	0.198 ± 0.017	0.173 ± 0.061	0.027	0.308	0.420	8.8	35.3
2025-08-09	0.210 ± 0.037	0.179 ± 0.038	0.031	0.165	0.283	17.7	21.3
2025-08-21	0.310 ± 0.057	0.286 ± 0.116	0.024	0.658	0.717	18.3	40.4
2025-08-29	0.232 ± 0.048	0.207 ± 0.079	0.024	0.494	0.593	20.7	38.1
2025-09-08	0.281 ± 0.069	0.204 ± 0.090	0.077	0.084	0.171	24.2	44.3
2025-09-19	0.206 ± 0.050	0.136 ± 0.380	0.068	0.018	0.043	24.4	28.0

n = 7.

Based on the collected data, the estimated cumulative carbon emissions over the measurement period were approximately 50% higher for plot A (197 g C m^{−2}) than plot B (131 g C m^{−2}). As the CO₂ emission measurements were only taken once a week, they are not as accurate as continuous measurements would have been. However, they are adequate for comparing the two plots, as the measurement method was the same for both.

3.3. Differences in Soil Properties at Plots A and B

A visual evaluation of the 0–1 m soil drilling revealed a notable difference in the thickness of the humus horizon between plots A and B (Figure 4a,b). For plot B, the humus layer ended at a depth of 35 cm, whereas for plot A it reached a depth of 90 cm.

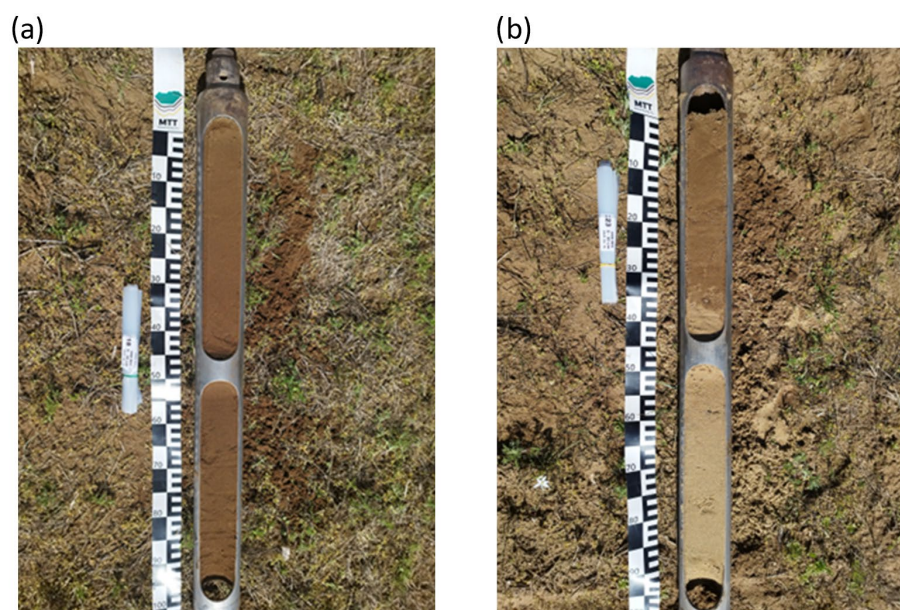


Figure 4. Humus thickness at plots A (a) and B (b).

The mean SOC content was 0.38% in plot A and 0.32% in plot B at a depth of 0–30 cm ($p < 0.05$; Table 5). Given this information and noting that samples for the 30–60 cm and 60–90 cm layers were only collected in spring, the SOC data were pooled for evaluation across these layers. A significant difference in SOC content was observed between plots A and B across the entire 30–90 cm depth range, with mean values of 0.29% and 0.11%, respectively. A difference in the POM content was also noted; in plot A this value was more than twice as high as in plot B (Table 2). The values in Table 5 differ from those in Table 2 because the latter are based on data from the initial drilling and apply to all layers.

Table 5. Soil organic carbon (SOC) and pH values in plots A and B.

Plot	Depth (0–30 cm)		Depth (30–90 cm)
	SOC (%)	pH (H ₂ O)	SOC (%)
A	0.38 a	7.68 a	0.29 a
B	0.32 b	8.01 a	0.11 b

Letters a–b indicate significant differences ($p < 0.05$). $n = 6$ for SOC values at all depths of both plots, and $n = 3$ for pH values at all depths of both plots.

PR measurements indicated significantly higher soil compaction at depths from 2 to 11 cm in plot B than in plot A. This layer contains a significant proportion of the crop's root mass and is therefore crucial for processes that determine CO₂ emissions. Below a depth of 13 cm, PR increases sharply, reaching values of 3 MPa which significantly inhibit root growth (Figure 5). On the day of the PR measurements, the SWC in plot A was recorded as 8.8%, 10.1% and 8.3% at depths of 5–10 cm, 15–20 cm and 30–35 cm, respectively. In contrast, plot B showed values of 8.9%, 9.6% and 10.5% at the same depths. A notable difference in SWC, exceeding 2%, was observed only in the deepest layer, while in the upper layers the differences were less than 0.5%.

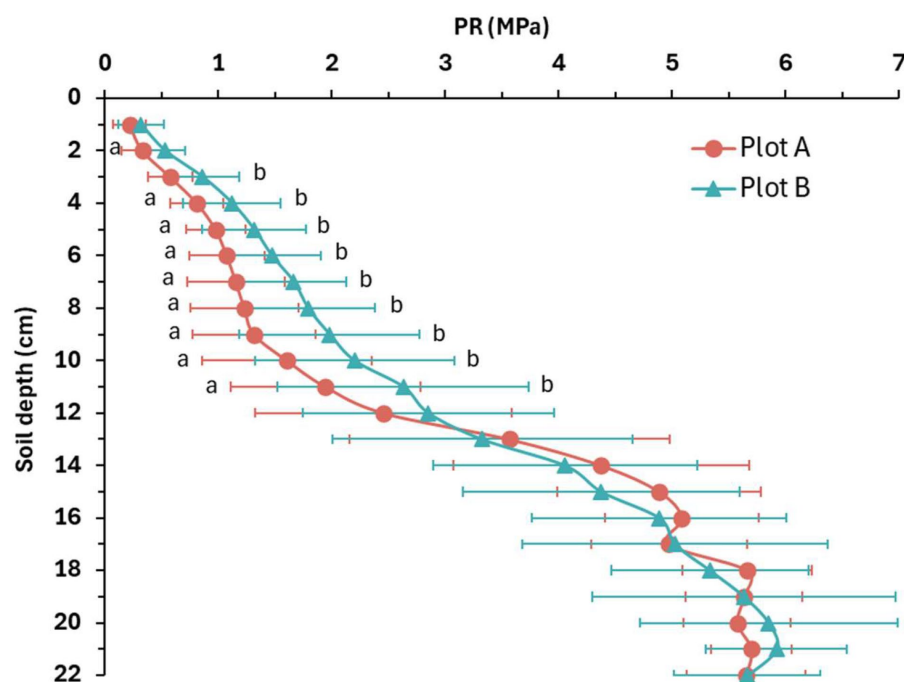


Figure 5. Soil penetration resistance (PR) at different soil depths in plots A and B, as measured by an Eijkelkamp penetrometer. Data are the mean $\pm$ SD ($n = 20$). Lowercase letters a and b indicate significant differences ($p < 0.05$).

At the end of the study period, camera surveys were conducted in five different areas within each plot. Based on these surveys, it was found that vegetation cover was significantly higher in plot A than in plot B ($p < 0.05$), with mean values of $14.4 \pm 3.3\%$ and $7.4 \pm 3.1\%$, respectively (Figure 6).

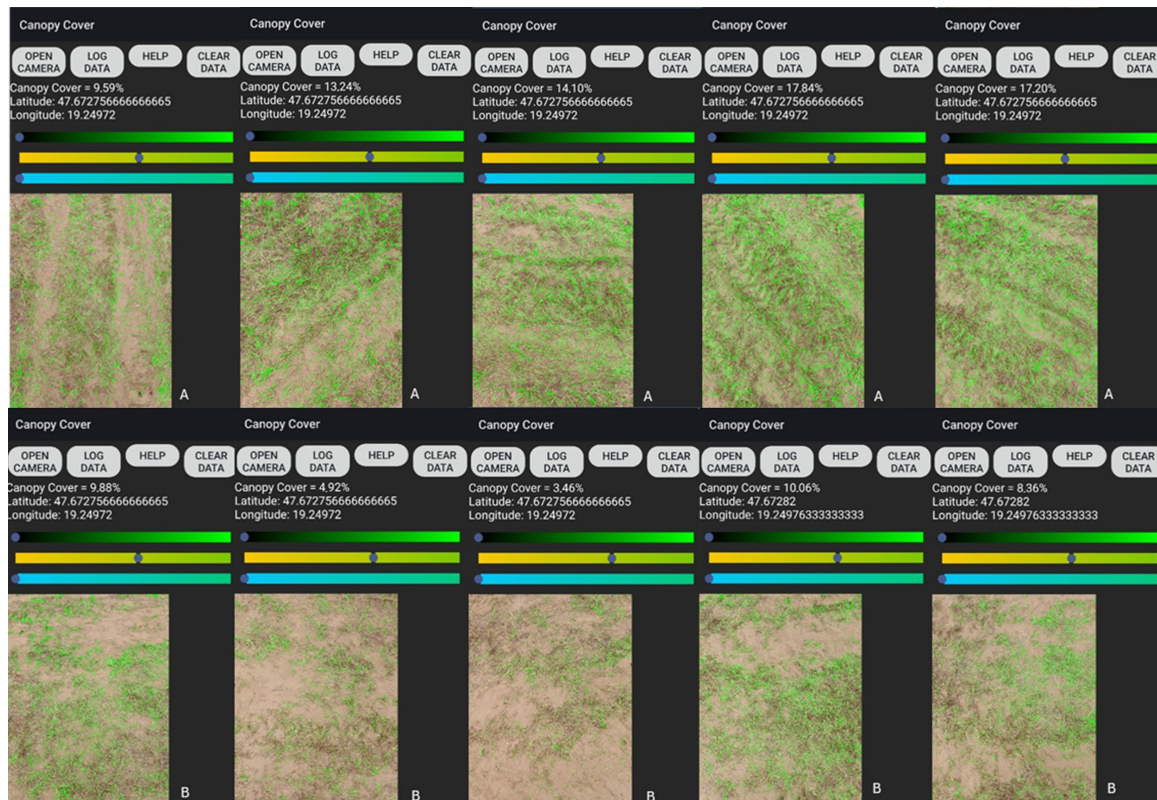


Figure 6. Representative RGB smartphone photographs and percentage vegetation cover (calculated using the Canopy Cover application) in plots A and B at the end of the study period. Green coloration indicates living plant canopy (foliage), while brown and yellowish areas represent exposed soil surface and non-green plant material or crop residue.

4. Discussion

Our findings support all three of the hypotheses established at the beginning of the study, albeit to varying degrees. These results emphasize that significant differences in soil carbon dynamics can arise due to small-scale environmental heterogeneity, even within the same field and under similar management practices.

4.1. Small-Scale Heterogeneity as a Driver of Soil CO₂ Emissions

Our first hypothesis was that small-scale soil heterogeneity could lead to varying intensities of soil CO₂ emissions. Our results strongly support this assumption. Despite plots A and B being relatively close together and having the same soil type and long-term management practices, they showed substantial differences in several soil physical and chemical characteristics (Table 2). While these variables may have contributed to the observed differences, the present case study design did not allow for the individual effects to be separated. Plot A had significantly higher humus and SOC content and notably higher POM content, as well as greater vegetation cover than plot B. Conversely, plot B was characterized by higher soil compaction and higher SWC levels throughout the study period. These differences in CO₂ emissions are likely to be attributed to small-scale heterogeneity in the soil physical, biological, and environmental conditions.

The soil carbon balance is influenced by autotrophic and heterotrophic respiration processes, which are strongly affected by environmental conditions and substrate availability [37]. In our study, plot A exhibited significantly higher CO₂ emissions than plot B, suggesting that local variations in soil properties and vegetation conditions create distinct microenvironments for soil respiration processes. Previous studies have reported similar findings, emphasizing the importance of spatial variability within fields. For example, Moitinho et al. [38] found a positive correlation between soil carbon content and soil CO₂ emissions ($r = 0.67$) based on measurements taken within a single agricultural field of the same soil type. Their findings highlighted that even relatively small spatial differences in soil properties can lead to substantial variations in soil CO₂ emissions.

The critical role of local-scale environmental heterogeneity, as observed in our study, is strongly supported by recent literature from various agricultural systems. It has been demonstrated that localized environmental variations and management practices exert a dominant influence on broader ecosystem processes [39]. Similarly, dos Santos et al. [40] confirmed that environmental heterogeneity at relatively small spatial scales has a substantial impact on agricultural outcomes and must be explicitly incorporated into predictive modelling to avoid systematic biases [40]. Finally, advanced methodological frameworks such as remote sensing and sparse regression approaches have illustrated modern pathways for successfully integrating this spatial variability into predictive models [41].

4.2. Effect of Soil Water Content and Soil Temperature Can Be Affected by Other Factors

Our second hypothesis was that Ts and SWC do not always have the greatest influence on soil CO₂ emissions. While both variables clearly impact soil respiration, our results suggest that their influence may be affected by other site-specific factors, such as SOC content, soil compaction, and vegetation cover.

The impact of Ts and SWC on CO₂ emissions is well-documented. It is evident that an increase in soil temperature leads to elevated CO₂ emissions from the soil surface [13,42]. However, the influence of soil water content is more complex, as extreme dryness and oversaturation can both limit microbial respiration and gas diffusion [9,43]. Furthermore, the interaction between soil moisture and soil temperature makes it difficult to isolate their independent effects [44,45]. No significant differences in soil temperature were detected between the two plots investigated. However, the average SWC in both the surface and lower layers was significantly higher in plot B than in plot A. Xu et al. [46] found that soil temperature became the main controlling factor when SWC content exceeded 0.15 m³ m⁻². Below this threshold, SWC content was the limiting factor. Similarly, Sun et al. [47] reported a decrease in CO₂ emissions when the SWC exceeded 7%. Sites with higher organic matter content show greater sensitivity of CO₂ emissions to changes in soil water content [48]. This may also explain why SWC is not evidently the primary driver of CO₂ emissions in sandy soils with lower organic carbon content.

Previous studies have sought to determine the optimal moisture conditions for microbial respiration. According to Schaufler et al. [9], microbial activity and root respiration generally peaked at around 40% WFPS across European land-cover categories. However, optimal values varied between 20% and 60% depending on the soil and vegetation characteristics. Similarly, Fairbairn et al. [49] observed maximum CO₂ emissions at 65% WFPS in Canadian Luvisol, further highlighting the site-specific nature of the effects of soil moisture [49].

In our study, we observed clear differences in soil water dynamics between the two plots. Plot A dried faster and to a greater extent following rainfall, whereas plot B showed deeper infiltration and retained a higher SWC after precipitation. During the investigation, the maximum WFPS values in plot A were 14%, 17% and 18% at the investigated

depths, while the maximum values were 37%, 37% and 34%, respectively. In plot B, the minimum WFPS values were 16%, 15% and 19%, with maximum values of 36%, 40% and 44%, respectively. While some values approached the threshold proposed by Schaufler et al. [9], soil moisture levels generally remained below the reported optimum WFPS of approximately 40%. However, it is also noteworthy that Schaufler et al. [9] indicated that microbial respiration in sandy soils may peak under relatively drier conditions, which is particularly relevant for our experimental site.

In our experiment, the maximum SWC values in the upper and middle layers of plot A were 15.7% and 15.9%, respectively. These values slightly exceeded the threshold reported by Xu et al. [46]. In contrast, the SWC values in the middle and lower layers of plot B were higher at 17.0% and 18.4%, respectively. These results suggest that SWC was an important limiting factor during the study period. However, despite plot B consistently having a higher SWC content, CO₂ emissions were significantly lower in plot B than in plot A, indicating that SWC values alone cannot explain the observed patterns.

The SOC content appears to play a significant role in influencing microbial respiration by determining substrate availability. Under similar soil conditions, a higher carbon content generally results in increased CO₂ emissions [16,50]. However, different outcomes can arise in tillage experiments where lower SOC content is combined with intensive aeration, resulting in higher soil CO₂ emissions [51]. In our study, plot A had significantly higher humus and SOC content, as well as higher CO₂ emissions than plot B. This aligns with the findings of Panosso et al. [52], who observed a 76% increase in cumulative CO₂ emissions following a 13% rise in soil carbon content during a 70-day experiment [52]. Furthermore, variations in management can restructure soil microbial community systems and alter biological functioning. This suggests that differences in SOC and biological activity substantially contribute to the spatial variability of CO₂ fluxes beyond the immediate drivers of temperature and moisture alone [53]. Finally, mineralization processes in sandy soils may be particularly sensitive to SOC content, as the low clay mineral content, clay composition and weak aggregate stability of these soils make carbon substrates more easily accessible for microbial decomposition [54,55].

Soil compaction may also have contributed to the observed differences between the two plots. Despite the higher SWC in the topsoil, plot B showed significantly higher PR and lower CO₂ emissions than plot A. Soil PR is a widely used indicator of compaction, which significantly influences soil pore structure and aeration [56]. Previous studies reported negative and non-linear relationships between PR and soil CO₂ emissions [18,57–59]. Generally, higher PR values indicate a decline in soil aggregate stability and structural collapse, which disrupts macropore continuity [60]. The loss of continuous gas transmission pores reduces soil permeability and restricts gas exchange between the soil and the atmosphere [61,62]. However, the relationship between PR and soil CO₂ emissions can vary depending on the management system and year [63]. The lower CO₂ emissions observed in plot B may be partially due to greater physical constraints on gas diffusion and microbial respiration. Similarly, Yang et al. [64] reported considerable spatial heterogeneity in soil PR within agricultural fields, indicating that local differences in compaction status significantly impact soil physical functioning and gas exchange [64].

These findings partially support our second hypothesis. While soil temperature and SWC level are clearly among the key drivers of soil respiration processes, they did not prove to be explanatory variables for the differences between plots in our study. Instead, higher CO₂ emissions were associated with higher SOC content, greater humus depth, and higher vegetation cover.

4.3. The Degree of Vegetation Cover Can Contribute to the Effects of the Main Environmental Drivers

Our third hypothesis suggested that the effects of the main environmental drivers may be influenced by vegetation cover. The observed differences in vegetation cover could be an additional factor contributing to the contrasting CO₂ emissions between the plots.

Despite consistent tillage and crop management practices over the long term, vegetation cover was significantly higher in plot A than in plot B. Cover cropping is recognized as a key component of conservation agriculture, providing numerous ecosystem benefits such as reduced soil erosion and evaporation, improved infiltration and soil structure, enhanced biodiversity, and increased SOC [65]. However, cover crops may also increase water depletion through transpiration, particularly during prolonged dry periods [66,67].

The lower SWC observed in plot A may be partly due to the higher abundance of cover crop vegetation. Many drought-tolerant cover crop species develop extensive root systems that can extract water from deeper soil layers, even under nutrient-poor conditions. This has been documented for species included in our cover crop mixture, such as *Lathyrus sativus* [68], *Phacelia tanacetifolia* [69], and *Trifolium incarnatum* [70]. Consequently, the increased vegetation cover in plot A probably accelerated soil drying, resulting in lower SWC values.

Furthermore, the higher soil carbon content and greater primary productivity of the cover crops in plot A could lead to an increased rate of SOC mineralisation and greater carbon loss, particularly following the few summer rainfall events [46]. This could result in increased CO₂ efflux from the soil. Higher levels of soil coverage imply greater levels of belowground biomass, root length density and root respiration, which also contribute significantly to CO₂ emissions [71,72]. Additionally, distinct modifications to the composition of the soil microbial community and biological processes resulting from vegetation management can optimize conditions for aerobic heterotrophic activity and further accelerate carbon turnover [53]. Although microbial decomposition and root respiration rates typically decrease in dry conditions due to limited substrate availability and metabolic dehydration [73], the aforementioned findings also help to explain why CO₂ efflux is higher in plot A than in plot B. As root and microbial respiration were not separated, the present study cannot determine the relative contribution of these processes.

The greater abundance of cover crops in plot A may help to explain the lower SWC. Therefore, our findings support the third hypothesis, highlighting that vegetation cover is a crucial factor that can modify the effects of traditional environmental factors on soil CO₂ emissions.

Overall, the results suggest that soil CO₂ emissions are affected by complex interactions between physical, chemical and biological soil properties. Significant variability in SWC, SOC content, vegetation cover, and soil compaction can lead to notable differences in CO₂ emission intensity, even over relatively small spatial scales. Although SWC and soil temperature are important factors in soil respiration, vegetation cover and the availability of SOC can modify their effects, particularly in sandy soils that exhibit strong spatial heterogeneity.

4.4. Limitation of This Study

We should note that this study has several limitations that must be considered when interpreting the results. The experiment was conducted on just two plots located close to each other within a single agricultural field. Although these plots were managed using identical agronomic practices, the observed differences may have been site-specific. The study focused on sandy soils with contrasting characteristics of the humus layer. The relationships identified between SOC, PR, vegetation cover and CO₂ emissions may differ

in soils of a different texture or with contrasting moisture conditions. Further investigations across a wider range of soil types are therefore required.

The study was conducted under extremely dry conditions, which limits the ability to apply the findings to wetter years. However, the significant differences observed between neighbouring plots under water-limited conditions emphasize the importance of spatial heterogeneity, particularly when soil moisture levels vary.

The chamber-based method of measuring CO₂ emissions that we use is not suitable for distinguishing between CO₂ sources, as it only measures total CO₂ efflux. SWC and Ts were measured, but other factors influencing soil respiration, such as the microbial community, root respiration and rhizomicrobial activity and temporal changes in the availability of soil nutrients and substrate quality, were not examined.

The analysis relied on measurements from a small spatial scale. While this was appropriate for examining within-field heterogeneity, it does not capture larger-scale variability or temporal dynamics. Repeating measurements across multiple fields and growing seasons would provide a more robust basis for these purposes.

Furthermore, it should be noted that although short-term observations such as this show how soil respiration changes in response to various environmental variables, it is challenging to extend these findings to long-term system behaviour.

Despite these limitations, the study demonstrates that substantial differences in soil CO₂ emissions can occur even between neighbouring plots that are managed identically.

5. Conclusions

The present study suggests the existence of small-scale spatial heterogeneity in soil water dynamics, humus and SOC content, soil structure, cover crop abundance and CO₂ emission rates within a uniformly managed arable field. The consistently higher CO₂ efflux observed in plot A compared to plot B throughout the sampling period could not be fully explained by short-term variation in soil moisture alone. Instead, the results indicate that differences in soil compaction, SOC content and cover crop productivity may also have contributed to the observed differences in CO₂ emissions. These findings emphasize the potential importance of assessing soil heterogeneity at the plot or field scale when establishing conservation agriculture experiments, as unrecognized variability may influence the interpretation of treatment effects. Our results suggest, however, that SWC alone may not always adequately explain spatial differences in CO₂ emissions under field conditions, particularly where marked heterogeneity exists in soil properties and vegetation. Nevertheless, further studies with better spatial coverage and more intensive sampling are required to confirm these findings and to better understand the combined influence of soil physical, chemical and biological properties on CO₂ emissions. Our observations highlight a potential source of uncertainty in the upscaling of soil CO₂ emissions, given the significant differences observed between sampling areas in close proximity to one another.

Author Contributions: Conceptualization, E.T. and M.M.; methodology, E.T. and M.M.; validation, E.T., I.C. and M.M.; formal analysis, E.T.; M.M. and I.C.; resources, E.T.; data curation, E.T. and M.D.; writing—original draft preparation, E.T. and M.M.; writing—review and editing, I.C.; visualization, E.T., I.C. and M.M.; supervision, E.T.; project administration, E.T.; funding acquisition, E.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Sustainable Development and Technologies National Programme of the Hungarian Academy of Sciences and by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences (grant no. BO/00548/23). The research was supported by the Hungarian Ministry of Agriculture.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: During the preparation of this manuscript, the authors used Grammarly and DeepL for the purposes of grammar checking. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

CO ₂	Carbon dioxide
SWC	Soil water content
Ts	Soil temperature
SOC	Soil organic carbon
WFPS	Water-filled pore space
PR	Penetration resistance

References

1. IPCC. 2023: Sections. In *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Lee, H., Romero, J., Eds.; IPCC: Geneva, Switzerland, 2023; pp. 35–115.
2. Ryan, M.G.; Law, B.E. Interpreting, measuring, and modeling soil respiration. *Biogeochemistry* **2005**, *73*, 3–27. [[CrossRef](#)]
3. Barba, J.; Cueva, A.; Bahn, M.; Barron-Gafford, G.A.; Bond-Lamberty, B.; Hanson, P.J.; Jaimes, A.; Kulmala, L.; Pumpanen, J.; Scott, R.L.; et al. Comparing ecosystem and soil respiration: Review and key challenges of tower-based and soil measurements. *Agric. For. Meteorol.* **2018**, *249*, 434–443. [[CrossRef](#)]
4. Georgiou, K.; Jackson, R.B.; Vindušková, O.; Abramoff, R.Z.; Ahlström, A.; Feng, W.; Harden, J.W.; Pellegrini, A.F.A.; Polley, H.W.; Soong, J.L.; et al. Global stocks and capacity of mineral-associated soil organic carbon. *Nat. Commun.* **2022**, *13*, 3797. [[CrossRef](#)] [[PubMed](#)]
5. Liu, J.; Fan, B.; Sun, Z.; Dai, L.; Duan, A. A global meta-analysis of soil respiration in response to elevated CO₂. *Soil Biol. Biochem.* **2025**, *203*, 109734. [[CrossRef](#)]
6. Andrews, J.A.; Harrison, K.G.; Matamala, R.; Schlesinger, W.H. Separation of Root Respiration from Total Soil Respiration Using Carbon-13 Labeling during Free-Air Carbon Dioxide Enrichment (FACE). *Soil Sci. Soc. Am. J.* **1999**, *63*, 1429–1435. [[CrossRef](#)]
7. Kuzyakov, Y.; Larionova, A.A. Root and rhizomicrobial respiration: A review of approaches to estimate respiration by autotrophic and heterotrophic organisms in soil. *J. Plant Nutr. Soil Sci.* **2005**, *168*, 503–520. [[CrossRef](#)]
8. Kuzyakov, Y. Sources of CO₂ efflux from soil and review of partitioning methods. *Soil Biol. Biochem.* **2006**, *38*, 425–448. [[CrossRef](#)]
9. Schaufler, G.; Kitzler, B.; Schindlbacher, A.; Skiba, U.; Sutton, M.A.; Zechmeister-Boltenstern, S. Greenhouse gas emissions from European soils under different land use: Effects of soil moisture and temperature. *Eur. J. Soil Sci.* **2010**, *61*, 683–696. [[CrossRef](#)]
10. Brockett, B.F.T.; Prescott, C.E.; Grayston, S.J. Soil moisture is the major factor influencing microbial community structure and enzyme activities across seven biogeoclimatic zones in western Canada. *Soil Biol. Biochem.* **2012**, *44*, 9–20. [[CrossRef](#)]
11. Ozlu, E.; Arriaga, F.J.; Bilen, S.; Gozukara, G.; Babur, E. Carbon Footprint Management by Agricultural Practices. *Biology* **2022**, *11*, 1453. [[CrossRef](#)] [[PubMed](#)]
12. Reth, S.; Reichstein, M.; Falge, E. The effect of soil water content, soil temperature, soil pH-value and the root mass on soil CO₂ efflux—A modified model. *Plant Soil* **2005**, *268*, 21–33. [[CrossRef](#)]
13. Hao, Y.; Mao, J.; Bachmann, C.M.; Hoffman, F.M.; Koren, G.; Chen, H.; Tian, H.; Liu, J.; Tao, J.; Tang, J.; et al. Soil moisture controls over carbon sequestration and greenhouse gas emissions: A review. *npj Clim. Atmos. Sci.* **2025**, *8*, 16. [[CrossRef](#)]
14. Wasikoyo, E.; Zsembeli, J.; Gashi, N.; Gumisiriya, C.; Csaba, J. Plant–Soil Microbe Interactions’ Effects on CO₂ Emissions, Soil Organic Carbon and Nutrients Under Different Tillage Systems. *Agriculture* **2026**, *16*, 429. [[CrossRef](#)]
15. Beylich, A.; Oberholzer, H.-R.; Schrader, S.; Höper, H.; Wilke, B.-M. Evaluation of soil compaction effects on soil biota and soil biological processes in soils. *Soil Tillage Res.* **2010**, *109*, 133–143. [[CrossRef](#)]
16. Dencső, M.; Horel, Á.; Bakacsi, Z.; Birkás, M.; Takács, T.; Füzy, A.; Szili-Kovács, T.; Balla, I.; Tóth, E. Is soil respiration of a chernozem under shallow cultivation similar to moldboard plowing or no-tillage? *Soil Tillage Res.* **2025**, *253*, 106644. [[CrossRef](#)]

17. Chen, X.; Yang, J.; Liang, A.; Zhang, X. Effects of Soil Compaction and Tillage Practices on Carbon Dioxide Efflux in Northeast China: Evidence from an Incubation Study. *Pol. J. Environ. Stud.* **2016**, *25*, 1769–1776. [\[CrossRef\]](#)
18. Gui, W.; You, Y.; Yang, F.; Zhang, M. Soil Bulk Density and Matric Potential Regulate Soil CO₂ Emissions by Altering Pore Characteristics and Water Content. *Land* **2023**, *12*, 1646. [\[CrossRef\]](#)
19. Rochette, P.; Desjardins, R.L.; Pattey, E. Spatial and temporal variability of soil respiration in agricultural fields. *Can. J. Soil Sci.* **1991**, *71*, 189–196. [\[CrossRef\]](#)
20. Herbst, M.; Prolingheuer, N.; Graf, A.; Huisman, J.A.; Weihermüller, L.; Vanderborght, J. Characterization and Understanding of Bare Soil Respiration Spatial Variability at Plot Scale. *Vadose Zone J.* **2009**, *8*, 762–771. [\[CrossRef\]](#)
21. Aranda-Barranco, S.; Serrano-Ortiz, P.; Kowalski, A.S.; Sánchez-Cañete, E.P. Spatial and temporal heterogeneity of soil respiration in a bare-soil Mediterranean olive grove. *Soil* **2025**, *11*, 213–232. [\[CrossRef\]](#)
22. Kim, N.; Jang, C.; Yang, W.H.; Guan, K.; DeLucia, E.H.; Lee, D. Spatial variability of agricultural soil carbon dioxide and nitrous oxide fluxes: Characterization and recommendations from spatially high-resolution, multi-year dataset. *Agric. Ecosyst. Environ.* **2025**, *387*, 109636. [\[CrossRef\]](#)
23. Tóth, E.; Kisić, I.; Galic, M.; Telak, L.J.; Brezincsak, L.; Dugan, I.; Dencső, M.; Gelybó, G.; Bakacsi, Z.; Horel, Á.; et al. Spatial mapping of soil respiration using auxiliary variables. A small scale study. *J. Cent. Eur. Agric.* **2021**, *22*, 657–668. [\[CrossRef\]](#)
24. Li, J. Sampling Soils in a Heterogeneous Research Plot. *J. Vis. Exp. (JoVE)* **2019**, *143*, e58519. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Smith, P.; Fang, C.; Dawson, J.J.C.; Moncrieff, J.B. Impact of Global Warming on Soil Organic Carbon. In *Advances in Agronomy*; Academic Press: Cambridge, MA, USA, 2008; Volume 97, pp. 1–43.
26. Yadav, D.; Wang, J. Modelling carbon dioxide emissions from agricultural soils in Canada. *Environ. Pollut.* **2017**, *230*, 1040–1049. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Wang, G.; Chen, S. A review on parameterization and uncertainty in modeling greenhouse gas emissions from soil. *Geoderma* **2012**, *170*, 206–216. [\[CrossRef\]](#)
28. IUSS Working Group WRB. World Reference Base for Soil Resources. In *International Soil Classification System for Naming Soils and Creating Legends for Soil Maps*; International Union of Soil Sciences (IUSS): Vienna, Austria, 2022.
29. Beck, H.E.; Zimmermann, N.E.; McVicar, T.R.; Vergopolan, N.; Berg, A.; Wood, E.F. Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Sci. Data* **2018**, *5*, 180214. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Available online: <https://metergroup.com/products/teros-12> (accessed on 25 August 2026).
31. Linn, D.M.; Doran, J.W. Effect of Water-Filled Pore Space on Carbon Dioxide and Nitrous Oxide Production in Tilled and Nontilled Soils. *Soil Sci. Soc. Am. J.* **1984**, *48*, 1267–1272. [\[CrossRef\]](#)
32. Xu, M.; Qi, Y. Soil-surface CO₂ efflux and its spatial and temporal variations in a young ponderosa pine plantation in northern California. *Glob. Change Biol.* **2001**, *7*, 667–677. [\[CrossRef\]](#)
33. Easlon, H.M. *Canopy Cover*, 1.0.4; Google Play Store: Davis, CA, USA, 2024.
34. Zimmermann, M.; Leifeld, J.; Schmidt, M.W.I.; Smith, P.; Fuhrer, J. Measured soil organic matter fractions can be related to pools in the RothC model. *Eur. J. Soil Sci.* **2007**, *58*, 658–667. [\[CrossRef\]](#)
35. Pribyl, D.W. A critical review of the conventional SOC to SOM conversion factor. *Geoderma* **2010**, *156*, 75–83. [\[CrossRef\]](#)
36. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021.
37. Schindlbacher, A.; Zechmeister-Boltenstern, S.; Jandl, R. Carbon losses due to soil warming: Do autotrophic and heterotrophic soil respiration respond equally? *Glob. Change Biol.* **2009**, *15*, 901–913. [\[CrossRef\]](#)
38. Moitinho, M.R.; Padovan, M.P.; Panosso, A.R.; Teixeira, D.D.B.; Ferraudo, A.S.; La Scala, N. On the spatial and temporal dependence of CO₂ emission on soil properties in sugarcane (*Saccharum* spp.) production. *Soil Tillage Res.* **2015**, *148*, 127–132. [\[CrossRef\]](#)
39. Rosa, J.M.; Marin, F.R. On-farm sugarcane water productivity influenced by environmental and management practices in Brazil. *Sci. Agric.* **2025**, *82*, e20230130. [\[CrossRef\]](#)
40. dos Santos, T.L.; Battisti, R.; Reichardt, K.; Gonçalves, I.Z.; Amaral, V.P.d.; Pilau, F.G. Why should space-time variability of rainfall be considered in precision agriculture for soybean in Piracicaba, São Paulo state? *Sci. Agric.* **2025**, *82*, e20240202. [\[CrossRef\]](#)
41. Guzman-Lopez, R.R.; Cuba, L.H.d.I.; Molina, K.A.F.; Cutipa-Luque, O.D.F.; Yucra, Y.T.; Rojas, H. From satellites to yield: Causal modeling of paddy rice production using sparse regression and dynamic remote sensing. *Sci. Agric.* **2026**, *83*, e20240267. [\[CrossRef\]](#)
42. Hashimoto, S.; Komatsu, H. Relationships between soil CO₂ concentration and CO₂ production, temperature, water content, and gas diffusivity: Implications for field studies through sensitivity analyses. *J. For. Res.* **2006**, *11*, 41–50. [\[CrossRef\]](#)
43. Liu, X.; Wan, S.; Su, B.; Hui, D.; Luo, Y. Response of soil CO₂ efflux to water manipulation in a tallgrass prairie ecosystem. *Plant Soil* **2002**, *240*, 213–223. [\[CrossRef\]](#)
44. Fang, C.; Moncrieff, J.B. The dependence of soil CO₂ efflux on temperature. *Soil Biol. Biochem.* **2001**, *33*, 155–165. [\[CrossRef\]](#)
45. Tang, M.; Li, W.; Xiaodong, G.; Pute, W.; Hongchen, L.; Qiang, L.; Chao, Z. Land use affects the response of soil moisture and soil temperature to environmental factors in the loess hilly region of China. *PeerJ* **2022**, *10*, e13736. [\[CrossRef\]](#) [\[PubMed\]](#)

46. Xu, L.; Baldocchi, D.D.; Tang, J. How soil moisture, rain pulses, and growth alter the response of ecosystem respiration to temperature. *Glob. Biogeochem. Cycles* **2004**, *18*, GB4002. [\[CrossRef\]](#)
47. Sun, Q.; Hu, J.; Jiang, J.; Gu, K.; Zhu, C.; Pan, C.; Yin, W. Effect of Soil Volumetric Water Content on the CO₂ Diffusion Coefficient. *Sustainability* **2023**, *15*, 12637. [\[CrossRef\]](#)
48. Bezyk, Y.; Dorodnikov, M.; Górka, M.; Sówka, I.; Sawiński, T. Temperature and soil moisture control CO₂ flux and CH₄ oxidation in urban ecosystems. *Geochemistry* **2023**, *83*, 125989. [\[CrossRef\]](#)
49. Fairbairn, L.; Rezanezhad, F.; Gharasoo, M.; Parsons, C.T.; Macrae, M.L.; Slowinski, S.; Van Cappellen, P. Relationship between soil CO₂ fluxes and soil moisture: Anaerobic sources explain fluxes at high water content. *Geoderma* **2023**, *434*, 116493. [\[CrossRef\]](#)
50. Harrison-Kirk, T.; Beare, M.H.; Meenken, E.D.; Condon, L.M. Soil organic matter and texture affect responses to dry/wet cycles: Effects on carbon dioxide and nitrous oxide emissions. *Soil Biol. Biochem.* **2013**, *57*, 43–55. [\[CrossRef\]](#)
51. Chaplot, V.; Abdalla, K.; Alexis, M.; Bourennane, H.; Darboux, F.; Dlamini, P.; Everson, C.; McHunu, C.; Muller-Nedebock, D.; Mutema, M.; et al. Surface organic carbon enrichment to explain greater CO₂ emissions from short-term no-tilled soils. *Agric. Ecosyst. Environ.* **2015**, *203*, 110–118. [\[CrossRef\]](#)
52. Panosso, A.R.; Marques, J.; Milori, D.M.B.P.; Ferraudo, A.S.; Barbieri, D.M.; Pereira, G.T.; La Scala, N. Soil CO₂ emission and its relation to soil properties in sugarcane areas under Slash-and-burn and Green harvest. *Soil Tillage Res.* **2011**, *111*, 190–196. [\[CrossRef\]](#)
53. Cezar, R.M.; Vezzani, F.M.; Joris, H.A.W.; Barth, G.; Kaschuk, G. Crop rotation restructures soil microbial communities in Subtropical Oxisol, South Brazil. *Sci. Agric.* **2025**, *82*, e20240134. [\[CrossRef\]](#)
54. Rakhsh, F.; Golchin, A.; Beheshti Al Agha, A.; Nelson, P.N. Mineralization of organic carbon and formation of microbial biomass in soil: Effects of clay content and composition and the mechanisms involved. *Soil Biol. Biochem.* **2020**, *151*, 108036. [\[CrossRef\]](#)
55. Yost, J.L.; Hartemink, A.E. Chapter Four-Soil organic carbon in sandy soils: A review. In *Advances in Agronomy*; Sparks, D.L., Ed.; Academic Press: Cambridge, MA, USA, 2019; Volume 158, pp. 217–310.
56. Silva, B.d.O.; Moitinho, M.R.; Santos, G.A.d.A.; Teixeira, D.D.B.; Fernandes, C.; La Scala, N. Soil CO₂ emission and short-term soil pore class distribution after tillage operations. *Soil Tillage Res.* **2019**, *186*, 224–232. [\[CrossRef\]](#)
57. Schwen, A.; Jeitler, E.; Böttcher, J. Spatial and temporal variability of soil gas diffusivity, its scaling and relevance for soil respiration under different tillage. *Geoderma* **2015**, *259–260*, 323–336. [\[CrossRef\]](#)
58. Buragienė, S.; Šarauskis, E.; Romaneckas, K.; Adamavičienė, A.; Kriaučiūnienė, Z.; Avižienytė, D.; Marozas, V.; Naujokienė, V. Relationship between CO₂ emissions and soil properties of differently tilled soils. *Sci. Total Environ.* **2019**, *662*, 786–795. [\[CrossRef\]](#) [\[PubMed\]](#)
59. Mordhorst, A.; Peth, S.; Horn, R. Influence of mechanical loading on static and dynamic CO₂ efflux on differently textured and managed Luvisols. *Geoderma* **2014**, *219–220*, 1–13. [\[CrossRef\]](#)
60. Panday, D.; Nkongolo, N.V. No Tillage Improved Soil Pore Space Indices under Cover Crop and Crop Rotation. *Soil Syst.* **2021**, *5*, 38. [\[CrossRef\]](#)
61. Feng, L.; Hu, J.; Jiang, J. Uncertainty in soil gas permeability measurements. *Front. Environ. Sci.* **2025**, *13*, 1474764. [\[CrossRef\]](#)
62. Ball, B.C. Soil structure and greenhouse gas emissions: A synthesis of 20 years of experimentation. *Eur. J. Soil Sci.* **2013**, *64*, 357–373. [\[CrossRef\]](#)
63. Kulmany, I.; Giczi, Z.; Beslin, A.; Bede, L.; Kalocsai, R.; Vona, V. Impact of environmental and soil factors in the prediction of soil carbon dioxide emissions under different tillage systems. *Ecocycles* **2022**, *8*, 27–39. [\[CrossRef\]](#)
64. Yang, P.; Reijneveld, A.; Lerink, P.; Qin, W.; Oenema, O. Within-field spatial variations in subsoil bulk density related to crop yield and potential CO₂ and N₂O emissions. *CATENA* **2022**, *213*, 106156. [\[CrossRef\]](#)
65. Francaviglia, R.; Almagro, M.; Vicente-Vicente, J.L. Conservation Agriculture and Soil Organic Carbon: Principles, Processes, Practices and Policy Options. *Soil Syst.* **2023**, *7*, 17. [\[CrossRef\]](#)
66. Mitchell, J.P.; Shrestha, A.; Irmak, S. Trade-offs between winter cover crop production and soil water depletion in the San Joaquin Valley, California. *J. Soil Water Conserv.* **2015**, *70*, 430–440. [\[CrossRef\]](#)
67. Krstić, Đ.; Vujić, S.; Jaćimović, G.; D'Ottavio, P.; Radanović, Z.; Erić, P.; Čupina, B. The Effect of Cover Crops on Soil Water Balance in Rain-Fed Conditions. *Atmosphere* **2018**, *9*, 492. [\[CrossRef\]](#)
68. Lambein, F.; Travella, S.; Kuo, Y.-H.; Van Montagu, M.; Heijde, M. Grass pea (*Lathyrus sativus* L.): Orphan crop, nutraceutical or just plain food? *Planta* **2019**, *250*, 821–838. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Żarczyński, P.J.; Mackiewicz-Walec, E.; Krzbiećka, S.J.; Sienkiewicz, S.; Żarczyńska, K. *Phacelia tanacetifolia* Benth. as a Multifunctional Plant: Support for Pollinators and Sustainable Agricultural Practices. *Agronomy* **2025**, *15*, 1843. [\[CrossRef\]](#)
70. Lloveras, J.; Iglesias, I. Morphological development and forage quality changes in crimson clover (*Trifolium incarnatum* L.). *Grass Forage Sci.* **2001**, *56*, 395–404. [\[CrossRef\]](#)
71. Nguyen, L.T.T.; Kravchenko, A.N. Effects of cover crops on soil CO₂ and N₂O emissions across topographically diverse agricultural landscapes in corn-soybean-wheat organic transition. *Eur. J. Agron.* **2021**, *122*, 126189. [\[CrossRef\]](#)

72. Breil, N.L.; Lamaze, T.; Bustillo, V.; Marcato-Romain, C.-E.; Coudert, B.; Queguiner, S.; Jarosz-Pellé, N. Combined impact of no-tillage and cover crops on soil carbon stocks and fluxes in maize crops. *Soil Tillage Res.* **2023**, *233*, 105782. [[CrossRef](#)]
73. Davidson, E.A.; Samanta, S.; Caramori, S.S.; Savage, K. The Dual Arrhenius and Michaelis–Menten kinetics model for decomposition of soil organic matter at hourly to seasonal time scales. *Glob. Change Biol.* **2012**, *18*, 371–384. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.