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Effect of tillage and crop type on soil respiration in a long-term field experiment on chernozem soil under temperate climate

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A R T I C L E I N F O

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A B S T R A C T

The objective of this study was to investigate the effect of soil tillage and crop type on soil respiration (Rs) in a typical Central European agricultural site characterized by crop rotation. The weekly Rs and supporting environmental variables were measured under different crop types (including winter and summer crops) for 5 consecutive years under mouldboard ploughing (MP) and no-tillage (NT) treatments. The long-term mean Rs was 0.093 mg CO_2 m^{-2} s^{-1} in NT versus 0.086 mg CO_2 m^{-2} s^{-1} in MP. Soil respiration was significantly higher in NT treatment regardless of crop type and weather conditions in most of the study period. The difference between the treatments was larger for summer crops than for winter crops. The observed differences were more pronounced during the growing season, which cannot be explained solely by the observed plant production related data. Soil temperature did not differ in the two contrasting treatments, but soil water content was significantly higher in the NT treatment which might contribute to the observed differences in Rs. Six models were tested to simulate Rs in MP and NT treatment based on the observed environmental variables (soil temperature and soil water content). Normalized Difference Vegetation Index (NDVI) was also included as a predictor in four models to serve as a proxy for root activity. Inclusion of NDVI clearly improved the performance of the Rs models when the entire dataset was simulated including vegetated and non-growing season data. Performance and structure of the proposed Rs models varied between crop types and also between treatments (MP and NT). The preferred models explained 42% and 44% of the observed Rs variance in MP and NT, respectively. We provided explicit Rs model equations for the entire time series and also for sunflower, maize and the non-growing season period. The results suggest that there is added value in the construction of crop-specific Rs models, and also treatment specific models. Methodology related uncertainty of the Rs observations calls for longer datasets and improved modeling approaches including Bayesian and probabilistic methods.

1. Introduction

Soil respiration (Rs) is the carbon dioxide (CO_2) efflux emitted by the soils to the atmosphere and is a major component of the global carbon cycle (Bond-Lamberty and Thomson, 2010; Hursh et al., 2017; Reichstein and Beer, 2008; Ryan and Law, 2005). Rs is related to the amount and quality of soil organic carbon (SOC) in the upper soil layers and litter on the surface as decomposition driven by microbial activity is the primary source of Rs (Numa et al., 2021; Yan et al., 2018). In the presence of active vegetation, root and rhizosphere activity also contribute to the CO_2 efflux (Kuzyakov, 2006; Li et al., 2020). According to earlier estimations, global Rs is between 68 and 100 Pg C yr^{-1} (Musselman and Fox, 1991; Raich and Schlesinger, 1992; Rustad et al., 2000). Based on Bond-Lamberty and Thomson (2010) global Rs was 98

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± 12 Pg C in 2008, similar to the recent estimation of 87.9 ± 18.6 Pg C year^{-1} obtained based on the Global Soil Respiration Database (Warner et al., 2019). Rs is a highly uncertain part of the global carbon cycle, potentially affecting atmospheric CO_2 concentrations under changing climatic conditions (Carey et al., 2016; Hursh et al., 2017; Jones et al., 2003).

The primary abiotic driver of microbial activity is soil temperature (Ts) (Lloyd and Taylor, 1994), and it has recently been shown that Rs measured at annual mean temperature is a good predictor of annual mean Rs (Jian et al., 2020). Under certain conditions, soil water content (SWC) also affects Rs (Balogh et al., 2016; Orchard and Cook, 1983; Reichstein et al., 2003). The abiotic drivers (Ts and SWC) directly influence microbial activity, but also affect the autotrophic contribution indirectly, as plant activity (photosynthesis, rhizodeposition, root development) co-vary with temperature and moisture conditions in the soils. Vegetation phenology is hence a major determinant of the temporal variability of Rs, and it was shown that autotrophic (root) respiration can be a major contributor to the total Rs depending on the root developmental phase (Hanson et al., 2000; Huang and Niu, 2013; Reichstein and Beer, 2008; Tong et al., 2017). The partitioning between autotrophic and heterotrophic contribution (Ra and Rh, respectively) is biome-specific, and Rh contribution was found to be higher in managed agricultural vegetation due to the non-permanent presence of active vegetation (Bond-Lamberty et al., 2004; Raich and Tufekciogul, 2000).

In the majority of the cases, abiotic drivers are used to explain and simulate the temporal and spatial variability of Rs (Jian et al., 2020; Lloyd and Taylor, 1994; Reichstein et al., 2003). The success of these methods might be related to the fact that the environmental conditions (most of all Ts and SWC) that affect microbial activity typically co-vary with plant phenology such as the annual course of photosynthesis, leaf development, allocation, etc. However, this co-variability partly fails in non-permanent agricultural vegetation where management causes abrupt changes in the phenological cycle. The best example for such a case is harvest, which removes aboveground biomass, also rapidly eliminating root and rhizosphere contribution to Rs (Bond-Lamberty et al., 2004; Huang and Niu, 2013). This potential problem calls for the inclusion of additional drivers to explain the observed variability of Rs.

In the case of croplands, which is the topic of the present study, the abiotic factors are further influenced by management, such as soil tillage. The applied agrotechnology affects the biological and physical properties of the soil, leading to alterations in water holding capacity, soil heat flux, porosity, oxygen availability, and the amount and vertical distribution and SOC (Blanco-Canqui and Lal, 2009; Jakab et al., 2017). These soil properties directly affect Ts and SWC. Other aspects of management also influence Rs, and even the relation between Rs and SWC (Moinet et al., 2019). Residue management practices can affect soil microbial activity (Nawaz et al., 2017; Singh et al., 2018) and soil water regime (Akhtar et al., 2019; Mu et al., 2016), both being major determinants of Rs (Kong et al., 2019).

Given the applied management practices in croplands (establishment of crop rotations with different crop types including winter and summer crops, amount and timing of fertilizer application, planting and harvest dates, decision on the fate of residue, etc.) short-term studies might not provide enough information about the effect of tillage on the abiotic drivers and Rs itself. Unfortunately, long-term investigations in arable fields with consecutive measurements of Rs are not very common, although quite a few continuous monitoring studies of 2–3 years under different climatic conditions can be found in the literature (Franco-Luesma et al., 2020; Savage et al., 2018; Wang et al., 2016). The relevance of long-term observations in croplands is also indicated by the data availability in the Global Soil Respiration Database v4.0 (SRDB; Bond-Lamberty and Thomson, 2010). Out of the 922 sites listed in agricultural ecosystems, SRDB 4.0 contains only one site (managed grassland) having more than five years (5.5 years) of data available. Long-term monitoring programs allow exploration of the crop-specific patterns in soil respiration for crop rotations.

In this study we focus on Rs and related ancillary measurements in a long-term tillage experiment established in Hungary for five consecutive years, under a complex crop rotation cycle. We investigated Rs, Ts, SWC, and other relevant, plant-related aspects in two contrasting tillage methods i.e. of mouldboard ploughing (MP) and no-tillage (NT).

The aim of the study was to find answers to the following questions. 1) Is there any difference between the environmental variables and plant production observed in MP and NT? 2) Is there any difference between Rs measured under MP and NT? 3) Is there added value in the inclusion of root activity proxy (satellite based vegetation index) in the Rs models? 4) Is there any difference between the performances of the Rs models in MP and NT? 5) Is there added value in the construction of crop specific Rs models?

The presented research aims to contribute to the understanding on the drivers of Rs in the drought-prone Central-European region and to expand the available Rs datasets that can be used in meta-analysis and modeling purposes.

2. Materials and methods

2.1. Site description

The Józsefmajor Experimental and Training Farm (JETF) site is located in Northeastern Hungary, near the city Hatvan (47° 41' 31.7" N, 19° 36' 36.1" E, 110 m a.s.l.; Fig. 1). At the site the soil type is classified as chernic calcic chernozem developed on loamy clay, which is common in this part of the country.

The climate of the Józsefmajor site is continental with oceanic and mediterranean influences. The mean annual precipitation (for the 1961–90 period, based on the CRU CL 2.0 gridded climate dataset of the Climatic Research Unit, University of East Anglia (New et al., 2002)) is 560 mm, where approximately 395 mm falls during the growing season (March-October). The mean annual temperature is 10.3 °C (15 °C during the growing season; (New et al., 2002)). The present study covers the 2013–2017 time period (annual temperature and precipitation data is shown in Table 1). Except for 2015 and 2017, all years received more precipitation during the growing season than the long-term average (514 mm in 2013; 503 mm in 2014 and 571 mm in 2016). Annual mean temperatures were somewhat higher than the climatological mean in the same measurement years.

The tillage experiment was set up in 2002 on a gross 5.05 ha with buffer strips and a net 4.68 ha field (Fig. 1). Six different tillage treatments have been applied systematically in a randomized split-plot design in four replicates: mouldboard ploughing with levelling (28–32 cm), deep cultivator (22–24 cm), shallow cultivator (18–20 cm), disking (16–20 cm), deep loosening (40–45 cm) combined by disking (12–16 cm), and no-tillage. To support soil conservation, 85% of crop residue is left at the site after harvest. Depending on tillage treatment, it is either incorporated in the soil by tillage or left on the surface (no-tillage). Each treatment plot has a size of 13 m × 150 m. The site is under crop rotation that is typical in Central Europe. Management is identical in all other aspects in all treatments (e.g. amount and timing of fertilizer use, rainfed conditions, application of pesticides/herbicides).

In the present study we focus on two treatments representing conventional and conservation soil tillage methods, i.e. mouldboard ploughing (MP) and no-tillage (NT). Our monitoring program has been initiated in the spring of 2013, before the start of the growing season, except for soil temperature (Ts) and soil water content (SWC) measurements, which started in fall, 2013. Crop rotation included both summer (2013, 2014, 2016) and winter crops (2015, 2017; Table 1).

2.2. Soil characteristics and plant measurements

Soil samples were regularly collected from 0 to 5 cm and 5–10 cm depths in three replicates. pH and SOC contents were determined once per year. For the determination of SOC content we followed the MSZ-

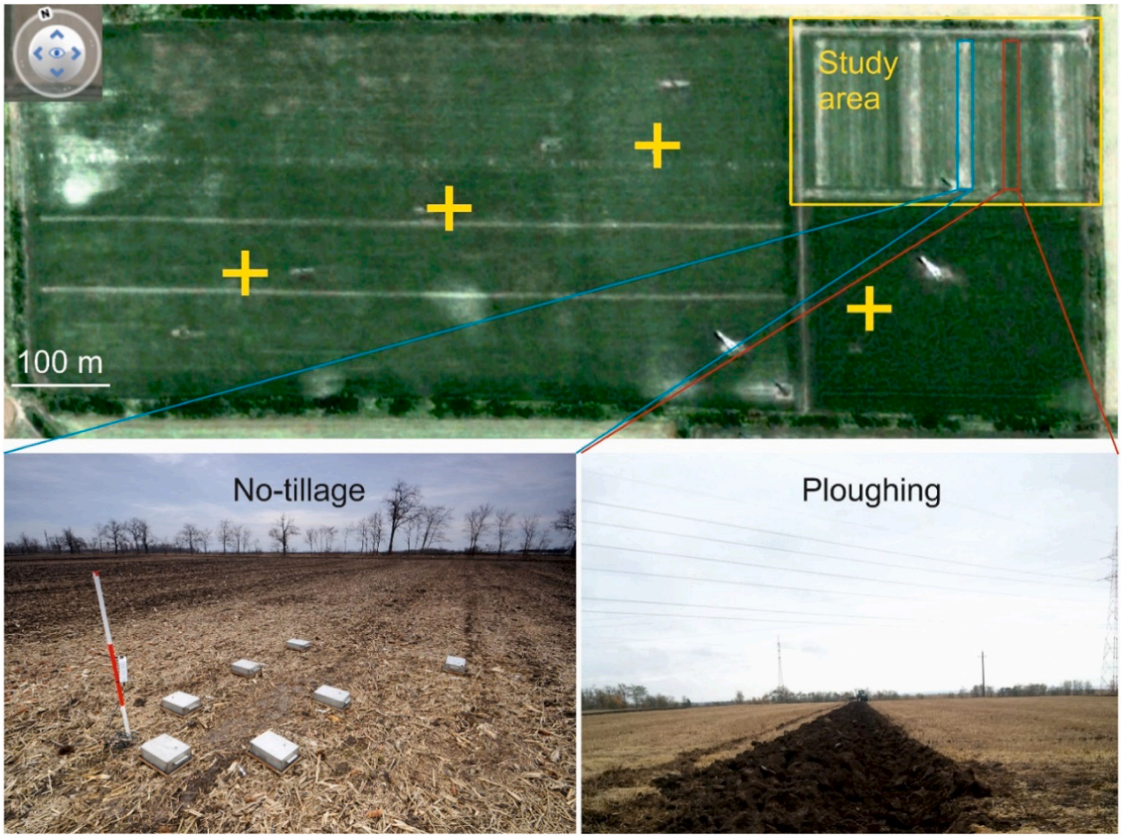

Fig. 1. Location of the long term field experiment at Józsefmajor. Symbols show the geographical location of the MODIS pixel that was used in the analysis. Soil respiration chambers are also visible on the bottom left image. The red-white rod denotes location of the soil water content probes.
(Source of the upper image: Google Earth).

Table 1
Crop types in the study period and the list of the major management activities. Annual mean temperature (T_{mean}) and total precipitation (P) is also shown, growing season precipitation is in brackets.

Crop type	2013 Spring barley (*Hordeum vulgare* L.)	2014 Sunflower (*Helianthus annuus* L.)	2015 Winter wheat (*Triticum aestivum* L.)	2016 Maize (*Zea mays* L.)	2017 Winter oat (*Avena sativa* L.)
Fertilization	8-Mar-2013	17-Oct-2013	29-Sep-2014	25-Mar-2016	27-Oct-2016
Planting	8-Mar-2013	14-Apr-2014	8-Oct-2014	18-Apr-2016	1-Nov-2016
Harvest	19-Jul-2013	25-Sep-2014	8-Jul-2015	24-Oct-2016	12-Jul-2017
Tillage*	28-Sep-2012	18-Oct-2013	2-Oct-2014	28-Oct-2015	28-Oct-2016
P (mm)	781 (514)	800 (503)	694 (243)	761 (496)	646 (195)
T_{mean} (°C)	11.3	12.3	11.9	11.2	11.2

* Tillage was not performed in the NT treatment

08–0210:1977 standard (Hungarian standard), based on the Tyurin method (Aleksandrova and Naidenova, 1976). The Tyurin titrimetric method is a wet combustion method. SOC is oxidized by 0.2 M potassium dichromate solution with sulphuric acid and heated at boiling point for precisely 5 min. After oxidation, excess dichromate is determined by titration with ammonium ferrous sulphate (Mohr's salt solution) (Aleksandrova and Naidenova, 1976; Jankauskas et al., 2006). pH was determined using the MSZ-08–0206–2:1978 standard (Hungarian standard) using 1 M potassium chloride solution in 1:2.5 soil:extractant ratio (w/v) and a WTW Multi 350i and MultiLine P4 meters (WTW, Weilheim Germany). Particle size fractionation was measured at the beginning of the investigation in 2014. Besides total nitrogen content, we determined inorganic nitrogen forms (NH_4^+ and NO_3^-) monthly in two consecutive years, in a summer crop (2016, maize) and in one winter crop year (2017, winter oat) to obtain information on plant usage of nutrients. The total nitrogen was determined using the modified Kjeldahl method (ISO 11261:1995; Buzás, 1993), while NH_4^+-N and NO_3^--N values were obtained based on KCl extraction and stream distillation technique (Buzás, 1993). We further refer to these data as total inorganic nitrogen (TIN) content of the soil. Basic soil physical and chemical properties can be found in Table 2, which shows average values for the five study years.

Soil properties such as soil water content and soil temperature were continuously monitored in both treatments (instrument failure caused gaps in the dataset). SWC-Ts sensors (type 5TM; Decagon Inc., USA) were installed in 5 depths (5–10; 15–20; 25–30; 35–40; 65–70 cm). The measurements started in fall of 2013. To utilize the most informative (and most complete) dataset here we present data for the top soil layer (5–10 cm).

Table 2
Soil properties at the study site under ploughing (MP) and no-tillage (NT). SOC and TN represent total nitrogen and soil organic carbon content, respectively. n = 21 ± SD Soil physical properties were measured in 2014.

Tillage type	pH	Clay fraction (%)	Sand fraction (%)	SOC (%)	TN (%)
MP	5.6 ± 0.2	34.4	35	1.59 ± 0.19	0.18 ± 0.01
NT	4.8 ± 0.1	35.4	34.3	2.27 ± 0.13	0.23 ± 0.02

We studied the traits of the cultivated plants such as the timing of emergence and flowering, plant height, aboveground biomass, root mass just before harvest, and the final yield. Plant samplings were performed at randomly selected locations in the middle of the plots, at the same location where soil conditions were measured. Three sampling points were designed at each plot, and thus, the total number of samples was 12 in total due to the four replicates. A wooden quadrate device with an area of 0.5 m × 0.5 m was used for sampling procedures. Aboveground biomass was removed manually from the unit area, by cutting the stalks 1 cm above the soil surface after measuring the height of plants. Both fresh and air-dried (samples were dried at 70 °C until constant weight was reached) weights were recorded. Plant roots were extracted with the soil cores to the depth of 45 cm, carefully cleaned before measuring the biomass. Favourable SWC conditions allowed for deep soil core sampling for each plant. One exception occurred in 2016, when soil was muddy in autumn therefore; maize roots had to be carefully washed.

2.3. Soil respiration measurements

Soil respiration measurements were carried out using the static chamber method (non-steady state, non-through flow; Pumpanen et al., 2004). Roots were not excluded, thus the efflux includes both root and heterotrophic respiration. Chambers were installed on bare soil, as plants and crop residue were removed before inserting the collars. As described in Tóth et al. (2018) square shaped collars (20 ×30 cm) were permanently installed in the soil (at 5 cm depth), while airtight chamber tops were placed on the frames for the incubation period. Gas samples were taken at t = 0 and t = 20 min that were subject to laboratory analysis to detect CO_2 concentrations of the samples. Gas samples were withdrawn with air-tight 10 mL syringes (Hamilton Co., Reno NV USA) and transferred into pre-vacuumed vials. Gas samples were analyzed for CO_2 concentrations using gas chromatography (FISONS 8000 series gas chromatograph, FISONS Instruments, UK). GC-FID instrument was used for analysis. Applied column parameters were 2 m by 3 mm, Porapak Q 80–100 mesh. The method used a splitless injection with hydrogen carrier gas (pressure: 90 kPa; flow rate: 30 mL min^{-1}). The injection volume of 250 μL was used. The detector temperature was set at 150 °C, while the oven temperature was kept constant at 80 °C for the duration of 180 s. The methanizer temperature was set at 350 °C. During the growing season, samples were taken once per week in seven spatial replicates, while in non-growing period sampling frequency was biweekly or monthly as weather permitted using seven replicates as well.

2.4. The remote sensing based dataset

NDVI data were used in the study to serve as a proxy for root activity. To derive NDVI time series for the study, the C006 MOD09Q1 surface reflectance product with 250 m spatial and 8-day temporal resolution was used (Vermote, 2015) from 2013 to 2017, derived from MODIS data on-board satellite Terra (Justice et al., 1998). Data for the tile h19v04 were downloaded from NASA LP DAAC (LP DAAC, 2020). The temporally composite MOD09Q1 contains atmospherically corrected surface reflectances for the visible bands 1 and 2, which are used to derive NDVI. Julian date information and State and Quality Control (QC) flags of the MOD09Q1 product were used as well for the pre-processing of the raw dataset containing information on the exact Julian dates of the reflectance measurements. The obtained dataset with a regular 8-day temporal resolution was based on the work of Kern and et al. (2016, 2020), where only data with the strictest quality criteria were kept.

The quality checked and gap-filled NDVI dataset was resampled into daily resolution using linear interpolation, where the actual Julian dates of the observations were taken into account. To ensure representativity, a composite time series was created to reconstruct the NDVI for the studied crops. For this purpose we used NDVI information from the neighboring larger fields, as plot size of the experiment was far smaller than the resolution of the NDVI product. In our approach it was not possible to capture between-field variability of NDVI per crop type, which means that the same NDVI curve was used as a proxy for root activity both for MP and NT. The collected crop type information from the neighboring fields allowed us the selection of the representative field, located west of the experiment (Fig. 1).

2.5. Quality control

Rs data were quality controlled and filtered. Quality control of the data included exclusion of data due to errors of known origin imperfect vacuum in vials or chamber closure, errors in GC measurements, etc. Then we created a database of the initial (t = 0) CO_2 concentrations of every collected sample and determined upper and lower percentiles of the series. CO_2 effluxes with outlier initial concentrations were excluded from the dataset.

Postprocessing of SWC data included removing data when probes were disturbed/removed because of agrotechnical applications, and data were filtered according to the methodology of the International Soil Moisture Database (Dorigo et al., 2013). SWC and Ts data were aggregated to a daily time scale.

2.6. Statistical analysis

When investigating the differences between treatments, data that lie outside the lower and upper 1.5 × interquartile range were identified as outliers and rejected from the analysis (Tukey, 1977). Residuals were checked for normal distribution and to ensure homogeneity and normality for the statistical analysis. Box-Cox transformation (Box and Cox, 1964) was applied on Rs data.

In most cases, to test statistical differences, the One-way analysis of variance (ANOVA) was used followed by a post-hoc Tukey honestly significant difference (HSD) test. For the soil chemical data nonparametric statistical analyses of unpaired *t*-test and the Mann Whitney *t*-test were used. All statistical calculations were performed using the software R (R Core Team, 2020) or GraphPad Prism (version 9.1.2, San Diego, California USA). Statistical significance of the data sets was determined at $p < 0.05$.

2.7. Soil respiration models

Six models with different complexity and number of input parameters were selected to simulate Rs in this study. The first (referred to as model 1) is the widely used Lloyd and Taylor (1994) model:

$$R_s = R_{10} e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right)} \tag{1}$$

where E_0 is the activation energy-like parameter (in K) and R_{10} is the base respiration at 10 °C (having the same unit as Rs), both values were set by the model fitting. In this model only the soil temperature from the 5–10 cm depth is used as a driving variable (provided in Celsius).

The second model is the extension of the Lloyd and Taylor (1994) model where the effect of SWC is considered (Balogh et al., 2011; Byrne et al., 2005):

$$R_s = R_{10} e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right) + \left(-0.5\left[\ln\left(\frac{SWC}{SWC_{opt}}\right)\right]^2\right)} \tag{2}$$

where SWC_{opt} is the optimum SWC for soil respiration. The other parameters are the same as in model 1. Eq. 2 is referred to as model 2. SWC_{opt} value was set by the model optimization together with the other parameters.

To include a proxy for root activity (i.e. to add an option to consider root respiration and rhizosphere activity), additional models were constructed where NDVI was introduced as a driving variable. Given the lack of continuous measurement of biomass or other plant phenology related parameters, NDVI seemed to be a good approach as it is closely related to leaf area index (LAI) hence potential photosynthesis and biomass (Gamon et al., 1995). These models were adopted from Yan et al. (2020). The third and fourth models are extensions of the Lloyd and Taylor (1994) model with two functional forms differing in terms of the effect of NDVI:

$$R_s = NDVI^p * R_{10}e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right)} \quad (3)$$

$$R_s = R_{10}e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right)+NDVI^p} \quad (4)$$

where p is the exponent of NDVI, and its value was set by model fitting. These models use soil temperature and NDVI as driving variables (SWC effect is not included). Eq. 3 is referred to as model 3, while Eq. 4 is as model 4.

Eq. 2 was also modified to include NDVI which resulted in two additional Rs models:

$$R_s = NDVI^p * R_{10}e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right)+\left(-0.5\left[\ln\left(\frac{SWC}{SWC_{opt}}\right)\right]^2\right)} \quad (5)$$

$$R_s = R_{10}e^{E_0\left(\frac{1}{56.02} - \frac{1}{T_s+46.02}\right)+\left(-0.5\left[\ln\left(\frac{SWC}{SWC_{opt}}\right)\right]^2\right)+NDVI^p} \quad (6)$$

These two models use Ts, SWC, and NDVI as driving variables. Eq. 5 is referred to as model 5, while Eq. 6 is referred to as model 6.

Model fitting was performed in R software environment (R Core Team, 2020), using the Levenberg-Marquardt method (which has advantages for model fitting as it is faster than the gradient descend method, and more stable than the Newton-Rapson method). We used the minpack.lm package (Elzhov et al., 2016) for the calculations. The package has support for defining bounds on model parameters that was used to ensure that the resulting parameters are physically correct. The full dataset consists of 149 (87 in growing season and 62 in non-growing season) and 151 (87 in growing season and 64 in non-growing season) Rs observations in MP and NT, respectively. For the modeling exercise only a subset of the entire Rs dataset was used. Rs data was retained and used in the model fitting if Rs, Ts, SWC and NDVI data were all available for the given days both in the MP and the NT treatment (NDVI was the same for both treatments). This consistent logic was used even if some of the drivers were not included in some of the equations (e.g. SWC is not used in model 1). After data filtering a total of 72 days remained that fulfilled the data selection criteria. Among the 72 days, 20 observations belonged to sunflower, 21 belonged to maize, and 22 belonged to bare soil observation (i.e. non-vegetated soil which was covered with crop residue in the NT treatment). The rest of the observations belonged to winter wheat and winter oat. First, we fitted the models for the entire dataset in one, then we fitted individual models for sunflower (2014), maize (2016), and bare soil. Individual model fitting was performed to check if there is any improvement in the models if we consider crop types separately. The other plant types were not simulated individually due to the low number of data. After model fitting, basic statistics were calculated to quantify model goodness (R^2, which is the linear correlation coefficient between the modeled and observed Rs; bias, which is the difference between the average of the simulations and the average of the observations; root mean square error (RMSE) and Akaike information criteria (AIC; Akaike, 1974). AIC quantifies the goodness of fit, while penalizing it with the number of parameters. Smaller AIC means a better model while larger AIC indicates possible overfitting.

During model evaluation we mainly focus on the ability of the models to explain the observed temporal variability of the Rs dataset, hence we mainly analyze R^2 (explained variance). The most appropriate model for the entire dataset and subsets of the dataset was selected based on the AIC.

3. Results

3.1. Comparison of observed soil parameters and biomass in MP and NT

3.1.1. Soil water content and soil temperature

Over the entire observation period, soil temperature values measured at 5–10 cm depth ranged between − 3 °C and 32 °C (Fig. 2a). Ts rarely fell below 0 °C. Ts was very similar in the MP and NT treatments ($p > 0.05$) for the whole year and during the growing season. Ts values reached higher maxima in the annual course in winter crop years when crops are harvested by the time of temperature peak not protecting soil from heating.

SWC in the 5–10 cm soil layer in MP and NT differed significantly during the entire experiment. Mean SWC in the individual years was significantly higher in the NT treatment ($p < 0.01$) compared to MP except in 2014 when MP was higher. Focusing on the growing season of the individual years, the daily average SWC was significantly higher in NT than in MP in all years regardless of the plant type, except in 2014 when sunflower was grown (Table 3; Fig. 2b). Growing season mean SWC was typically lower than the annual average. During summer, after full canopy development, a decrease was observed in SWC in each year.

3.1.2. Soil parameters

Total inorganic nitrogen content generally reflected plant development: it decreased throughout the growing season and increased again after tillage and simultaneous inorganic fertilizer application. Annual courses of TIN were similar in the two treatments but the amount in NT tended to be higher than in MP (data not shown).

SOC content in the upper 10 cm of the soil was found to be significantly higher ($p < 0.01$) in NT (2.27 ± 0.13%) than in MP (1.59 ± 0.19%) treatment (average of all observations in the 5 years). We also found a trend of accumulation of humified material in the upper layers in the NT treatment, while a more stable SOC content characterize the ploughed soil layers (data not shown). SOC content was slightly higher even in the upper 40 cm soil layer in NT on the average (1.71 ± 0.17% in MP vs 1.79 ± 0.36% in NT in 2015), but this difference was not statistically significant ($p > 0.05$).

3.1.3. Plant traits

Sprouting of the cereals in the NT treatment was faster compared to the MP treatment, probably due to the solid seedbed base. At the same time, plant development was slower and plant height usually lagged behind the MP treatment. The wide-row crops (sunflower and maize) sprouted faster and emerged earlier in the MP treatment. Flowering began 1–2 days later in the no-till treatment, but after 7–8 days it approached the uniformity of plants at MP.

Aboveground biomass was lower in the NT treatment, but the difference between the two cases was low (2% and 10% in 2013 and 2016, respectively; Table 4). We observed significant differences between root biomass in the treatments except for 2017 (winter oat). All other parameters showed less consistent results.

Plant height and grain yield in the MP treatment were notably higher for winter wheat and winter oat, while values were very similar for spring barley and maize (Table 4).

3.2. Comparison of Rs in MP and NT

During the 2013–2017 measurement period Rs showed a pronounced annual course in each year with summer peak followed by wintertime low values (Fig. 3). There is a notable difference between the annual courses of Rs for winter (years 2015 and 2017) and summer crops (years 2013, 2014, 2016; Fig. 3). For winter crops, the highest Rs values were usually followed by a sudden drop after plants were harvested. Rs ranges were similar in all years: between 0.02 and 0.19 mg CO_2 m^{-2} s^{-1}

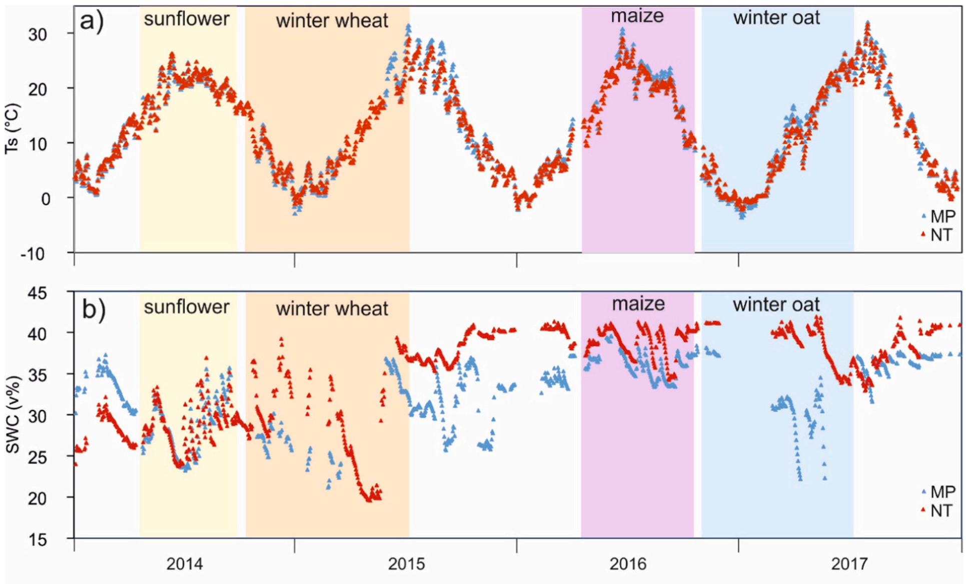

Fig. 2. (a) Soil temperature (Ts; 5–10 cm) and (b) soil water content (SWC; 5–10 cm) time series for the investigated period in the moulboard ploughing (MP) and no-tillage (NT) treatments. Coloured boxes denote growing season (from sowing till harvest) of different crops.

Table 3
Mean soil water content (SWC) values (5–10 cm) for the growing seasons and statistical significance of the differences (*p*) between the treatments based on one way ANOVA.

Year	mean SWC [%] in NT	mean SWC [%] in MP	*p*
2014	28.8	28.9	$>>0.05$
2015	35.4	29.6	<0.01
2016	38.8	36.1	<0.01
2017	39.5	27.2	<0.01

in spring barley; 0.01 and 0.19 mg CO_2 m^{-2} s^{-1} in sunflower, 0.02 and 0.23 mg CO_2 m^{-2} s^{-1} in winter wheat; 0.01 and 0.24 mg CO_2 m^{-2} s^{-1} in maize and 0.004 and 0.21 mg CO_2 m^{-2} s^{-1} in winter oat in both tillage treatments.

During the investigated five years, mean annual Rs ranged between 0.070 and 0.109 mg CO_2 m^{-2} s^{-1} in NT and 0.078 – 0.109 mg CO_2 m^{-2} s^{-1} in MP. Mean annual respiration rates in NT did not significantly vary among calendar years ($p >> 0.05$) except for the year 2017. In the MP treatment, Rs in the year 2013 was significantly higher ($p < 0.01$). The difference in annual mean Rs between the MP and NT treatments were not significant in years 2013, 2015, and 2017, when winter crops grew on the fields. Overall mean Rs was higher in NT (0.093 mg CO_2 m^{-2} s^{-1}) compared to MP (0.086 mg CO_2 m^{-2} s^{-1}) (Fig. 4).

Focusing on the growing seasons, higher Rs means with greater interannual variability were found (Table 5), with significant differences among the years in both treatments ($p << 0.01$ in both cases). Note that number of observations was much lower in 2013 compared to other years due to the initial phase of the experiment. When averaging the Rs data from all growing seasons, mean Rs values were higher in NT compared to MP (Fig. 4).

The degree of discrepancies in growing season mean Rs measured in NT and MP treatments varied among years. Although averaged Rs values were higher in NT treatment in each growing season separately, these differences were statistically significant only in some years (Table 5). In 2015 and 2017 and also in 2014 growing season only small differences were detected (Table 5).

Contrary to growing seasons, we found no significant difference in soil respiration between treatments in the non-growing seasons over the entire period ($p > 0.05$; Table 5). Either considering all 5 years or each year separately, Rs values are similarly low, significant differences were only measured in 2014.

3.3. *Modeling results*

3.3.1. *Models for the entire dataset*

Table 6 shows the error statistics for the six models that were used to simulate Rs for the complete dataset. Model fitting in this case covers different crop types from the crop rotation and observations made during non-growing periods as well.

Models 1 and 2 perform better in the MP treatment relative to NT, while models 3–6 are more suitable in NT as compared to MP in terms of explained variance (Table 6). The best model for both the MP and the NT treatments is model 5. The inclusion of NDVI as a predictor clearly improved the performance of the models.

RMSE was consistently lower in the MP treatment than in the NT.

Table 4
Plant traits in the ploughing (MP) and no-tillage (NT) treatments. Biomass and grain yield refers to dry matter. n = 4; ± SD. Different letters indicate statistically significant differences between treatments ($p < 0.05$).

Year		2013 Spring barley	2014 Sunflower	2015 Winter wheat	2016 Maize	2017 Winter oat
Stem biomass (kg ha^{-1})	MP	2.42 ± 0.6^a	3.8 ± 2^a	5.6 ± 0.4^a	11.8 ± 0.24^a	1.85 ± 0.05^a
	NT	2.38 ± 0.5^a	2.5 ± 0.1^b	4.4 ± 0.2^b	10.7 ± 0.15^a	1.34 ± 0.04^b
Root biomass (kg ha^{-1})	MP	1.55 ± 0.2^a	2.99 ± 0.1^a	1.2 ± 0.1^a	8.2 ± 0.06^a	3.54 ± 0.02^a
	NT	1.82 ± 0.2^b	2.3 ± 0.1^b	1.1 ± 0.04^b	6.5 ± 0.06^b	2.9 ± 0.06^a
plant height (cm)	MP	52 ± 7^a	167 ± 7^a	118 ± 6^a	238 ± 14^a	104 ± 8^a
	NT	55 ± 8^a	160 ± 14^a	91 ± 6^b	239 ± 2^a	78 ± 7^b
grain yield (kg ha^{-1})	MP	2959^a	3055^a	5591^a	8410^a	6245^a
	NT	3000^a	2395^b	4859^b	8247^a	4461^b

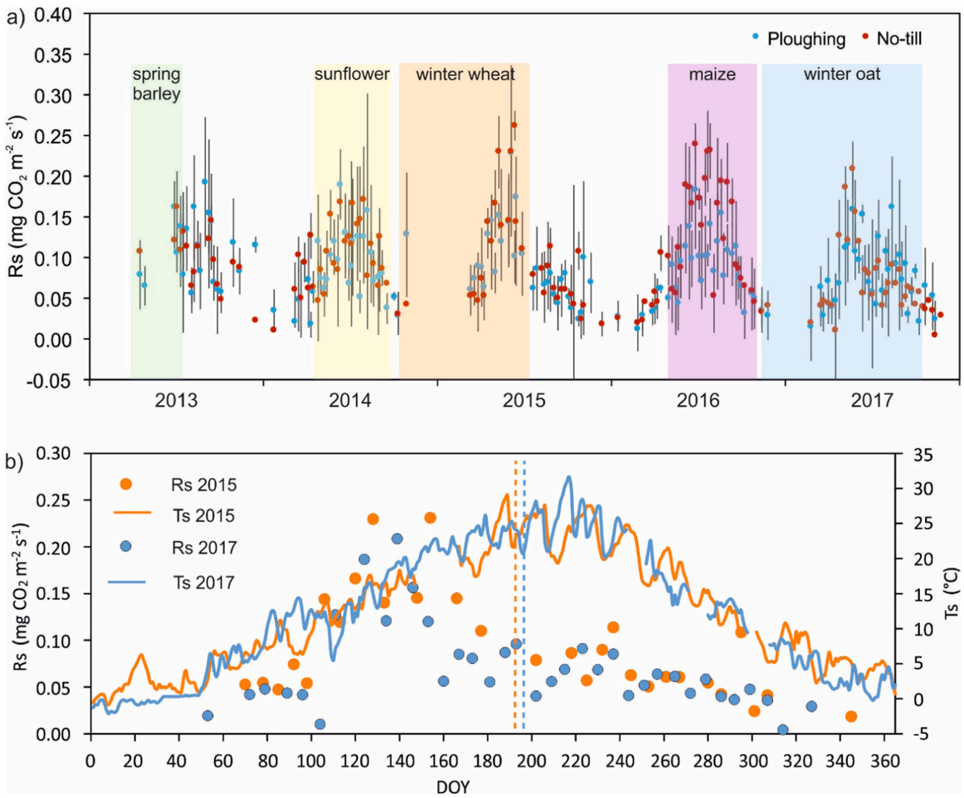

Fig. 3. a) Time series of soil respiration (Rs) between 2013 and 2017. Shaded boxes denote growing season for the specific crops (from sowing to harvest). Dots represent mean Rs of seven spatial replicates. Uncertainty of the observations is also plotted (± SD). b) Annual courses of soil respiration (Rs) and soil temperature (Ts) in winter crop years. Dashed lines represent date of harvest in 2015 and 2017.

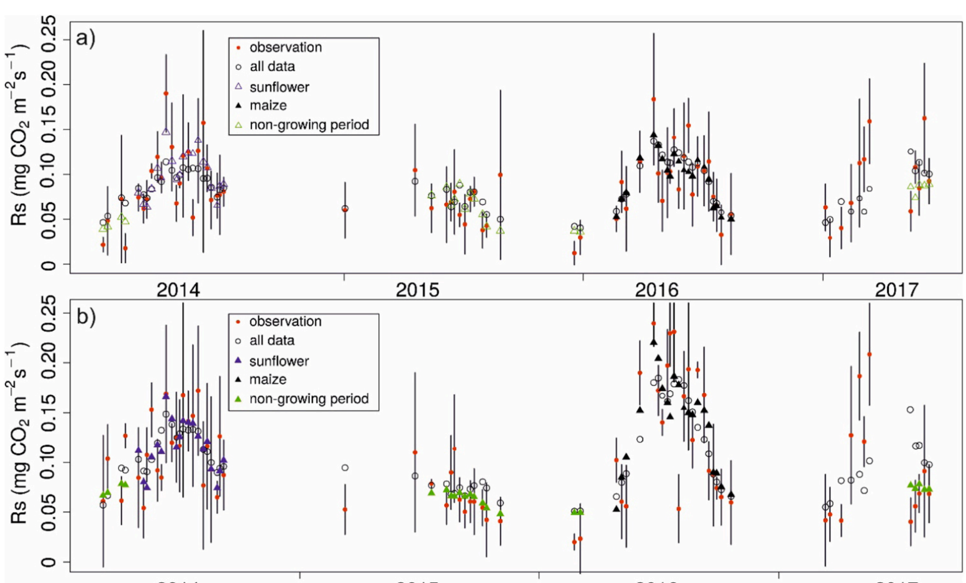

Fig. 4. Model results based on model the preferred models for the entire dataset, for sunflower, for maize and for the non-growing period for a) ploughing (MP) and b) no-tillage (NT) treatments. Observations are also plotted with uncertainty bounds (± SD of the observations per day). See text for details.

Bias remained low in most of the cases with a small general over-estimation of Rs (model 3 in NT is an exception). The magnitude of the bias indicates that the models captured the differences between the treatments (cf. Table 5). AIC values are more negative for models 3–6 as compared to models 1 and 2 for both MP and NT. For MP model 3, while for NT model 4 is associated with the lowest AIC value, which means that they are selected as the preferred models.

Fig. 4 shows the time series of the observed Rs together with the results of model 3 (MP) and model 4 (NT) for the complete dataset used for model construction. The figure shows that the best models were able to capture the dynamics of Rs for the different crop types.

Table 10 summarizes the best models for the entire dataset that were selected based on the AIC values. Different models were constructed for MP and NT.

Table 5
Mean soil respiration in ploughing (MP) and no-tillage (NT) treatments during the growing season, the non-growing periods, and the whole year. Different lowercase letters denotes statistical differences between treatments within a given year, while different uppercase letters indicate significant differences between years per treatment ($p < 0.05$). The values in the brackets show the number of observations.

year	Mean soil respiration [mg CO_2 m^{-2} s^{-1}]					
	NT growing season	MP growing season	NT non growing season	MP non growing season	NT whole year	MP whole year
2013	0.151^{Aa} (24)	0.105^{ABb} (36)	0.111^{Aa} (74)	0.113^{Aa} (68)	0.1^{Aa}	0.109^{Aa}
2014	$0.110B^{Ca}$ (124)	0.098^{BCa} (118)	0.070^{Ba} (34)	0.040^{Cb} (30)	0.096^{Aa}	0.085^{Bb}
2015	$0.126A^{BCa}$ (69)	0.118^{Aa} (99)	0.058^{Ba} (79)	0.060^{Ba} (81)	0.097^{Aa}	0.088^{Ba}
2016	$0.138A^{Ba}$ (129)	$0.096B^{Cb}$ (134)	0.043^{Ca} (46)	0.040^{Ca} (44)	0.109^{Aa}	0.079^{Bb}
2017	0.085^{Ca} (77)	0.078^{Ca} (64)	0.056^{Ba} (114)	0.071^{Ba} (108)	0.07^{Ba}	0.078^{Ba}
overall mean	0.122^{a} (423)	0.099^{b} (451)	0.068^{a} (347)	0.070^{a} (331)	0.093^{a}	0.086^{b}

Table 6
Results of the statistical evaluation of the six fitted models covering the entire dataset for ploughing (MP) and no-tillage (NT).

	R^2		RMSE (mg CO_2 m^{-2} s^{-1})		bias (mg CO_2 m^{-2} s^{-1})		AIC	
	MP	NT	MP	NT	MP	NT	MP	NT
model 1	0.292	0.199	0.03195	0.04889	0.00019	0.00024	-285.54	-224.3
model 2	0.287	0.194	0.03207	0.04905	0.00015	0.00006	-283.03	-221.82
model 3	0.418	0.443	0.02898	0.04076	0.00016	-0.00002	-297.6	-248.47
model 4	0.401	0.445	0.02938	0.04068	0.00017	0.00017	-295.63	-248.77
model 5	0.424	0.449	0.02883	0.04055	0.00013	0.00000	-296.33	-247.21
model 6	0.408	0.445	0.02922	0.04070	0.00014	0.00018	-294.42	-246.7

3.3.2. Models for specific crops and non-growing periods

Statistical assessment of the individual models for sunflower is presented in Table 7. Explained variance is higher for all models except model 3 for MP, and for all models for NT relative to the results of the complete dataset (see Table 6). Considering the difference between MP and NT for sunflower, models 1, 2, 5, and 6 perform better in MP than in NT. Model 6 can be considered as the best in terms of explained variance (~60% for MP and 48% for NT), but model 5 shows a very similar R^2.

RMSE values are lower in the case of sunflower-specific models than in the case of the entire dataset. Bias shows that the models underestimate Rs for MP but they exhibit a smaller overall positive bias for NT. AIC values are much larger (less negative) than for the complete dataset used for the modeling. The inclusion of NDVI decreases overall AIC in NT. Model 6 is associated with the lowest AIC in MP, while model 3 shows the lowest AIC in NT (i.e. they are the preferred models), though model 4 has almost the same AIC value. Fig. 4 shows the Rs estimations of the preferred models for sunflower.

Table 8 shows the results of the statistical assessment of the fitted models for maize. All models have a higher explained variance than in the case of sunflower (see Table 7). The best predictive model in terms of explained variance is model 5 (and model 6 for MP with very similar R^2).

RMSE values are lower for maize than for sunflower in MP, but they are higher in NT. Considering bias, in MP the models slightly underestimate Rs while they typically overestimate it (models 1 and 2 are exceptions here). AIC values are larger for maize than in the case of sunflower for NT but they are lower (more negative) for MP. The lowest AIC values are associated with model 1 in this case. Fig. 4 shows the results of model 1 for maize for MP and NT treatment.

Table 9 summarizes the error statistics of the six models for non-growing periods. Overall performance of the models is weaker than for sunflower and for maize. Clearly, the inclusion of SWC as a predictor greatly affects the model goodness for the no-till case (models 2, 5, and 6). The best models for the non-growing season are models 5 and 6 (model 5 is marginally better than model 6 in MP, but model 6 is slightly better than model 5 for NT). Interestingly, model 2 is almost as good as models 5 and 6 for MP and NT.

RMSE values are typically lower in NT relative to the MP treatment. Bias indicates that in MP the models underestimate Rs, while there is a slight overestimation in NT. AIC values are higher here than in the complete dataset case (Table 6) but somewhat lower than the values of the individual crops (Table 8). AIC is the lowest for model 1 in MP and for model 2 in NT. Fig. 4 shows the results of the preferred models (model 1 and model 2 for MP and NT, respectively) for the non-growing period with separate symbols.

Table 10 summarizes the best models that were selected based on the AIC values. Due to data coverage issues, some crop types (e.g. winter wheat) were not represented.

4. Discussion

4.1. Abiotic environmental variables

The annual course of Ts was very similar in the two treatments meaning that tillage had no systematic effect on soil temperature in the top 5–10 cm. In contrast, SWC was significantly higher in the NT soils (Fig. 4). This can be attributed to the presence of surface cover material

Table 7
Error statistics of the model results for sunflower in the ploughing (MP) and no-tillage (NT) treatment. n = 20.

	R^2		RMSE		bias		AIC	
	MP	NT	MP	NT	MP	NT	MP	NT
model 1	0.346	0.317	0.02746	0.02836	-0.00018	0.00001	-81.04	-79.75
model 2	0.400	0.318	0.02632	0.02835	-0.00013	0.00004	-80.74	-77.77
model 3	0.403	0.468	0.02624	0.02504	-0.00012	0.00008	-80.85	-82.74
model 4	0.404	0.468	0.02622	0.02504	-0.00012	0.00008	-80.89	-82.73
model 5	0.521	0.481	0.02351	0.02474	-0.00038	0.00008	-83.26	-81.22
model 6	0.522	0.481	0.02349	0.02472	-0.00037	0.00007	-83.30	-81.24

Table 8
Error statistics of the model results for maize in the ploughing (MP) and no-tillage (NT) treatment. n = 21.

	R^2		RMSE		bias		AIC	
	MP	NT	MP	NT	MP	NT	MP	NT
model 1	0.577	0.502	0.02290	0.04472	-0.00003	-0.00012	-93.03	-64.91
model 2	0.581	0.505	0.02279	0.0446	-0.00005	-0.00010	-91.22	-63.02
model 3	0.577	0.520	0.02288	0.04392	-0.00002	0.00009	-91.06	-63.67
model 4	0.577	0.513	0.02288	0.04424	-0.00005	0.00008	-91.05	-63.37
model 5	0.582	0.520	0.02276	0.04391	-0.00005	0.00009	-89.29	-61.68
model 6	0.582	0.513	0.02276	0.04421	-0.00005	0.00008	-89.28	-61.39

Table 9
Error statistics of the model results for non-growing periods in the ploughing (MP) and no-tillage (NT) treatment. n = 22.

	R^2		RMSE		bias		AIC	
	MP	NT	MP	NT	MP	NT	MP	NT
model 1	0.337	0.079	0.02711	0.02535	-0.00003	0.00004	-90.32	-93.27
model 2	0.365	0.253	0.02653	0.02282	-0.00007	0.0019	-89.26	-95.89
model 3	0.360	0.082	0.02662	0.02530	0.00006	0.00002	-89.12	-91.36
model 4	0.351	0.082	0.02682	0.02530	0.00004	0.00002	-88.79	-91.35
model 5	0.376	0.263	0.02629	0.02267	-0.00005	0.00051	-87.66	-94.18
model 6	0.370	0.276	0.02642	0.02247	-0.00005	0.0009	-87.45	-94.57

Table 10
Proposed models for the entire simulated dataset, for sunflower, for maize and for the non-vegetated dataset in ploughing (MP) and no-tillage (NT). The proposed equations were selected based on the calculated AIC.

Data type	Treatment	Equation
all data	MP	$R_s = NDVI^{0.49} \bullet 0.0876 \bullet e^{147.08\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right)}$
all data	NT	$R_s = 0.0334 \bullet e^{100.68\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right) + NDVI^{1.78}}$
sunflower	MP	$R_s = 0.0197 \bullet e^{309.25\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right) + \left(-0.5\left[\ln\left(\frac{SWC}{49}\right)\right]^2\right) + NDVI^{p1.82}}$
sunflower	NT	$R_s = NDVI^{0.84} \bullet 0.0797 \bullet e^{320.69\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right)}$
maize	MP	$R_s = 0.0596 \bullet e^{258.89\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right)}$
maize	NT	$R_s = 0.0639 \bullet e^{318.75\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right)}$
non-growing period	MP	$R_s = 0.045 \bullet e^{160.78\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right)}$
non-growing period	NT	$R_s = 0.0882 \bullet e^{53.14\left(\frac{1}{56.02} - \frac{1}{T_s + 46.02}\right) + \left(-0.5\left[\ln\left(\frac{SWC}{15}\right)\right]^2\right)}$

Note that in the equations soil water content (SWC) is expressed as v/v%.

in the NT treatment in the form of plant residue from the previous crop (i.e. mulch), and probably to the different distribution of organic matter along the upper soil profile in the NT and the well-mixed MP soils, as both can greatly influence soil evaporation and infiltration (Keesstra et al., 2018; Tolk et al., 1999). The summer decrease of SWC that was observed in both treatments is influenced by crop type and phenology in a given year. When crop water uptake was high and atmospheric conditions were favorable during summer (higher irradiation, higher atmospheric water demand) (i.e. in the years of 2013, 2014, 2016, when summer crops were cultivated), it negatively influenced SWC. Meanwhile, as crop residue remained undisturbed and left on site after harvest until fall tillage in both treatments (in NT also afterward), it supported soil moisture preservation by decreasing soil evaporation during the dormancy phase (Lal, 1995).

4.2. Biotic variables

The highest observed respiration values were usually out of phase with temperature peaks in the case of winter crops (Fig. 3b), highlighting the importance of autotrophic respiration at peak growing season that largely affects the annual course and magnitude of Rs. According to the available information, autotrophic (root) respiration can contribute up to 50–70% of total emission from soil (Hanson et al., 2000; Raich and Mora, 2005; Reichstein and Beer, 2008; Li et al., 2020; Huang and Niu, 2013; Balogh et. al, 2016; Tong et al., 2017). Given the role of the biotic factors in Rs, an attempt was made to relate the observed, treatment-specific differences of Rs to available field and plot scale plant data (Table 4). The comparison revealed no clear evidence that there is a relationship between Rs and the investigated plant traits. In our case root biomass was smaller in NT, hence, it cannot contribute to the larger Rs. Instead, the higher SOC content and the higher SWC (see Sections 3.1.1 and 3.1.2) and probably interaction among the main driving factors eventually led to the overall higher emission in the NT treatment. It has to be noted that the representativity of Rs and field-scale yield data were clearly different, and the same might stand for randomized plant height measurements, which also aimed to represent the whole treatment.

The amount and vertical distribution of SOC have been extensively documented in the literature, and results generally agree that SOC content decreases in NT treatment downward in the soil profile (Balesdent et al., 2000; Blanco-Canqui and Lal, 2008; Deen and Kataki, 2003; Kern and Johnson, 1993; Ussiri and Lal, 2009). Sleutel et al. (2006) focused on the partitioning of SOC between different pools in the fourth year of the Józsefmajor long-term tillage experiment, and found that the accumulation of the more labile SOC components had been relatively larger in NT compared to MP, which can enhance Rs, and also affect temperature sensitivity of Rs (Moinet et al., 2020).

4.3. Soil respiration

The measured amounts of CO_2 emitted from the investigated soils in the present study are well within the range of soil respiration values reported in the literature. Peak respiration values of 0.036–0.418 mg CO_2 m^{-2} s^{-1} have been obtained for maize (Forte et al., 2017; Jia et al., 2016; Lee et al., 2009; Omonode et al., 2007; Oorts et al., 2007; Ussiri and Lal, 2009; Zhang et al., 2013), which is in agreement with our results of 0.184 and 0.240 mg CO_2 m^{-2} s^{-1} in NT and MP treatment, respectively, in maize. There are also numerous studies focusing on Rs under wheat with measured peak respiration rates ranging from 0.041 to 0.330 mg CO_2 m^{-2} s^{-1} (Chatskikh et al., 2008; Dong et al., 2017; Franzluebbers et al., 1995; Oorts et al., 2007; Zhang et al., 2013), which are somewhat lower than that in the case of maize, but support our results (0.228 mg CO_2 m^{-2} s^{-1} in NT; 0.262 mg CO_2 m^{-2} s^{-1} in MP for wheat). For oat, we measured slightly higher respiration rates compared to previous findings (Aslam et al., 2000), but oat is not a well-represented plant type in soil respiration studies, hence there are limited data available on peak respiration values. The same deductions stand for sunflower.

Based on five years of field measurements (presented in Fig. 3), we can conclude that overall Rs was greater in NT than in MP in the investigated period (for annual, growing, and non-growing season sub-period averages see Table 5). However, the magnitude of the difference was not identical in all years, it varies with crop type, i.e. differences are bigger in two summer crop years, in 2013 and 2016. Findings by Bilandžija et al. (2016) support our results that significant differences in soil CO_2 emissions between different tillage treatments with crop presence were recorded during maize but not during winter wheat growing season. It has been reported in other studies that SWC can limit respiration rate (Buchmann, 2000; Scott-Denton et al., 2003). Recent studies reported higher Rs in NT and concluded that the observations were a result of higher SWC compared to MP (Du et al., 2021; Gong et al., 2021).

In general, water availability directly affects microbial processes and via plant functioning root respiration, hence Rs. The difference between Rs rates in the two treatments can be related to the combined effect of plant (root) contribution, SOC content, and SWC, where the latter two were generally significantly higher in the topsoil of NT treatment. However, in 2015 and 2017 the annual average Rs difference was not significant, although topsoil SWC was lower in the MP treatment as these two years received less precipitation in the growing season than usual (see Section 2.1), which can be related to winter crops' insensitivity to SWC variability during the growing season (Kern et al., 2018). The growing season of winter crops fell in the spring period when SWC deficit is typically low in the lower soil layers, though the top soil layer easily loses moisture in the MP soil in the absence of the mulch layer. It is likely that under the current climate in Hungary the water stored in the lower soil layers provides ample moisture for plant functioning maintaining a high root respiration rate.

There has been an ongoing debate on the effect of long-term soil tillage practices on Rs rates. Based on 15 papers published between 1995 and 2017 with regard to Rs rates in different tillage systems, no clear conclusion could be drawn whether soil CO_2 efflux in NT exceeds that in MP or not (Abdalla et al., 2014; Aslam et al., 2000; Chatskikh et al., 2008; Dong et al., 2017; Forte et al., 2017; Franzluebbers et al., 1995; Hendrix et al., 1988; Jia et al., 2016; Laudicina et al., 2014; Lee et al., 2009; Omonode et al., 2007; Oorts et al., 2007; Ussiri and Lal, 2009; Yonemura et al., 2014; Zhang et al., 2013). Four of the studies report higher emission in NT and five found MP emission to be higher, while the rest came up with mixed results within one year or no clear differences. Some earlier studies provided mixed results, i.e. Rs in NT was higher/lower than that in MP depending on crop type or season (Franzluebbers et al., 1995). Ussiri and Lal (2009) studied seasonal fluxes of soil respiration and found Rs to be higher under MP than NT in each season, in continuous maize in long-term tillage experiment (since 1962) based on biweekly (growing season) to monthly (non-growing period) sampling frequency. This is in conflict with our results, where we found opposite order and the largest difference between treatments under maize among all plant types.

Besides the diversity of measurement methodology, comparison of the results is also difficult because some of the studies (6 out of 14) have been carried out in recently established tillage experiments, where soil structural differences due to systematic no-till practice could not develop yet. Despite the relatively large amount of available literature, it is not easy to reveal any systematic discrepancies considering the contradicting results they present. This can be due to several reasons, including the need for an agreement on standardized measurement methodology – at least for croplands. Note that in reviewing the literature we focused on measurements carried out regularly covering at least one growing season, and excluded pilot studies that were limited to investigate only the short-term effect of tillage.

4.4. Modeling

Six different models were used in this study in order to test their ability to capture the temporal variability of the observed Rs data in the MP and NT treatment. One model was driven only with soil temperature, while the others were extended with SWC (3 models) and by NDVI (4 models).

Performance of the models was comparable to those available in the literature for croplands (Ding et al., 2007; Frank et al., 2006; Han et al., 2007; Huang and Niu, 2013; Huang et al., 2012; Sánchez et al., 2003; Tong et al., 2017). It has to be mentioned that many studies found in the literature cover only 1–2 years of data, or one growing season, where the models indicate better performance. In our case the exceptionally long dataset inevitably resulted in lower R^2 (42–45% explained variance for MP and NT, respectively). It is interesting to note that using data from calendar years provided a better fit in our case (not shown here), but this analysis was out of the scope of the study given that we focus on the entire dataset and on the growing season of specific crops.

Performance of the models (in terms of explained variance) differed among the crop types, and also for cases when the entire dataset or the non-vegetative period was used for model fitting. Performance of the models also differed between the treatments (MP and NT). This means that there is added value in the construction in crop-specific (or generic) Rs models, and also treatment specific models. As it is summarized in Table 10, the models also differ in terms of structure (number and type of predictors) and coefficients. This finding might be related to the differences between the crop types (biomass, phenology, and timing to reach maturity) and the observed difference of Rs between the treatments (Section 4.2). For example, sunflower is known to deplete SWC in the soils more than other crops, which can explain the differences in the model structure for maize and sunflower. Model fitting was not possible for winter crops due to a low number of concurrent Ts and SWC observations. Future studies should focus on the construction of Rs models in winter crops as well. Validity and possible generalization of the models and their prediction capacities should be examined using data from other experimental sites. Thus, long-term Rs data from other crop rotations are highly needed to study the validity of the presented approach at other geographical locations under different climatic conditions.

Due to methodological issues, soil respiration data are characterized by high variability. However, the simple empirical models used in the majority of the studies use fitting techniques and error metrics that do not consider observation uncertainty. Consequently, widely used error statistics like R^2 and RMSE might provide misleading information on the goodness of the models. In our case the large inherent uncertainty of the observed Rs demonstrated that most of the modeled values were well within the uncertainty bounds (see Fig. 4). Probabilistic or Bayesian methods should be introduced and tested in the future to exploit the information content of the Rs observations beyond the simple but intuitive model fitting using e.g. the presented Levenberg-Marquardt method (see e.g. the method of Reichstein et al., 2003 and Richardson et al., 2006).

We demonstrated that the inclusion of NDVI in a simple way provided better model results when the entire dataset was used for model fitting (and also in the case of sunflower). In croplands, harvest causes a sudden drop in the autotrophic contribution of Rs which means that biotic factors decouple from the abiotic factors (e.g. photosynthate input decouples from soil temperature). As a consequence, co-variation of the predictors will not be present anymore. It necessitates the extension of the Rs models with further drivers. However, in some cases co-linearity might be present among the driving processes. If e.g. NDVI correlates well with soil temperature, then the inclusion of NDVI is not expected to improve the model performance. In other words, NDVI as a plant phenology indicator may not provide additional information compared to the combination of abiotic drivers. Maize is a summer crop and for such crop temperature, phenological state and SWC (summer drying of the soil) typically co-varies in Hungary, which is in accordance with our finding that modeling results did not improve with the inclusion of NDVI data.

In a mathematical sense, this logic might be criticized because models with a higher number of parameters are always prone to overfitting. In our study AIC was used as an indicator of possible overfitting. As we selected the 'best' model per crop type and per treatment according to AIC, overfitting is not likely. The results indicate that process representation requires the construction of more complex models even if the uncertainty of the model parameters is affected. The inclusion of NDVI as a predictor in the Rs models is not new. Earlier studies already attempted to use satellite based spectral vegetation indices to provide information about the autotrophic contribution of Rs for forests and croplands (e.g. Huang and Niu, 2013; Sánchez et al., 2003; Yan et al., 2020) though its widespread application is still lacking.

4.5. Assessment of the validity of the results

The results obtained from field studies based on the static chamber technique, which is the method used in this study, should be cautiously interpreted in the general context of agriculture. There are several factors impeding potential generalization of the plot scale studies focusing on such complex systems as field crops. Measurement uncertainty resulting from the experimental system in manual, closed-chamber measurements is heavily influenced by human originated errors (Lee, 2018; Rochette and Hutchinson, 2005).

During the five-years-long observation period presented here, measurements were carried out under different cultivated plants grown on the experimental field in each year. On one hand, this can limit the validity of our conclusions for one specific plant type as no repeated observations are available under different weather conditions. On the other hand, such diversity of sown crops suggests that the overall results are independent of crop type (though differences between treatments tend to be smaller in winter crop years). Further investigations and even longer Rs time series are needed to corroborate the validity of this result.

The main restriction for the validity of the chamber based soil respiration measurements is their spatial coverage, which is a reason of concern because of the spatial variability originated from soil and plant heterogeneity. The seven replicates used in the current study might not provide spatially representative results for the whole treatment. However, chambers were relocated after each disturbance event (when necessary) meaning that 5–10 different locations were monitored throughout the whole study period. The consistency of the results (higher Rs in NT than in MP in most years) suggests that the observed differences are not related to the relocations of the chambers.

Investigations have been previously carried out to explore the spatial heterogeneity of soil hydraulic properties of the same field, which strongly determine soil water content at the present site, in all treatments (unpublished data). The results showed that between-treatment differences were larger than within-treatment spatial heterogeneity, i. e. indeed, the observed Rs trend can be attributed to treatment effect and not to natural inhomogeneity. The degree of within-treatment variations of soil structural properties differed between the treatments. Soil moisture content and water retention curves showed greater spatial variability in NT than in MP treatment, which can be the result of the homogenizing effect of ploughing.

The site represents the general farming practice of conventional tillage, also considering alternative tillage methods. Chernozem soils, that is present at the study site, are the second most important soil type in Hungary (Nagy, 2013) being also the most frequently utilized soils from the agricultural aspect. Management – apart from soil tillage – reflects the general practices followed by farmers in the country. No-tillage management practice is currently not widespread in the country, only 8000 ha (approx. 0.2% of the total cultivated area) is associated with this type of tillage (Bádonyi, 2006). Nevertheless, as the NT method is widely used in Western Europe and in other regions worldwide, the observation record presented in the study might provide valuable additional information for future studies focusing on continental or global scale.

5. Conclusions

Based on field observations we found that average soil respiration was higher in most (but not all) periods in the NT treatment regardless of crop type, or weather conditions, although the observed differences are not significant in some periods. The difference between CO_2 emissions was more pronounced during the growing season compared to the whole year, which is probably due to the overall effect of higher SOC content and soil water content, which could overcompensate the respirative contribution of lower biomass and plant activity in the NT treatment. Differences in the vertical distribution and amount of top soil organic matter content may also contribute to the findings. Six different models were tested for a representative subset of the observations. It was found that the inclusion of plant activity proxy (NDVI) in the model improved the performance of the models for the entire observation period including different crops and non-vegetated time periods. The performance and structure of the proposed Rs models varied between crop types and also between treatments (MP and NT). We provided equations for the entire time series and also for sunflower, maize, and the non-vegetated period. These equations can be tested at other sites but we acknowledge that the coefficients might not be stable due to the uncertainty of the dataset. Longer data series are needed to provide better models for Rs in different treatments, and model construction should exploit the uncertainty of the observations.

The study highlights the methodological challenges of soil gas efflux measurements under field conditions. Synthesis studies are strongly needed to increase our confidence in the retrieved results.

The database is available from the authors for further studies or for inclusion in the Global Soil Respiration Database.

Declaration of Competing Interest

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

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