RESEARCH PAPER

CONTRIBUTION ANALYSIS OF PERMANENT AND SPORADIC CONTROLS OF CO_2 EFFLUX FROM CHERNOZEMS OVER FOUR SEASONS

Dmitry V. Karelin*[1], Olga E. Sukhoveeva[1]
[1]Institute of Geography RAS, Staromonetny Lane, 29, 119017, Moscow, Russia
*Corresponding author: dkarelin7@gmail.com
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ABSTRACT. We analyzed four years field observations (2017–2020) of soil CO_2 efflux from Chernozems of arable and forest-steppe ecosystems of Kursk region (Russia), which correspond to the period of the maximal current warming. Three well-known simulation models of different structure and variable sets (DNDC, RothC, T&P) and nonparametric regression analysis were used to estimate annual CO_2 emission from soil and contributions of constant and sporadic controls. The applied models satisfactorily predict both the rate of annual soil CO_2 emission and its seasonal dynamics on arable Chernozems. However, while RothC is suitable for the whole set of crops considered, DNDC is most suitable for cereals and T&R for bare soils only. A comparison of the contributions of permanent and sporadic factors to soil respiration showed that on an inter-annual scale soil temperature and moisture are less important than yearly crop rotation in Chernozem plowlands, making the latter the most important predictor apart from general land-use type. Although the combination of significant permanent and sporadic factors is able to explain 41% of the soil CO_2 emission variance, the leading involvement of spatial controls prevents the construction of quantitative regression models that are able to make forecasts, requiring the use of more sophisticated simulation models (i.e. RothC) in this case. However, the use of the latter does not yet solve the problem of predicting soil CO_2 emission and its net balance in forest-covered or steppe areas of Chernozem forest-steppe landscape.

KEYWORDS: Haplic Chernozems, Luvic Chernozems, soil respiration, carbon dioxide emission, natural and anthropogenic controls, simulation and regression modelling

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INTRODUCTION

The problem of identifying and quantifying permanent factors of CO_2 emission from various types of soils has now been elaborated in sufficient detail (Zavarzin and Kudeyarov 2006; Kuzyakov 2006; Luo and Zhou 2006; Kudeyarov et al. 2007; Naumov 2009; Stepanov 2011; Chen et al. 2014; Karelin et al. 2014, 2020 a,b; Kurganova et al. 2020) and might be considered close to final solution. Importantly, the results of these studies have been «digitized» in the form of simulation mathematical models at various scales (Jenkinson et al. 1987; Li et al. 1992; McGuire et al. 2001; Raich et al. 2002; Chertov and Komarov 2013). This is of great importance for calculations of the carbon balance and assessment of greenhouse gas contributions to climate change and prediction of their dynamics from individual ecosystems to the biosphere (Tian et al. 2016). In addition to improving existing models, the attention of researchers in this field is now shifting to more specific issues. These include the identification and assessment of the relative contribution of short-term (impulse, sporadic) or highly localized environmental drivers. These are likely to include factors whose marked effects are infrequent, only when they reach a certain degree of severity or threshold. The increased attention to such sporadic or locally acting CO_2 emission controls is due to the fact that their contribution to the annual carbon budget can often be significant (Kuzyakov and Blagodatskaya 2015; Leon et al. 2014; Ohashi et al. 2007; Karelin et al. 2017).

The latter is particularly important under conditions of ongoing warming, increasing frequency of droughts and storm events in Russia (Zolotokrylin et al. 2007; The second Roshydromet assessment 2014; Kurganova et al. 2020; Leskinen et al. 2020). In forests, the most significant are sporadic soil CO_2 emission and C-balance drivers associated with tree stand mortality caused by fires, logging and phytophages (Leskinen et al. 2020; Karelin et al. 2020b).

In agro-landscapes, these controls include, in particular, horizontal wind speed creating lower surface pressure, which leads to the so-called «pressure pumping effect» (Takle et al. 2004), i.e., additional degassing of soil, including CO_2, into the atmosphere, which greatly enhances the no-wind diffusion rate. This effect is particularly noticeable when wind intensifies in arid flat or mountainous ecosystems with low vegetation canopy, such as steppes (Roland et al. 2015; Sánchez-Cañete et al. 2013) or agro-ecosystems (Smagin and Karelin 2021).

Another well-known sporadic emission factor in soil ecology is the so-called «Birch effect»[1], in the understanding of the mechanism of which, perhaps, clarity has now arrived (Unger et al. 2010; Fraser et al. 2016). However, there is still no consensus on its biospheric significance (Moyano et al. 2013; Oikawa et al. 2014). The one-time contribution of the additional emission caused by this effect can be very noticeable, especially after prolonged droughts (Karelin et al. 2017), although the overall reduction of soil respiration caused by drought significantly negates this contribution (Lopes de Gerenyu et al. 2018). The winter analogue of such «wetting-drying» cycles can probably be considered sporadic «freezing-thawing» cycles, which also cause a substantial pulse release of CO_2 (Kurganova and Lopes de Gerenyu 2015).

In agro-landscapes, sporadic factors related to agronomic practices (e.g., no-till technology; amount, nature, and form of fertilizers applied; crop rotation in fields, etc.) are also involved. A known pulse component of soil CO_2 emission is the release of carbon dioxide during mechanical tillage (ploughing, harrowing), harvesting, the passage of machinery over the fields, and any sufficientl mechanical load (Markovskaya et al. 2014; Cherkassov et al. 2013; Stupakov 2014; Akbolat et al. 2009; Bojarszczuk et al. 2017; Fiedler et al. 2016).

An additional difficulty in solving the problem is posed by the fact that widely practiced micrometeorological methods of monitoring net CO_2 fluxes are not feasible to instrumentally separate their main components, which has to be done by means of modelling (Suleau et al. 2011). At the same time, the pulse components of C fluxes are usually even more difficult to separate and, hence, to model. Therefore, only instrumental observation methods of soil CO_2 emission on a multiyear basis remain at the disposal of researchers, but such long-term data are still clearly insufficient (Kurganova et al. 2020).

All of the above translates the problem of quantifying the contribution of pulse factors to soil CO_2 emissions into the category of potentially high importance. Our study focuses on the analysis of permanent and sporadic controls of soil carbon dioxide emission in the agronomically well-developed forest-steppe zone of the European territory of Russia, where arable Chernozems are widely distributed.

The goal of the study is to compare estimates of annual soil CO_2 emissions obtained from field observations and by various methods of modelling and statistical analysis, and use them to identify relative contributions of permanent and sporadic carbon dioxide emission drivers in the Chernozem landscape under different land-use variants.

OBJECTS AND METHODS

Field observations

The statistical analysis included field observations during four consecutive growing seasons (2017–2020) in the vicinities of Kursk Biosphere Station of the Institute of Geography of the Russian Academy of Sciences (KBS IG RAS) and Alekhine Central Chernozem Reserve, where the full range of forest-steppe ecosystems is represented compactly. The study area (51.5°N, 36.1°E; ca. 40 km^2), is located in the forest-steppe subzone, in the Medvensky and Kursky districts of the Kursk region (Russia). According to the analysis of the high-resolution satellite image (SCOPE, 14.10.2019), the site is dominated by agro-landscape (arable land and vegetable gardens: 57%); broad-leaved forests and forest strips occupy 17%, perennial fallows, forest-steppe areas, overgrown balks and ravines – 12%, mowed meadows – 10%, roads – 2%, residential areas – 2%.

Soil respiration measurements were carried out with infrared CO_2 analyzers and closed chamber method according to the original technique (Karelin et al. 2014, 2015, 2017, 2020 a,b). Amongst the associated indicators, carbon and nitrogen content in the 0–15 cm soil layer (%), volumetric soil moisture in 0 – 6 cm layer (%), air temperature in vegetation canopy and temperature in soil at 1, 5 and 10 cm depth (°C), total projective plant cover (%), average plant height by tier, and current phenophase were assessed. Measurements were taken annually at 12 permanent observation sites, 1–4 times per month, from April to November. diurnal measurements were performed during daylight hours. As the post hoc analysis showed, there was no significant effect of the measurement time on the emission rate at particular sites. Additionally, winter emission estimates were carried out in January 2019 and January–March 2021 (n=20). The sites represent the most characteristic elements of the local landscape. Each measurement at individual site was carried out in 5–15 site replications.

The total number of intra-season measurements across all sites was 466 (2017: 125; 2018: 116; 2019: 32; 2020: 193), or, including repeats, 4,195. Biotopes in the analysis include mature and overmature forest (>150-year-old oak forest; >60-year-old ash forest; >80-year-old maple-oak forest); ecotone between oak forest and meadow steppe; mature >70-year-old meadow steppe; 2 – 5 years old fallows; permanently used unfertilized vegetable garden with rotating crops; and perennial fertilized arable land (5 plots) with rotating grain or raw crops.

In all cases the soils were Haplic Chernozems (Loamic, Pachic) on forest-steppe plots and agricultural fields, and Luvic Chernozems (Loamic, Pachic) under broad-leaved forest, according to WRB classification (IUSS Working Group 2015).

Statistical analysis and modeling

Soil CO_2 emissions were estimated in several ways:
(a) integration of field observations using trapezoidal method[2]. Winter emission data (December–March) were obtained in January 2019, and January–March 2021.
(b) Using three simulation models:

[1]Short-term (up to several days) but powerful release of nitrogen oxides and CO_2 from dry soil into the atmosphere in response to rewetting. The effect has been known since the early 20[th] century and was named by H.F. Birch after his detailed field and laboratory experiments in Kenya (Birch 1958).
[2]Trapezoid(al) method – follows the so-called Trapezoidal Rule. Under this integration rule, the area under an experimental or observation curve is evaluated by dividing the total area into little trapezoids rather than rectangles. Used when data are obtained unevenly.

• DNDC (DeNitrification-DeComposition, version 9.5), a process-based model of carbon and nitrogen cycles in agricultural soils (Li et al. 1992). This daily-step model consists of three subunits (thermo-hydrological, nitrogen and carbon), requires a large amount of input data and uses many assumptions on the controls of GHG emissions per soil type. The model is considering climatic variables, soil characteristics, and agricultural technologies.
• RothC (Rothamsted Long Term Field Experiment Carbon Model, version 26.3), a model of organic carbon cycling in the upper layers of non-waterlogged soils (Jenkinson et al. 1987). It uses a monthly time step to calculate total organic carbon, microbial biomass carbon and CO_2 emission from soil and allows to evaluate the effects of soil type, temperature, moisture content and plant cover on the turnover process of organic matter.
• T&P (Temperature and Precipitations, version 2), a climate-dependent regression model estimating heterotrophic CO_2 flux from soil to atmosphere for a wide range of terrestrial ecosystems (Raich et al. 2002). It allows to determine the influence of interannual temperature and precipitation variations on global CO_2 emission at monthly step but it doesn't take into account vegetation.

Note that all three models, originally derived from field observations, simulate carbon dioxide production and transport to the atmosphere, but T&P differs in that. It is only describing the heterotrophic (microbial) component of soil respiration without considering roots.

Different land uses, soil characteristics and meteorological variables were tested for the role of emission drivers. The set of the analyzed permanent and sporadic emission controls is given in Table 1. To assess sensitivity of the models to individual factors, simulation experiments were used, where the known value of factor change was compared with the response value of CO_2 emission from soil. The models were verified by field data on soil CO_2 release.

Simulation using RothC was evaluated for each crop over the entire observation period, as the time step of the model is one month, which significantly reduces the size of the data series for validation. The diurnal step of the DNDC model allowed to carry out its verification sequentially for each year. To assess the adequacy of the models, we used:
• Nash-Sutcliffe Efficiency coefficient (*NS*). The coefficient values are in the range of (-∞;1]; if NS < 0, it indicates the failure of the model. It is effective when NS > 0; the closer the value is to 1, the more accurately the process is reproduced.
• Theil's inequality coefficient (T). The coefficient values lie in the range [0;1], and the closer the coefficient is to zero, the more accurate the simulation. Normally in environmental studies its threshold of significance is T ≤ 0.3.
• One-way ANOVA assesses the equality of mean values of samples: mean estimated and field values are equal if $F_{comp} < F_{crit}$ and p > 0.05.

The principles of using the above criteria, as well as the preparation of input information for the models and their adjustment to the conditions of the Chernozem zone of Russia have been described in detail earlier (for DNDC: Sukhoveeva and Karelin 2019; for RothC: Sukhoveeva 2020).

Since the first two models are applicable only to agricultural lands, we calculated the annual emission estimates in case (a) only for arable plots.

Meteorological data were obtained from a Davis Instruments (USA) stationary full-profile wireless weather station owned by KBS IG RAS, as well as from RIHMI WDC data base (Obninsk, Russia) for Kursk weather station (#34009, 51.76° N, 36.16° E, 247 m a.s.l.).

The data processed using MS Excel and SPSS 27 (IBM). Means and their standard errors used elsewhere in the text. The means were compared by one-way ANOVA or Mann-Whitney test at p=0.05. The coefficient of variance was calculated as CV = (standard deviation / mean) · 100%. Nonparametric regression analysis of CO_2 emission drivers performed using PRIMER V. 7 (PRIMER-E Ltd.). In the latter case, all study plots, including forest and steppe, were involved in the analysis. The set of investigated soil CO_2 emission factors is given in the "Results and Discussion" section.

RESULTS AND DISCUSSION

Weather conditions of the observation period

According to Kursk meteorological station (Fig. 1), the average annual air temperature was above the climatic norm (7.1 ± 0.9°): 7.6° in 2017, 7.5° in 2018, 8.7° in 2019 and 8.9° in 2020. Moreover, the last two years were the warmest on record, in line with the global trend (Leskinen et al., 2020). At the same time, the amount of precipitation fluctuated within the norm: from 455 mm in 2020 to 655 mm in 2017, with a norm of 637 ± 103 mm. Based on Selyaninov's hydro-termal coefficients, wetting during active growing seasons was sufficient: 1.00 in 2017, 0.99 in 2018 and 1.03 in 2020, (except 2019: 0.80), with a norm value of 1.1 ± 0.4, which corresponds to the northern boundary of the steppe zone.

Estimates of annual CO_2 soil efflux from arable Chernozems

The results of different methods of estimating annual CO_2 efflux from arable Chernozems are presented in Table 2. The average value of emission from field estimates under different crops for three years was 6742 ± 482 kg C ha^{-1} yr^{-1} (n = 12). This exceeds (p = 0.041) the estimates for agrocenoses on typical and leached Chernozems made in 1961 – 1984 in the same area (5652 ± 642 (n = 14), calculated from Kudeyarov and Kurganova (2005)), which could be attributed to the climate warming. However,

Table 1. Set of permanent and sporadic variables (factors) used in the analysis of their influence on CO_2 emission from arable Chernozems of Kursk region, according to three simulation models

Type of variable	Model Variables	DNDC	RothC	T&P
Permanent	Soil organic carbon storage	+	+	-
	Temperature	-	+	+
	Precipitation		-	+
	Atmospheric concentration of CO_2	+	-	-
Sporadic	Change of crops between years	+	+	-
	Heavy rainfall events	+	-	-
	Agrotechnical practices (ploughing etc.)	+	-	-

«+» in the table denotes the presence of the variable in the model experiments, «-» its absence

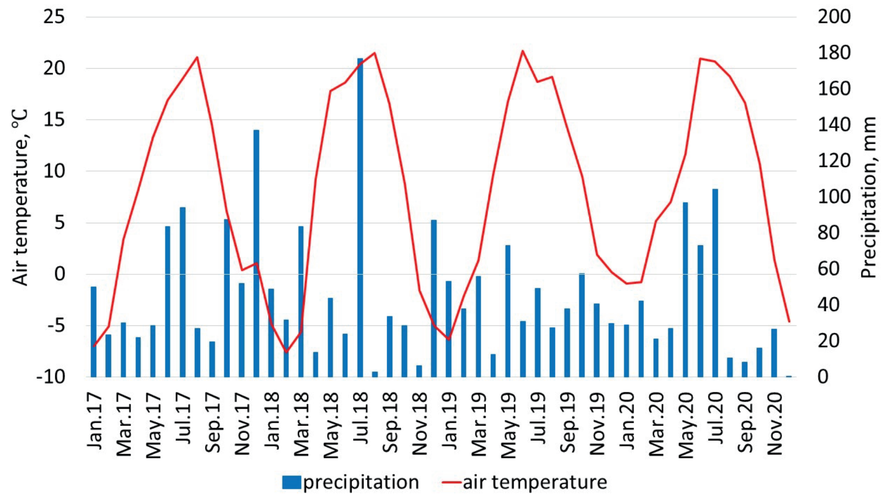

Fig. 1. Meteorological conditions of the period of the study (2017–2020, Kursk region)

it should be noted that the 1961 – 1984 estimates were made by alkaline CO_2 absorption method, whereas now infrared gas analyzers are used for this purpose. In addition, crop and variety sets are somewhat different in the cases compared, which also makes a correct comparison difficult.

The mean estimates obtained from the models do not differ significantly from the field (DNDC: 5929 ± 392 kg C $ha^{-1} yr^{-1}$ (Mann-Whitney, $p = 0.27$); RothC: 5444 ± 111 ($p = 0.08$)) and from each other ($p = 0.1$), although RothC tends to be underestimated. The variation in the obtained estimates of annual emissions is small (CV = 22%) and depends more on crop type (CV = 9.3%) than on year (CV = 3.2%), which is partly due to the short series of observations.

The highest values of soil respiration by mixed estimates for all years and by all methods were obtained for winter wheat (6522 ± 424 kg C $ha^{-1} yr^{-1}$), the lowest for potato (5902 ± 463), but all differences are insignificant ($p > 0.05$).

The results of the verification of the DNDC and RothC models on field data are shown in Table 3.

The RothC model performed better: it was verified in

Table 2. Estimates of annual soil CO_2 emission (kg C $ha^{-1} yr^{-1}$) from arable Chernozems in Kursk region obtained by different methods

Method	Year / Crops	Winter wheat	Sunflower	Soybean	Barley	Maize	Potato	Bare soil
Trapezoidal on field data	2017	7835	6915	-	6327	-	7044	-
	2018	7847	-	10 725	-	4827	4627	-
	2020	-	5856	4981 6940**	6985	-	-	4196
	Average	7841	6386	7549	6656	4827	5534	4196
DNDC*	2017	5860	6645	-	6695	-	7368	-
	2018	6050	-	3919	-	4063	6114	-
	2020	-	6835	4200	7469	-	-	1956
	Average	5955	6740	4060	7082	4063	6741	1956
RothC	2017	5539	4920	-	5250	-	4905	-
	2018	5999	-	5366	-	5994	5356	-
	2019	-	5433	5448	-	-	5431	--
	2020	-	5411	5375	5772	-	-	4912
	Average	5769	5255	5396	5511	5994	5231	4912
T&P	2017	-	-	-	-	-	-	3870
	2018	-	-	-	-	-	-	3344
	2019	-	-	-	-	-	-	3852
	2020	-	-	-	-	-	-	3429
	Average	-	-	-	-	-	-	3624

* 2019 was excluded from the DNDC simulation due to insufficient data

** for two different fields

Table 3. Verification of models based on field observations of CO_2 emissions from arable Chernozems in Kursk region

Crops		Winter wheat		Sunflower		Soybean		Barley		Potato		Maize
Coefficients of effectiveness and their critical values*	Model	DNDC										
	Year	2017	2018	2017	2020	2018	2020**	2017	2020	2017	2018	2018
Nash-Sutcliffe coefficient (NS > 0)		0.23	0.01	0.26	-1.02	-1.43	-0.20 0.02	0.02	0.38	-0.02	-0.77	0.60
Theil coefficient (T < 0.3)		0.27	0.29	0.26	0.35	0.53	0.36 0.39	0.20	0.23	0.26	0.26	0.16
One-way ANOVA ($F_{comp} < F_{crit}$, $p > 0.05$)	F_{comp}	0.59	2.07	1.41	0.70	18.34	1.21 3.15	0.98	0.06	1.02	5.12	0.0001
	F_{crit}	4.15	4.17	4.17	4.15	4.17	4.15 4.17	4.15	4.15	4.17	4.17	4.17
	p	0.45	0.16	0.25	0.41	< 0.01	0.28 0.09	0.33	0.81	0.32	0.03	0.99
Model		RothC										
Nash-Sutcliffe coefficient (NS > 0)		0.07		0.19		0.06		-0.03		0.32		0.30
Theil coefficient (T < 0.3)		0.25		0.24		0.29		0.27		0.19		0.20
One-way ANOVA ($F_{comp} < F_{crit}$, $p > 0.05$)	F_{comp}	1.74		3.28		3.61		1.66		0.57		0.01
	F_{crit}	4.20		4.10		4.11		4.17		4.13		4.97
	p	0.20		0.08		0.06		0.21		0.46		0.92

* The values when the modelling is effective and modelled soil CO_2 emissions is equal to measured one
The cases for which the correspondence between measured and modelled values has not been confirmed are highlighted in grey
** For two different fields as numerator and denominator

at least two of the three criteria in 100% of cases, while DNDC in only 75% of cases. However, the mean values for each of the three criteria for RothC and DNDC did not differ significantly ($p > 0.21$). Nevertheless, DNDC is slightly better for estimating the mean annual respiration as well as soil respiration of cereal crops. Of the crops considered, the best, in terms of model reproducibility, was shown for maize, while the most unsatisfactory result is shown for soybean.

A comparison of calculations of annual emissions on cropland under crops (DNDC; RothC; interpolation from field data) and under bare soil (T&P; interpolation from field data) further estimates the proportion of microbial soil respiration in arable Chernozems as 66.7%, which is the same as independently estimated (66%; Kudeyarov et al. 2007).

Permanent controls of CO_2 emission from arable Chernozems

When calculating the main C fluxes, the widely used simulation models DNDC and RothC use in their structure mostly permanent-acting factors, which can be spatial (e.g., soil type) or temporal (e.g., air temperature), as well. In order to assess the relative impact of the factors tested (Table 1) on annual CO_2 emissions from soil, we introduced a standard perturbation of the factor value per year (±10%) compared to the baseline value. The perturbation chosen corresponds to the observed average inter-annual variation in temperature and precipitation, and in case of soil organic carbon (SOC) it matches its spatial variability in Chernozems.

The results of estimating the impact of both permanent and sporadic impacts (Tables 4 – 6) are partly determined by specificity of mathematical apparatus of the models: type of functions, the presence of increasing or decreasing coefficients, variables considered, time step, and different sets of equations used. While DNDC has more than 120 equations (Zhang et al. 2002), the T&P model has only one, using two variables and hence unable to estimate the contribution of sporadic controls.

Influence of functional description of the processes on the model outputs is illustrated by an example, in particular, SOC content, which largely determines spatial variance of CO_2 emission (Table 4). Thus, in the DNDC model the dependence of CO_2 emission on SOC stock is parabolic, which is conditioned by introduction of reduction coefficient (μCN) characterizing the carbon to nitrogen ratio in the formula for mineralization of organic matter. This objectively reflects that when SOC stocks increase, nitrogen content becomes limiting for soil respiration and it decreases. Thus, for example, for every 10% increase in SOC stocks, annual soil respiration decreases from 16-18% for potatoes to 33-34% for sunflowers. But for initially low SOC stocks, the respiration rate is also low, and for every 10% decrease in the initial pool, the emission rate drops with the same intensity: from 17–18% in potatoes to 35% in sunflowers. In contrast, in the RothC model, the relationship is direct and linear. With 10% change in SOC stock, annual soil respiration changes by 8.1–9.2%.

Air temperature, soil temperature and moisture are the most important permanent controls governing the formation and emission of CO_2 from the soil surface (Kudeyarov et al. 2007). In our study, only the effects of air temperature and precipitation evaluated, which is related to the original meteorological data (Table 4).

In the models considered, the response of CO_2 emission to changes in temperature and soil moisture represented as simple empirical non-linear functions (Davidson et al. 2006). In RothC,

Table 4. Simulation model experiments with influence of 10% perturbations of permanent variables on annual CO_2 emission from arable Chernozems, %

Variables	Model	Variable	Crop Year	Winter wheat	Sunflo-wer	Soy-bean	Barley	Maize	Potato
Soil Organic Carbon (SOC)	DNDC	Decrease of SOC stocks by 10%	2017	-23.6	-35.2	-	-25.6	-	-18.2
			2018	-30.5	-	-26.4	-	-23.8	-16.9
			2020	-	-35.3	-28.6	-27.4	-	-
		Increase of SOC stocks by 10%	2017	-17.0	-33.6	-	-22.5	-	-17.5
			2018	-28.4	-	-25.5	-	-22.9	-16.4
			2020	-	-33.4	-27.4	-24.5	-	-
	RothC	Increase of SOC stocks by 10%	2017	+8.1	+8.7	-	+8.5	-	+9.1
			2018	+8.2	-	+9.2	-	+8.2	+9.2
			2019	-	+8.8	+9.2	-	-	+9.2
			2020	-	+8.8	+9.1	+8.6	-	-
Meteorological factors		Increase of annual air temperature by 10%	2017	+9.7	+10.2	-	+9.9	-	+10.7
			2018	+10.2	-	+11.1	-	+10.5	+11.2
			2019	-	+10.4	+10.8	-	-	+10.8
			2020	-	+10.3	+10.6	+10.0	-	-
	T&P	Increase of annual air temperature by 10%	2017	+6.8					
			2018	+8.2					
			2019	+7.3					
			2020	+7.9					
		Increase of annual precipitation by 10%	2017	+4.3					
			2018	+4.3					
			2019	+4.8					
			2020	+4.5					

Note. The deviations in %% of the annual CO_2 emission rate from its initial values in the same year taken as 100% are given. The color density of the cells is proportional to the absolute values of the deviations; the sign indicates the direction of the deviation. Positive values are green, negative – brown. Dash means no specific crop in a given year.

these variables are accounted indirectly through the temperature and moisture coefficients. While the former directly contains the variable of interest, air temperature, the latter, in addition to precipitation, includes evapotranspiration and soil moisture capacity. According to calculations based on this model, annual soil respiration changes by 9.7–11.2% for every 10% change in temperature. Note that for conditions of sufficient moistening the moisture coefficient should be excluded from the formula, otherwise it contributes to underestimation of the summer CO_2 emission, which does not correspond to the observed dynamics.

In T&P model, the general equation for both variables is direct, i.e., soil respiration increases with rise of air temperature or precipitation, or declines if the controls are decreasing. The equivalent change in CO_2 emission is 6.8–8.2% for every 10% change in temperature and 4.3–4.5% for every 10% change in precipitation. The greater response of soil respiration to changes in temperature compared to precipitation reflects the predominant influence of the former on the rate of decomposition of soil organic matter (Reichstein et al. 2005).

The stimulating effect of contemporary increase in CO_2 concentration on global photosynthesis has been widely stated (Idso and Idso 2000; Ghannoum et al. 2000; Boretti and Florentine 2019). DNDC model not only taking this into account, but also estimates its impact on other carbon fluxes, including soil respiration. For example, at the current rate of increase in atmospheric CO_2 concentration of 3 ppm per year, according to this model, soil respiration would increase under winter wheat by 1.0%, under sunflowers by 0.5%, under potatoes by 0.4% and under barley by 0.2%.

Sporadic controls of CO_2 emission from arable Chernozems

Because the DNDC has a daily time step and contains large variety of input variables, this allows the assessment of the effects on soil respiration of sporadic factors such as crop and fallow rotation, heavy rainfall events, and agronomic practices separately.

DNDC analysis shows that amongst all basic agro-technical operations (ploughing, cultivation, sowing and fertilizing, pesticide treatment, etc.) it is harvesting that has the greatest impact on soil CO_2 emissions, due to a rapid removal of phytomass and the death of roots, which are responsible for almost one third of soil respiration. The day after harvest, it can decrease (winter wheat by -35 (2018) to 50% (2017); barley by -43% (2017); maize by

-33% (2018); potatoes by -11% (2020)), or increase (sunflowers by +13 (2017) to 96% (2020); potatoes by +34 (2018) to 51% (2017); soybeans by +23 (2018) to 45% (2020); barley by +67% (2020)) soil respiration, as well. However, the contribution of harvesting does not exceed tenths or hundredths of a percent of annual CO_2 emissions. Even if the effects of all agricultural practices summed over the year, it would not exceed 1% of annual carbon dioxide efflux. Crops can be divided into two groups based on their contribution to annual CO_2 soil emission: cereals (winter wheat and barley), where harvesting adds 0.10–0.30% to annual soil respiration, and broad-seeded crops (potato, maize, sunflower, soybean), where harvesting adds only 0.02-0.09% to annual soil respiration.

Among sporadic atmospheric controls, heavy rainfall has the greatest short-term effect on CO_2 emissions (Table 5). On the day of its fallout, compared with the previous day, the flux of CO_2 from the soil increases sharply, and the respiration rate can rise 2.5 times for winter wheat and barley crops, almost 3-fold for soybeans and more than 5-fold for sunflowers. This is due to the coefficient (μw) introduced into DNDC, according to which the rate of mineralization of SOC increases in proportion to the square of the soil moisture content. However, in the model the rate of respiration is not only proportional to the amount of rainfall but also depends on the length of the preceding period without rainfall (this partly accounts for the Birch effect) and the phenological phase. Nevertheless, the contribution of this sporadic factor to annual CO_2 emissions is rather small, amounting to only 0.7–0.8% for cereals (winter wheat, barley) and 1.0–2.0% for crops with wide spacing between rows (sunflower, potato, soybean and maize).

However, crop rotation is found to be the most important sporadic factor affecting annual soil respiration (Table 6). If we take as a reference value for comparison the rate of soil respiration from bare soil in 2020, DNDC under the different crops predicts 3.0-3.8 fold increase of emissions, whereas the surplus predicted by RothC is much smaller and is in the range +0-22%. Thus, the DNDC and RothC results for the five studied crops do not always coincide in terms of magnitude of change.

Table 5. Enhancement of CO_2 emission from arable Chernozems after heavy rainfalls (by DNDC modeling), %

Year	Number of Julian day	Amount of heavy rainfall per day, mm	Winter wheat	Sunflower	Soy-bean	Barley	Maize	Potato
2017	160	34.7	+37.8	+21.1	-	+37.8	-	+53.3
	183	27.9	+25.2	+190.5	-	+29.3	-	+32.6
	352	34.9	+160.1	+40.9	-	+148.5	-	+63.5
	Increase of annual CO_2 emission due to heavy rain events, %		+0.8	+1.0	-	+0.8	-	+1.4
2018	141	31.1	+54.8	-	+136.3	-	+115.4	+42.6
	182	24.1	+18.6	-	+26.6	-	+36.4	+37.6
	188	37.0	+54.5	-	+104.4	-	+115.1	+75.5
	197	23.4	+9.4	-	+15.3	-	+33.9	+22.1
	Increase of annual CO_2 emission due to heavy rain events, %		+0.8	-	+1.6	-	+1.8	+1.1
2020	151	18.3	-	+288.6	+52.2	+37.4	-	-
	181	22.3	-	+53.1	+24.2	+7.8	-	-
	196	57.6	-	+444.5	+388.2	+95.6	-	-
	Increase of annual CO_2 emission due to heavy rain events, %		-	+1.5	+2.0	+0.7	-	-

Note. Soil respiration increase is given in relation to the previous day taken as 100%. The color density of cells is proportional to the absolute values of the deviations; positive sign denotes increase of CO_2 emission. Dash means no specific crop in a given year. The increase of annual emissions due to sum of heavy rainfall events for a given crop in a given year are highlighted in grey.

Table 6. Effect of crop rotation on annual CO_2 emissions from arable Chernozems by two simulation models, %

Year	Model	Winter wheat	Sunflower	Soybean	Barley	Maize	Potato
2017	DNDC	+199.6	+239.7	-	+242.3	-	+276.7
	RothC	+12.8	+0.2	-	+6.9	-	0.0
2018	DNDC	+209.3	-	+100.4	-	+107.7	+212.6
	RothC	+22.1	-	+9.2	-	+22.0	+9.0
2019	RothC	-	+10.6	+10.9	-	-	+10.6
2020	DNDC	-	+249.4	+114.7	+281.9	-	-
	RothC	-	+10.2	+9.4	+17.5	-	-

Note. Soil respiration increase is given in relation to the bare soil respiration rate in 2020, taken as 100%. The color density of cells is proportional to the absolute values of the deviations; positive sign denotes increase of CO_2 emission. Dash means no specific crop in a given year.

In general, we can conclude that annual crop and fallow rotation may be more significant factor for carbon dioxide emissions from arable Chernozems (mean increment: 95.4 ± 21.3 %, n = 25) than the effect of changes in permanent meteorological variables (8.8 ± 0.3 %, n = 36), because the latter change much more slowly. This follows from the fact that the annual increment for the permanent factors (10%) established for computer experiments is close to the observed average variation between consecutive years (for temperature: 6.7%, for precipitation amount: 10.9%).

Assessment of the relative inputs of drivers of CO_2 efflux from Chernozems under different land use

Finally, a non-parametric stepwise multiple regression analysis on similarity matrices (Distance based linear modeling) was performed on available field data on soil CO_2 emissions. The statistical method well applied to the models that contain qualitative and quantitative independent variables, as well, allowing the assessment of their relative contribution. Besides it is well suited for model design with a large number of variables, and is therefore a more powerful tool compared to quantitative or categorical parametric regression analyses (Anderson et al. 2008). The dependent variable was the field values of soil CO_2 emission over the years of observation for all sites (biotopes). All independent variables (18) used in the analysis and their characteristics are given in Table 7.

Among them, in different combinations: 12 permanently acting, and 6 sporadic; 7 spatial and 11 temporal; 6 qualitative and 12 quantitative variables. The sporadic variable, TIMERAIN, reflects the «Birch effect» on CO_2 emission, WIND - the pressure pumping effect.

The results of the analysis are summarized in Table 8.

The optimal model derived from the stepwise analysis of all variables explains 40.6% of CO_2 emission variance, with temporal (hydrothermal) variables accounting for only 35% of the explained variance, and biotope characteristics (spatial) for 65%; qualitative variables for 55.5% and quantitative for 44.5%. Input of the sporadic factors (TIMERAIN, PRECDAY) to the variance explained by this model is rather small (10.3%). Thus, spatial, qualitative

Table 7. Set of factors (independent variables) used for non-parametric regression analysis of CO_2 emissions from Chernozems of Kursk region

ID of the independent variable in the analysis and in the text	Full description of the variable and measuring units	Variable characteristic (a)	Variable characteristic (b)	Variable characteristic (c)
1. SITE	Site number (1-12)	qualitative	permanent	spatial
2. LANDUSE	Type of land use: 1 – plow land, 2 - fallow (self-restoration stages), 3 - climax community, 4 - ecotone	qualitative	permanent	spatial
3. CULTURE	Type of crops: 0 – bare soil, 1 – winter wheat, 2 – maize, 3 – potato, 4 – soybean, 5 – buckwheat, 6 – barley, 7 – sunflower, 8 – beetle, 9 –lupine, 10 – spring wheat, 11 - garlic	qualitative	sporadic	spatial
4. FERTIL	Regular application of fertilizers: 1 – yes. 0 - no	qualitative	sporadic	spatial
5. HOUR	Time of SR measurement (hour of the day, 1-24)	categorial	permanent	temporal
6. MONTH	Number of months in a year (1-12)	categorial	permanent	temporal
7. YEAR	Number of year A.D.	quantitative	permanent	temporal
8. SM	Volumetric soil moisture (%)	quantitative	permanent	temporal
9. TA	Air temperature (°C)	quantitative	permanent	temporal
10. T5	Soil temperature at 5 cm (°C)	quantitative	permanent	temporal
11. T10	Soil temperature at 10 cm (°C)	quantitative	permanent	temporal
12. FITO1	Total live phytomass storage at the moment of SR measurement, t ha^{-1} a.d.m	quantitative	permanent	spatial
13. FITO	Average annual total live phytomass, t ha^{-1} yr^{-1} a.d.m	quantitative	permanent	spatial
14. PROD	Total primary production (t ha^{-1} yr^{-1} a.d.m.)	quantitative	permanent	spatial
15. TIMERAIN	Time to previous rainfall (hours) more than 0.6 mm in 1 h.	quantitative	sporadic	temporal
16. PRECDAY	Sum of precipitation over the previous 10 days before SR measurement (mm)	quantitative	sporadic	temporal
17.RAD	Average solar radiation (w/m^2) per 1 hr of SR measurements	quantitative	sporadic	temporal
18. WIND	Average wind speed per 1 hr over SR measurements (m/s)	quantitative	sporadic	temporal

and constant factors are predominate. Wind speed and soil moisture not found to be significant. The most influential variable in terms of individual contribution is SITE (20.9%), but its disadvantage is that it is too generalized. After excluding the SITE variable from the analysis, the share of variance it explained taken over by yearly rotation of crops (CULTURE) and by land use type (LANDUSE), largely responsible for spatial differences in CO_2 emission between individual biotopes (Table 8). In this case significant sporadic factors (CULTURE, TIMERAIN, PRECDAY) explain 20.5% of the total soil CO_2 emission variance, or 54% of the explained variance. In fact, this statistical analysis reveals that soil CO_2 emission from Chernozem agrolandscape is poorly predictable by weather-related hydrothermal variables (the best among them, T5, explains only 12.2% of variance). It is much more important to know the type of crop, or type of land use. Note that in this case we are using the observation scale «hour-day». In the simulation models described above, a daily and monthly step applied, which tends to increase the influence of weather factors (Karelin et al. 2019).

In this model, hydrothermal controls take 39.3% of the explained variance and biotope characteristics (spatial) take 60.7%. Qualitative variables take 51.3% and quantitative variables - 48.7%. Thus, in both variants of the models spatial factors sharply prevail, which does not allow to apply a single regression model for quantitative forecast.

CONCLUSIONS

Simulation models of different structure and variables sets (DNDC, RothC, T&P) were successfully parameterized and verified using field measurements of CO_2 efflux from arable Haplic Chernozems and Luvic Chernozems in 2017–2020, which corresponds to the period of the most intense contemporary warming. Computer experiments based on DNDC and RothC allow estimating the influence of not only permanent (air temperature, annual precipitation, SOC, atmospheric CO_2 concentration), but also a number of sporadic controls (events of heavy rainfalls, agronomic practices (harvesting), crop rotation) on carbon dioxide emission from soil.

While temperature and precipitation growth increase annual soil CO_2 emissions unambiguously (by 6.8–11.2% for a 10% temperature increment; and by 4.3–4.8% for a 10% precipitation increment), the response of annual soil CO_2 efflux to changes in organic carbon stocks, though more pronounced depends on the mathematical structure of the models: DNDC shows a reduction (-13.8...-36.4% / 10%), while RothC shows an increase (+8.1...+9.2% / 10%). In comparison with this, the influence of the annual increase of CO_2 concentration in the atmosphere on the annual gain of soil emission is very small and amounts to tenths of a percent.

Table 8. Non-parametric regression analysis on similarity matrices applied to data on CO_2 emissions from Chernozems: general model with stepwise inclusion of variables

Independent variables included in the model	Adj. R^2	P	Prop.	Cumul.	res.df	regr.df
T5	0.12	< 0.01	**12.22**	12.22	284	2
SITE	0.29	< 0.01	**20.85**	33.06	268	18
TIMERAIN	0.32	< 0.01	**3.53**	36.59	267	19
FITO1	0.34	0.01	**1.67**	38.26	266	20
TA	0.34	0.10	0.68	38.93	265	21
SM	0.35	0.13	0.55	39.48	264	22
PRECDAY	0.35	0.08	0.68	40.16	263	23
T10	0.35	0.20	0.39	40.55	262	24
After exclusion of the variable SITE:						
T5	0.12	< 0.01	**12.22**	12.22	284	2
CULTURE	0.25	< 0.01	**16.11**	28.33	273	13
TIMERAIN	0.29	< 0.01	**3.61**	31.94	272	14
LANDUSE	0.33	< 0.01	**3.27**	35.21	270	16
T10	0.32	0.11	0.65	35.86	269	17
SM	0.32	0.08	0.66	36.52	268	18
PRECDAY	0.33	0.09	0.67	37.12	267	19
TA	0.33	0.11	0.64	37.83	266	20

Note. Field data for all habitats from 2017–2020 are used. Adj R^2 – partial coefficients of determination of variables, p - significance level of contribution of the variable, Prop. – % of variance explained by the variable, Cumul. – % of the explained variance accumulated by the model, res.df – residual number of degrees of freedom, regr.df – number of degrees of freedom of the regression. Bold font denotes variables significant at p = 0.05. The variables described in table 7.

Among sporadic factors, crop rotation has the most significant effect on CO_2 emissions from arable Chernozems as measured by the potential increase in CO_2 flux between minimum (bare soil) and maximum annual emissions of 22.1% (RothC; winter wheat), 155% (trapezoidal method on field data; soybean), and 281.9% (DNDC; barley). In general, annual crop and fallow rotation is more valuable for CO_2 emissions from soil than the influence of interannual changes of weather and climate, and is much more significant than the other impulse drivers considered (agronomic practices, events of heavy rainfall), whose total contribution does not exceed 1-2% per year.

As shown by statistical analysis for all zonal biotopes, CO_2 emission from forest-steppe Chernozems poorly predicted by commonly used hydrothermal controls (soil temperature and moisture, or air temperature and precipitation amount). In this case, the nature of its long-term use (arable land, fallow, mown meadows, steppe, broad-leaved forest, their ecotones), or the type of crop or fallow used in a given year, if arable, are much more important for predicting the magnitude of carbon dioxide emission from the surface of a given area. However, the use of such indicators does not allow the construction of regression models with quantitative prediction, so the simulation models discussed above are recommended for this purpose. Among them, RothC is the most versatile and suitable for the whole set of crops considered, including bare soil plots; while DNDC is better suited for cereals but underestimates CO_2 emission from fallow areas, and T&R is only suitable for bare soil areas.

Nevertheless, the problem of predicting soil CO_2 efflux and net carbon balance in forested or steppe areas of Chernozem landscapes remains unsolved.

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