Soil carbon emissions in a temperate mixed forest (Tatarstan, Russia) revisited

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Abstract. The article presents the results of a study of soil carbon dioxide emissions in a mixed forest within the framework of the Carbon-Povolzhie project (Republic of Tatarstan, Russia), aimed at assessing the carbon budget of the ecosystems of the Middle Volga region (Russia). The work continues the study of soil respiration, which began in 2022. Fifteen measurements were taken from April to November 2023 in five replicates. The average monthly carbon emission during the growing season and pre-winter period was 0.15 g C h/m^2. The largest emissions were observed at the warmest month – July. The main driver of soil respiration during daylight hours is topsoil temperature. The contribution of soil moisture to carbon emissions is nonlinear and can be considered minor compared to ambient temperature. 20% soil moisture increases soil CO_2 emission.

1 Introduction

Soils play a crucial role in carbon cycling within ecosystems. They serve as significant carbon reservoirs and a source of CO_2 emissions through microbial activity and decomposition processes [1-2]. Understanding these functions is essential for managing ecosystems and mitigating climate change [3-4].

Soil respiration is intensively studied. There are works covering the entire globe [5-6], forest ecosystems [7-9] and arable lands [10-12]. For the territory of Russia, substantial number of studies can be distinguished for the taiga zone of the European part [13-17]. Studies of soil emissions in the broad-leaved forest zone of the European part of Russia are rare. There are practically no data on soil respiration in the literature for the territory of the Middle Volga region, for example, for the territory of the Republic of Tatarstan. Broadleaved forests produce significantly higher soil CO_2 emissions than coniferous forests, because of greater net primary productivity and distinct microbial communities that thrive in the warmer, more humid conditions [18-19], so mixed forest soils exhibit intermediate characteristics.

The studies [7-9, 20] demonstrated that the temperature of the surface air layer and the topsoil temperature are good predictors of soil carbon dioxide emission, whereas soil moisture can both enhance and block soil respiration [8, 17, 21].

This work continues of soil carbon emissions research, which began in temperate mixed forest on the territory of the “Carbon-Povolzhye” site in 2022 [20]. In 2022, habitat

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measurements included only air and soil temperature, while the 2023 data presented in the current report include added soil moisture measurements.

2 Materials and methods

The Carbon-Povolzhie project aims to assess the carbon budget of the ecosystems of the Middle Volga region (Russia). Studying carbon dioxide emissions is one of the tasks within the framework of this project. The current study presents results obtained in 2023 about soil respiration of mixed forest. A detailed description of the study site and the methodology for measuring emissions is presented in the previous article [20].

3 Results

The seasonal dynamics of the intensity of soil CO_2 emission from April to November of 2023 was measured (Figure 1). The average monthly carbon emission during the study period was 0.14±0.01 g C $h^{-1}m^{-2}$. The summer months demonstrated the largest volumes of carbon emitted with an average monthly CO_2 flux around 0.16–0.18 g C $h^{-1}m^{-2}$ (Table 2). The emission increased till the beginning of August; median emission detected on 2nd August was 0.24 g C $h^{-1}m^{-2}$. The lowest average monthly emissions were observed in the coldest months of the study period: in April and November, 0.06 and 0.08 g C $h^{-1}m^{-2}$ respectively (Table 2) (Figures 1-2).

Table 1. Calculated statistics on carbon emissions and environmental variables in 2023.

Month	C_{mean}	C_{95lo}	C_{95hi}	$T_{airmean}$	$T_{soil1mean}$	$T_{soil5mean}$	$H_{soil5mean}$
April	0.06	0.04	0.08	13.2	6.3	4.7	13.2
May	0.14	0.11	0.16	19.8	13.7	12.2	19.8
June	0.17	0.12	0.21	20.3	14.7	14.3	20.3
July	0.18	0.15	0.22	25.2	19.3	16.8	25.2
August	0.16	0.12	0.21	17.3	15.2	14.8	17.3
September	0.13	0.10	0.17	20.1	15.0	13.0	20.1

The seasonal change in emissions generally follows the seasonal course of air and soil temperatures, whereas the relationship with soil moisture is not obvious. At the same time, the peak of emission on August 2 coincides with the local maximum of soil moisture (Figure 2).

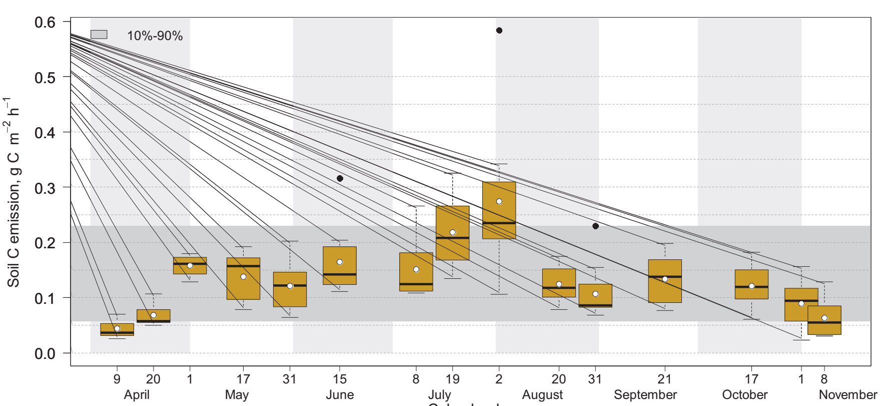

Fig. 1. Seasonal dynamics of carbon flux from April to November 2023.

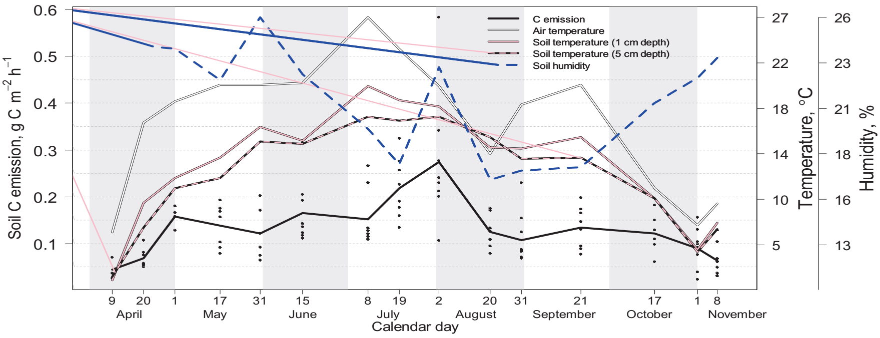

Fig. 2. Seasonal dynamics of carbon emission and environmental variables in 2023.

Suggesting the same rate of CO_2 flux during the day (very rough suggestion), then the daily emission can be proposed as 33.6 kg C ha^{-1} day^{-1} for the growing season and pre-winter period (April-November).

Robust simple linear regressions were chosen to assess the link between carbon emission and environment temperature variables, because the positive relationship is complicated by several outliers (Figure 3 A–C). The coefficient of models fitted are presented in the Table 3.

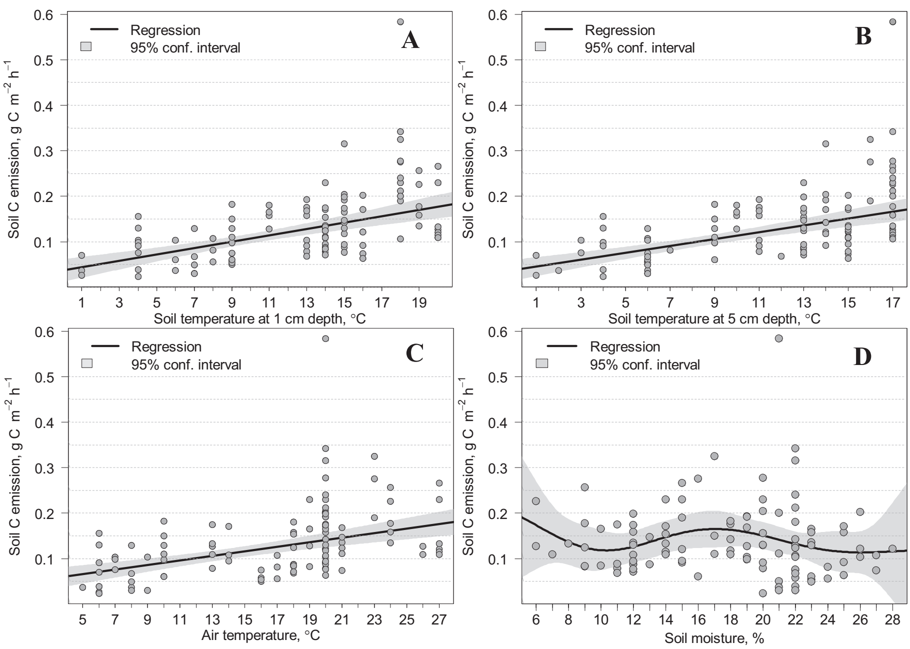

Fig. 3. Carbon emission as a function of (A) surface air temperature; (B) soil temperatures at a depth of 1 cm; (C) soil temperatures at a depth of 5 cm; (D) soil moisture at a depth of 5 cm.

Table 2. Coefficients of robust simple linear regressions fitted to predict soil C emission (g C h^{-1}m^{-2}) by air and soil temperature.

Predictor term	Intercept	Slope	P-value	R-squared
Air temperature, °C	0.046	0.005	<0.001	0.22
Soil temperature at a depth of 1 cm, °C	0.037	0.007	<0.001	0.29
Soil temperature at a depth of 5 cm, °C	0.038	0.007	<0.001	0.30

The impact of soil moisture to carbon emission looks nonlinear, so a linear additive model was chosen to assess the relationship between carbon emission and soil moisture (Figure 3D). The generalized additive model fitted non-significant smooth link (p-value > 0.1, Figure 3D) with moisture 15-20% maximizing soil carbon flux, but the deviance explained by model is low (4.4%).

The next carbon emission model attempted included two significant terms (Figure 4): nonlinear link for soil moisture (p-value < 0.05) and linear relationship for soil temperature measured at 5 cm depth (p-values < 0.001). This model has 34% of the deviance explained. The model shows that the soil temperature is the primary control on carbon emission, but 20% soil moisture increases carbon emission for the same soil temperature (Figure 4).

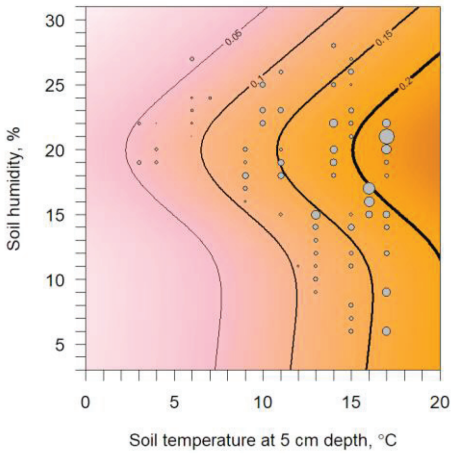

Fig. 4. Expected soil carbon emissions (g C $h^{-1}m^{-2}$) predicted by the generalized additive model. Expectations are shown by labelled contours. Grey filled points shows average measured soil C emission.

4 Discussion

Comparing the 2023 measurement results with the published data for 2022 [20] is not straight, since the observation periods differ, and the soil moisture is unknown in 2022. In 2023, the observation period was longer: from April to November in 2023, versus from May to September in 2022. However, similar patterns can be highlighted for both years: the highest habitat temperature and the highest carbon dioxide emissions were recorded in July. At the same time, 2023 had lower average carbon dioxide emissions compared to 2022.

Comparing the average soil carbon dioxide emission in 2023 (0.13 g C $h^{-1}m^{-2}$) with other published data, its level is closest to the 2014–2015 emission of the southern taiga spruce forest on soddy-podzolic soils (0.15 g C $h^{-1}m^{-2}$) [13], while exceeding the emission in the pine forest in the middle taiga [15] and the emission in the mature bilberry–sphagnum pine forest [14].

A longer series of observations in 2023 compared to 2022 showed that the surface air temperature is a more reactive characteristic of the environment, which is noisier and less closely related to soil carbon dioxide emissions. Thus, in 2023, the best predictors of emissions were soil temperatures at a depth of 1 and 5 cm. In this case, soil temperature is probably the main driver of soil emissions, while soil moisture may enhance or weaken emission to some extent. The percentage of explained variance of the regression model for predicting emissions from soil temperature and soil moisture data is only 4% higher than the model that does not include moisture.

Soil moisture in the period from April to November 2023 fluctuated between 7 and 25%. Based on these data, it was found that the relationship of soil emission with moisture is likely nonlinear: 20% moisture maximizes CO_2 emission, while moisture deficit and excess block microbial activity, as was shown by [14, 19]. In the current study, measurements were not followed precipitation, but it can be assumed that since moisture above 20% is associated with lower emission, precipitation is likely to block it, because soil moisture after rainfall will be at its highest, as demonstrated by [21].

5 Conclusion

The paper presents the results of measuring daylight carbon emissions from soddy-podzolic soil in the form of carbon dioxide in a mixed linden forest for the period from April to November 2023. The average emission for this period was 0.13 g C $h^{-1}m^{-2}$, reaching 0.18 g C $h^{-1}m^{-2}$ in the warmest month – July.

The main driver of soil respiration during daylight hours is topsoil temperature. The contribution of soil moisture to carbon emissions is nonlinear and can be considered minor compared to ambient temperature. At the same time, future studies can test the hypothesis that excess soil moisture reached after rains can completely stop emissions for some time.

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