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DYNAMICS AND DRIVERS OF CARBON DIOXIDE EMISSIONS IN TWO TYPES OF WETLAND SOILS

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Abstract

Wetlands sequester substantial carbon due to their unique biogeochemical soil properties, yet they can emit significant carbon dioxide (CO_2), especially in the context of climate change. This study examined the complexity of CO_2 emissions from two distinct soil types in a natural wetland area formed along the Dambovita River. The results revealed significant positive correlations between CO_2 emissions and both soil temperature ($r=0.813$; $p<0.01$) and air temperature ($r=0.793$; $p<0.01$) at the SC location, while emissions peaked at 0.7282 $g\ m^{-2}\ h^{-1}$ in SP following flooding, demonstrating distinct emission patterns driven by environmental factors. Extrapolation of CO_2 emissions highlighted the importance of accounting for environmental uncertainties. Therefore, adjusting the monthly mean values yielded a more precise depiction of emissions by including day/night variations. Regression models predicting future CO_2 emissions based on meteorological and physical parameters showed that multiple predictor models explained more variance in CO_2 emissions. The investigation of these interactions improves predictions of CO_2 fluxes from wetlands and their impacts on climate change, contributing with a higher level of confidence to the GHG emissions inventory.

Keywords: *Greenhouse gas; Soil respiration; Chambers; Climate change; Temperature; Soil moisture*

Introduction

Climate change is a global problem, with increasingly severe implications for the environment. A critical component of this issue is the role of wetland ecosystems and their soils in the carbon cycle, as these unique environments can act both as sources and sinks of greenhouse gases, significantly influencing atmospheric carbon dioxide (CO_2) concentration [1, 2]. Wetlands are renowned for their remarkable ability to sequester and store significant amounts of carbon, a process mediated by the unique biogeochemical characteristics of their soils [3, 4]. However, the same soils can also serve as a significant source of CO_2 emissions, particularly in response to the negative effects of climate change [5]. As global temperatures rise, the delicate balance of wetland ecosystems is disrupted, which can lead to accelerated rates

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of decomposition, altered vegetation growth patterns and changes in microbial community dynamics. These are triggers that can contribute to increased CO_2 emissions from wetland soils [6, 7]. Given this complexity, this study aims to analyse the complex interaction between wetland soils and climate change which has profound implications for mitigation efforts. The study seeks to support policy development efforts to preserve these essential ecosystems in the context of climate change [8].

Also, understanding the complex relationship between CO_2 emissions and meteorological parameters is crucial to addressing the global challenge of climate change [9-11]. The exchange of CO_2 in wetland soils is intricately linked to various meteorological parameters and the moisture regime, which significantly impact the rates of greenhouse gas emissions. Meteorological parameters such as temperature and precipitation play a vital role in regulating the biogeochemical processes occurring in wetland soils [12, 13]. Temperature influences microbial activity and decomposition rates, affecting the release of CO_2 into the atmosphere. Precipitation patterns determine the water table level and soil moisture content, which in turn influence the availability of oxygen and nutrients for microbial processes.

The moisture regime of wetland soils, characterized by fluctuations in water table depth and soil saturation, is a key determinant of greenhouse gas emissions [14, 15]. Waterlogged conditions create anaerobic environments that promote methanogenesis, resulting in the production and release of methane [16, 17]. Conversely, fluctuations in water table levels can lead to periods of aerobic conditions, favouring CO_2 emissions through microbial respiration [18]. Understanding the complex interplay between meteorological parameters, moisture regime and greenhouse gas emissions from wetland soils is essential for accurately assessing the carbon balance of these ecosystems.

This study focuses on investigating these interactions with the aim of improving predictions of CO_2 flows from wetlands and their impact on climate change, contributing to a higher level of confidence in the inventory of GHG emissions.

How these factors interact and influence the dynamics of CO_2 emissions improves prediction models of greenhouse gas fluxes from wetlands and anticipates their impact on global climate change. Also, another objective is to highlight the importance of accounting for environmental uncertainties in the extrapolation of emissions, with corrected monthly means providing a more accurate representation of emissions by including day/night variations.

Materials and methods

In the peri-urban area of Bucharest, wetlands have naturally formed along the Dambovita river. Thus, according to figure 1, two locations (SC and SP) were chosen for monitoring CO_2 emissions and were selected based on the identified vegetation type and soil flooding regime. Also, in the study area, two types of soil were identified: potentially flooded soil and flooded soil, but also two types of vegetation species, *Cattail*s and *Phragmites australis*. The SC location is situated in the drainage area of the Dambovita River, in the upstream part and is covered in *Cattails* vegetation. From a water management standpoint, this soil has the potential to flood, however, it was not submerged by river waters during the monitoring period. The SP location is positioned downstream and is characterized by vegetation predominantly of the *Phragmites australis* species. It had a varied soil moisture regime throughout the year; thus, in the first part of the year, between January and July, it presented the characteristics of drained soil and after August until December, it was flooded. The two selected locations represent contrasting hydrological regimes and dominant wetland species effectively capturing key soil moisture variations and plant interactions influencing CO_2 emissions, making the findings relevant to similar temperate wetlands.

Fig. 1. The location of the study plots: SC (44°27'59"N 25°58'54"E) and SP (44°27'41"N 25°59'51"E)

The approach for measuring the fluxes from the soil-atmosphere interface is to measure CO_2 concentrations within a closed, opaque chamber with a specific surface area. The EGM-5 portable CO_2 gas analyser was used to monitor CO_2 emissions, specifically the difference in CO_2 concentration between entering and leaving the chamber through recirculation. Its main features are a volume of 1171mL and a covering area of 78cm^2 [19]. This closed chamber method captures the dynamics of CO_2 emissions in situ, offering reliable real-time data. However, some limitations of this method include potential alterations to natural air exchange, as the chamber traps the air, possibly leading to small microclimatic changes. Also, the short-term measurements might miss transient emission peaks, especially after rain events or soil disturbances, thus introducing some variability in results.

The method was applied in-situ in the research area during the year 2022, with measurement sessions occurring at least once a month. Monthly intervals were chosen to capture broader seasonal trends, but such frequency may not fully account for short-term fluctuations driven by rapid changes in local variables.

Field measurements, laboratory analyses and meteorological observations were all employed to examine the variables influencing CO_2 emissions. Field experiments also involved measuring physical parameters such as air (T_{air}), top-soil temperature (T_{soil}) and soil moisture (M_{soil}) at 0-20cm. To further emphasize the impact of precipitation on CO_2 emissions, it was investigated if this effect is amplified over time and thus the correlation of CO_2 emissions with cumulative precipitation over seven days was chosen. To determine the soil quality parameters, soil samples were collected from each plot in May, at 15 and 30cm depths and laboratory analyses focused on pH, nutrient levels (N, P), organic carbon (C_{org} (%)) and soil humus.

The SPSS 29.0 software was used for factorial analysis. The Pearson correlation product was also analyzed to examine the impact of parameters on the variability of CO_2 emissions, while simple and multiple regression analysis were used to test and validate the CO_2 emission models.

Results and discussion

In order to characterise the soils in each location, soil samples were collected after identifying two types of vegetation and distinct water management regimes in which the soil was likely to change. Table 1 shows the results for soil quality indicators at 15 and 30cm depths.

Table 1. Soil physiochemical features by depth and sample plot

		SC		SP	
Indicator		**15cm**	**30cm**	**15cm**	**30cm**
pH	**unit pH (°C)**	7.06/23.3	7.42/23.3	6.21/23.3	7.49/23.3
N_{total}	**(%)**	0.433	0.488	0.074	0.008
P_{total}	**(%)**	0.083	0.058	0.072	0.082
C_{org}	**(%)**	2.13	2.74	1.95	6.38
Humus	**(%)**	3.67	4.73	3.37	11

Soil pH values at the SC location at a depth of 15cm indicate a slightly alkaline condition [20], however, at a depth of 30cm, the pH increases to 7.42, suggesting a further shift towards alkalinity [20]. In the SP location, at a depth of 15cm, the soil pH is lower with a value of 6.21, indicating a more acidic condition compared to the SC location. However, like the SC location, as the soil horizon reaches to 30cm, the pH increases significantly to 7.49. In SC, at a depth of 15cm, N_{total} is 0.433% and P_{total} is 0.083%, indicating a moderate level of nitrogen and phosphorus content [21], but as the soil horizon reaches to 30cm, N_{total} increases to 0.488, while P_{total} decreases to 0.058%, suggesting a slight increase in nitrogen concentration and a decrease in phosphorus concentration with depth. In SP, at a depth of 15cm, both N_{total} and P_{total} are substantially lower than in SC, with a value of 0.074% and 0.072%, respectively. At a depth of 30cm, N_{total} further decreases to 0.008%, which may be indicative of nitrogen leaching, where nitrogen compounds are washed through the soil profile, while P_{total} increases slightly to 0.082%. In SC, at a depth of 15cm, soil organic C is 2.13%, indicating a moderate level of organic carbon content [22]. At the same time, the humus content is 3.67%, which suggests a moderate level of humus accumulation [23]. At 30cm, organic C increases to 2.74% and humus content increases to 4.73%. This suggests an increase in both organic carbon and humus concentration by depth. At a soil depth of 15 cm, organic C is slightly lower at 1.95% than in the SC location and humus content is 3.37%. However, 30cm, both organic C content and humus content increase significantly, with organic C reaching 6.38% and humus content reaching 11%. This abrupt increase in both organic C and humus content with depth in SP suggests a higher rate of organic matter accumulation or preservation processes [24] compared to SC location.

CO_2 emissions measured in-field

Figure 2 depicts CO_2 emissions from the soil in SC location in the context of temperature variations (T_{air} and T_{soil} values), as well as soil moisture (M_{soil}) corresponding to the monitoring days related to each month. It was observed that the values of CO_2 emissions and temperatures follow an increasing trend of dependence along the series of measurements; thus, at T_{air} and T_{soil} that exceed 20°C (May-August), CO_2 emissions tend to increase considerably, with values up to $0.5871 g\cdot m^{-2}\cdot h^{-1}$. Also, the lowest temperature values recorded during the measurements, between 3.5°C and 5°C for T_{air} and 3.5°C and 6.7°C for T_{soil}, also correspond to the lowest values recorded for CO_2 emissions, with the lowest emissions observed in this area being $0.0918 g\cdot m^{-2}\cdot h^{-1}$ in January. The minimum and maximum values for each of the two variables indicate the dependency of CO_2 emissions on M_{soil}. Thus, low M_{soil} percentages of

22.6-24.8% resulted in the lowest emissions values, also recorded in January. Similarly, at the highest M_{soil} level of 50.75%, a value of $0.5715 g \cdot m^{-2} \cdot h^{-1}$ was measured.

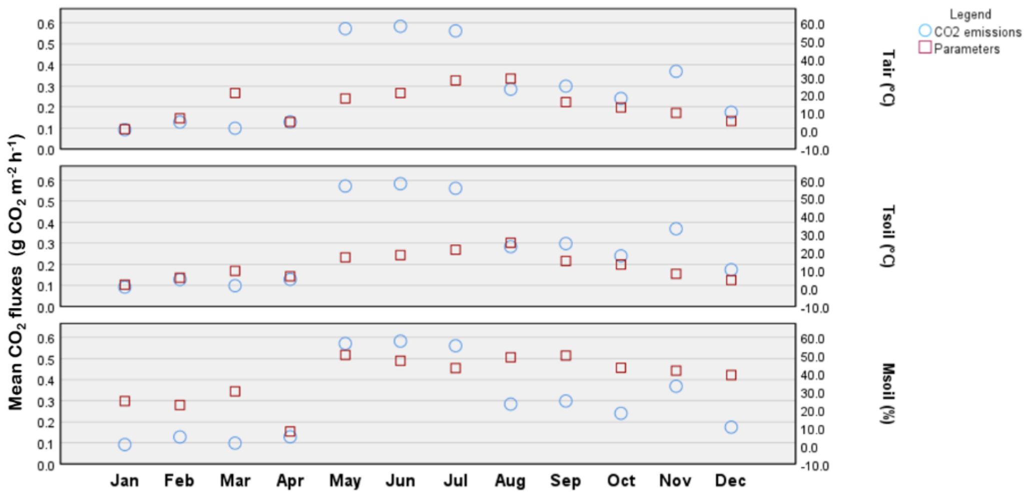

Fig. 2. The variation of CO_2 emissions depending to the temperatures and soil moisture in SC

To emphasise the dependence relationship between CO_2 emissions and the key physical factors at the SC location, statistical analysis was carried out employing the Pearson correlation product and linear regressions to examine how well each variable could predict CO_2 emissions values (Table 2). A strong positive and significant correlation [24, 25] proved to be in relation to T_{air} ($r = 0.602$; $p < 0.01$) and T_{soil} ($r = 0701$; $p < 0.01$). Also, significant positive correlation with M_{soil} ($r = 0.689$; $p < 0.01$) and Precipitation (Pp) ($r = 0.808$; $p < 0.01$) over a seven-day period has been found. Wind speed, however, exhibits a weak negative correlation, although this is not statistically significant. The regression equations for predicting CO_2 emissions from the physical parameters analysed suggest that higher temperatures increase CO_2 emissions by 79.7% for T_{air} and by 74.7% for T_{soil}. Precipitation plays a crucial role in predicting CO_2 emissions, as shown by the strong correlation ($r = 0.808$, $p < 0.01$) and high explanatory power ($R^2 = 0.813$). This is likely because SC's soil, though potentially flooded, is not continuously submerged, making CO_2 emissions highly sensitive to precipitation-driven changes in soil moisture and oxygen availability for microbial activity.

Table 2. Pearson correlation and linear regression of CO_2 emissions and the main physical parameters in SC

Variable	r	R^2	Regression Equation	*p* Value
T_{air}	0.602*	0.797	$y = 0.018x$	<0.001
T_{soil}	0.701**	0.747	$y = -6.382*10^{-2}-4.605*10^{-2}x-1.0449*10^{-3} x^2$	<0.001
M_{soil}	0.689*	0.742	$y = --0.17-9.841*10^{-3}x+3.139*10^{-4}x^2$	<0.001
Pp (7 days)	0.808*	0.813	$y = 0.165+9.0621*10^{-3}x+6.1754*10^{-4}x^2$	<0.001
Wind speed	-0.396	0.439	$y = 0.511x^{-0.826}$	0.255

* Correlation is significant at the 0.05 level (1-tailed).
** Correlation is significant at the 0.01 level (1-tailed).

Figure 3 shows CO_2 emissions from the soil in the SP location and how the key physical parameters affect them. T_{air} and T_{soil} values generally coincide with the increase in CO_2 emission values, as in the case of the SC location. However, the relationship is strongly dependent on temperature, but other factors like soil moisture (M_{soil}) also play a significant role. Considering the change in the moisture regime of the SP location (Figure 4), until August, the values of CO_2 emissions were influenced by the evolution of M_{soil}, so that, at a minimum soil moisture of 12.9% and 16.6%, recorded emission values of 0.076 and 0.147$g \cdot m^{-2} \cdot h^{-1}$, respectively, representing the lower extremes of the variation. The second part of the results from the series of measurements was no longer included for the M_{soil} values since the soil moisture regime had changed the location into a flooded area.

Thus, in August, when the moisture regime suddenly changed, the maximum peak in CO_2 emissions of 1.3755$g \cdot m^{-2} \cdot h^{-1}$ was observed, which was caused by ecosystem disruption and, implicitly, by an acceleration of CO_2 emissions from soil. Furthermore, while the area remained flooded after this month, emission data showed a decreasing pattern, indicating that the carbon sequestration capacity in the flooded soils is favourable, according to the IPCC Guidelines [26].

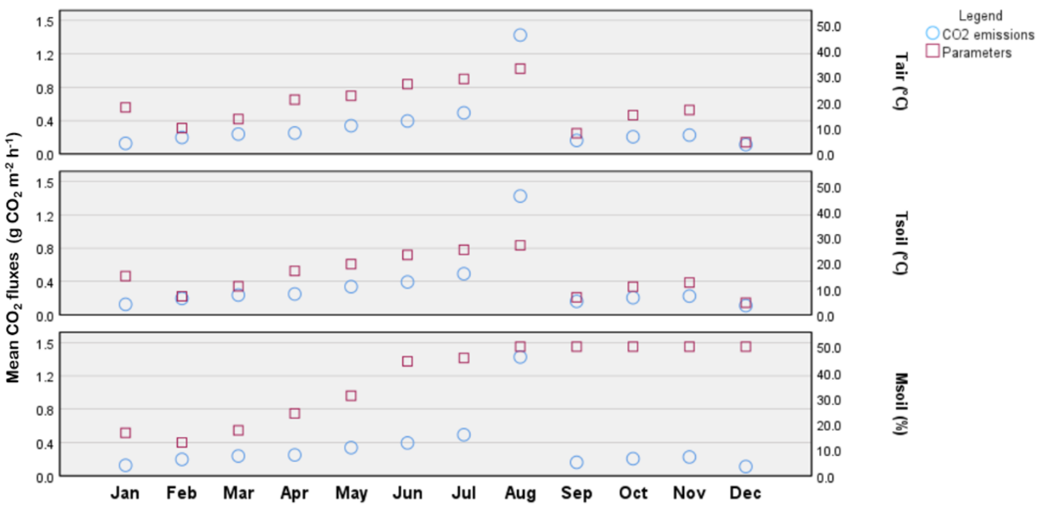

Fig. 3. The variation of CO_2 emissions depending to the temperatures and soil moisture in SP

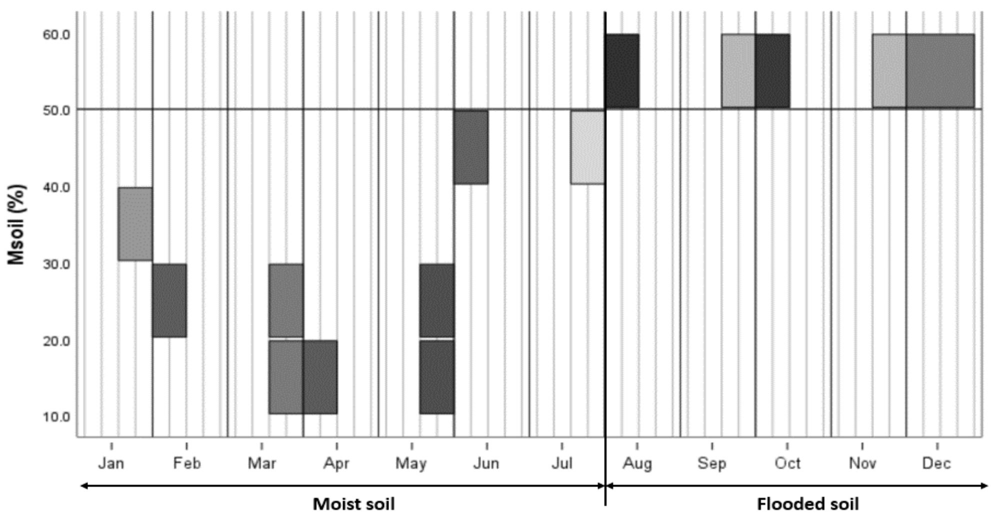

Fig. 4. The temporal distribution of soil moisture (M_{soil}) at the SP location

As the soil transitions to a flooded regime, temperature and soil moisture become more dominant predictors of CO_2 emissions ($r = 0.862$ for T_{air}, $r = 0.871$ for M_{soil}, $p < 0.01$). Here, precipitation plays a lesser role because the area is saturated, reducing the immediate impact of rainfall on soil gas exchange. This is also supported by the statistically significant regression equations for T_{air}, T_{soil} and M_{soil}, indicating that these variables have a predictive relationship with CO_2 emissions.

Table 3. Pearson correlation and regression of CO_2 emissions and the main physical parameters in SP

Variable	r	R^2	Regression Equation	*p* Value
T_{air}	0.862**	0.896	$y = 0.446\text{-}6.26{*}10^{-2}x+2.474{*}10^{-3}x^2$	<0.001
T_{soil}	0.852**	0.843	$y = 0.497\text{-}7.836{*}10^{-2}x+3.533{*}10^{-3}x^2$	<0.001
M_{soil}	0.871**	0.841	$y = 0.854\text{-}6.569{*}10^{-2}x+1.373{*}10^{-3}x^2$	<0.001
Pp (7 days)	0.074	0.005	$y = 0.228+0.002x$	0.397
Wind speed	0.475	0.003	$y = 0.141x$	0.427

** Correlation is significant at the 0.01 level (1-tailed).

Extrapolation of CO_2 emissions

The extrapolated monthly mean emissions for SC and SP locations along with standard deviations (SD), 95% confidence intervals and confidence coefficients are presented in Table 4. The variation across the year was significant for both locations. In SC location, the emissions range from $2.326 g·m^{-2}·d^{-1}$ in January to $13.564 g·m^{-2}·d^{-1}$ in May, while in SP location, emissions range from $1.540 g·m^{-2}·d^{-1}$ in December to $31.604 g·m^{-2}·d^{-1}$ in August. The 95% confidence intervals are relatively narrow for all months, suggesting precise estimates of the mean CO_2 emissions. These narrow intervals provide confidence in the predictive accuracy of the models, as they suggest that the observed data closely represent actual emissions under similar environmental conditions. The confidence coefficients are all around 64-65%, indicating that the data is moderately reliable.

Table 4. Extrapolated mean CO_2 emissions, based on models derived from data measured in-situ

Location	Month	CO_2 emissions ($g·m^{-2}·d^{-1}$)		95% Confidence interval ($g·m^{-2}·d^{-1}$)		Confidence coefficient
		Mean	SD	Lower limit	Upper limit	
SC	Jan	2.326	0.039	2.311	2.340	64.35%
	Feb	3.199	0.038	3.184	3.214	64.46%
	Mar	2.484	0.056	2.463	2.504	64.35%
	Apr	3.116	0.053	3.097	3.136	64.39%
	May	13.564	0.209	13.487	13.641	65.38%
	Jun	13.549	0.111	13.508	13.591	64.39%
	Jul	12.902	0.137	12.852	12.953	64.35%
	Aug	6.523	0.037	6.509	6.536	64.35%
	Sep	7.055	0.100	7.018	7.093	64.39%
	Oct	5.807	0.070	5.781	5.833	64.35%
	Nov	9.064	0.152	9.007	9.121	64.39%
	Dec	4.394	0.080	4.365	4.423	65.38%
SP	Jan	1.925	0.032	1.914	1.937	64.35%
	Feb	3.687	0.044	3.670	3.704	64.46%
	Mar	4.726	0.107	4.686	4.765	65.38%
	Apr	4.852	0.083	4.822	4.883	64.39%
	May	6.843	0.106	6.804	6.882	65.38%
	Jun	8.016	0.006	8.013	8.018	64.39%
	Jul	10.186	0.108	10.146	10.226	64.35%
	Aug	31.604	0.180	31.538	31.670	64.35%
	Sep	2.643	0.037	2.629	2.657	64.39%
	Oct	3.768	0.045	3.751	3.784	64.35%
	Nov	4.317	0.073	4.290	4.344	64.39%
	Dec	1.540	0.028	1.530	1.550	65.38%

Further analysis explored the hypothesis that considers the day and night average variation. The monthly CO_2 emissions were corrected and adjusted, considering the differences in emissions between day and night, as shown in Table 5. The corrected mean CO_2 emissions show notable differences in monthly emission patterns compared to the initial values (Table 4). Figure 5 shows that in location SC, emissions peak in June at 22.582g·m^{-2}·d^{-1}, suggesting increased biological or environmental activity, while August presents a significant decrease to 7.708g·m^{-2}·d^{-1}. In contrast, location SP experiences the highest emissions in August at 37.350g·m^{-2}·d^{-1}, indicating an intense period of CO_2 release. Both locations exhibit generally higher confidence coefficients around 73-76%, indicating more consistent data under the hypothesis of diurnal variation.

Table 5. Extrapolated mean CO_2 emissions based on the hypothesis that considers the day and night variation

Location	SC		SP	
Month	**Corrected Mean**	**Confidence coefficient (%)**	**Corrected Mean**	**Confidence coefficient (%)**
Jan	1.661	73.27	1.375	73.27
Feb	2.707	76.03	3.120	76.03
Mar	2.484	73.27	4.726	74.03
Apr	3.683	73.29	5.735	73.29
May	18.990	74.03	9.580	74.03
Jun	22.582	73.29	13.359	73.29
Jul	18.063	73.27	14.260	73.27
Aug	7.708	73.27	37.350	73.27
Sep	7.055	73.29	2.643	73.29
Oct	4.914	73.27%	3.188	73.27%
Nov	6.474	73.29%	3.083	73.29%
Dec	2.636	74.03%	0.924	74.03%

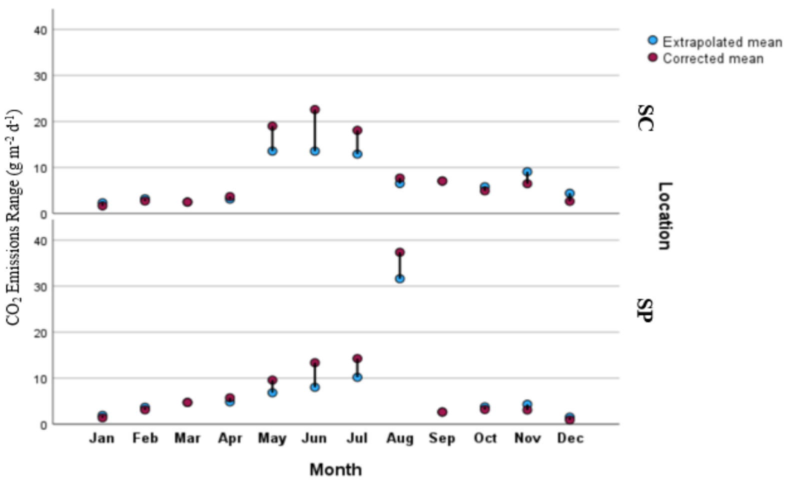

Fig. 5. Comparison of extrapolated CO_2 emissions based on data measured in-situand corrected means based on day and night variation

Understanding the seasonal and local variability of CO_2 emissions is vital to reduce the uncertainties for monitoring of environmental health and changes over time and contributes to broader models and predictions regarding climate change. Thus, the boxplot from Figure 6 shows that the emissions are lowest in winter and highest in summer at both locations, with SC showing a moderate increase and SP a more pronounced rise with greater variability. Spring and autumn have intermediate emission ranges, with SC consistently higher than SP. This suggests that CO_2 emissions are influenced by seasonal temperature changes, with SP exhibiting more variability due to different soil conditions during the summer, when the floods occurred.

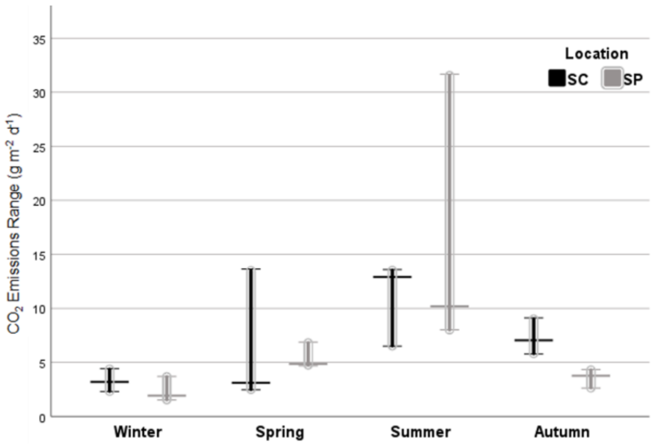

Fig. 6. The seasonal variation of CO_2 emissions from SC and SP locations

CO_2 emissions were predicted for both SC and SP locations employing bivariate or multiple regressions utilizing different environmental variables such as temperature, pressure and M_{soil}. Table 6 provides the coefficients for evaluating model performance based on the coefficient of determination (R^2) which indicate how well the models explain the variability in CO_2 emissions, the regression equation (Eq.) and the standard deviation of residuals (SD) [27, 28]. The proportion of variance explained by the temperature predictor has an $R^2 = 0.761$ in location SC, while location SP has a slightly higher R^2 of 0.795, indicating that 79.5% of the variability in CO_2 emissions are explained by temperature.

Table 6. Regression models between CO_2 emissions and the main soil physical parameters for SC and SP

Parameter		SC	SP
Simple regression ***E=f(T)***	R^2	0.761	0.795
	Eq.	$y=0.6442T^{0.9809}$	$y=0.0094T^{2.3604}$
	SD	4.994	6.474
Simple regression ***E=f(P*)***	R^2	0.760	0.796
	Eq.	$y=0.662P^{0.973}$	$y=1.133*10^{-2P2.306}$
	SD	5.002	6.462
Simple regression ***E=f(M_soil)***	R^2	0.655	0.973
	Eq.	$y=7.1808-0.556M_{soil}+0.012\ M_{soil}^2$	$y=5.912+3.536\ M_{soil}-0.0628\ M_{soil}^2$
	SD	6.1298	3.9885
Multiple regression ***E=f(T,P*)***	R^2	0.823	0.801
	Eq.	y=0.586T+0.422P	y=0.814T-0.565P
	SD	4.988	8.0206
Multiple regression ***E=f(T,P*,M_soil)***	R^2	0.831	0.863
	Eq.	$y=0.505T-1.989P+0.094M_{soil}$	$y=-0.813T-14.373P+1.235\ M_{soil}$
	SD	5.1453	7.2944
P=P/1000*			

The variance explained by the pressure predictor is like temperature predictor, with location SC having an $R^2 = 0.760$ and location SP an $R^2 = 0.796$. Soil moisture alone explains less variance in SC, with $R^2 = 0.655$, but much higher variance in SP, where $R^2 = 0.973$ and depicts that the model explains 97.3% of the variance in CO_2 emissions, which is a very strong correlation [24]. The multiple regression in which temperature and pressure were combined improves the variance explained, with SC having an R^2 of 0.823 and SP an R^2 of 0.801. Including all three predictors in the multiple regression, the model for SC has an R^2 of 0.831 and SP has $R^2 = 0.863$, showing the highest explanatory power among the models.

Conclusions

The results of the assessment of CO_2 emissions show that the two selected locations (SC and SP) had distinct emission models. The monitoring results indicate a clear correspondence between CO_2 emissions and variations in temperatures (T_{air} and T_{soil}). By statistical analysis at the SC location was found a significant positive correlation between CO_2 emissions with T_{soil} ($r = 0.813$; $p < 0.01$) and T_{air} ($r = 0.793$; $p<0.01$). Furthermore, positive correlations were found with M_{soil} and Precipitation (Pp) over a seven-day period, indicating the significant role of these parameters in determining the CO_2 emissions from wetlands soils. On the other hand, in the SP location, CO_2 emissions peaked in August due to the sudden change in moisture regime, reaching a maximum of $0.7282 g \cdot m^{-2} \cdot h^{-1}$. This increase in emissions was due to ecosystem disturbance by flooding events, which accelerated the release of CO_2 from the soil. Subsequently, under conditions of continuous water saturation and combined with the decreasing of temperature, the emission values showed a decreasing trend, indicating a favourable potential for CO_2 sequestration in flooded soils. The transition of the SP location from a drained to a flooded regime introduces variability in CO_2 emissions that might not be fully explained by the parameters measured. Factors such as oxygen availability, nutrient fluxes and soil redox potential were not directly monitored but could significantly impact CO_2 emissions during flooding.

The needs for extrapolation of CO_2 emissions based on measured data, considering time intervals and local implications, highlighted the importance of accounting for uncertainties in environmental conditions. Also, corrected monthly means provided a more accurate representation of CO_2 emissions by incorporating day/night variations, which significantly affect emission levels. The relatively high-confidence coefficients (73.27%-76.03%) suggest that these corrected values are consistent and dependable across different months.

Regression models used to predict future levels of CO_2 emissions based on analyzed meteorological and physical parameters showed that regression models with multiple predictors explained more variance and had lower residual standard deviations, indicating better predictive accuracy. The best performance for SC was achieved with a multiple regression with temperature, pressure and M_{soil} (R^2=0.831), while for SP, the single regression with M_{soil} provided a fitted corelation (R^2=0.973). A deeper exploration of potential factors that can significantly contribute to total CO_2 emissions, such as plant respiration or external pollution sources, would improve the accuracy and reliability of the CO_2 emissions data. These factors could have influenced the recorded CO_2 levels, potentially introducing bias in attributing emissions solely to wetland processes.

These findings provide valuable insights into the complex dynamics of CO_2 emissions from wetland ecosystems and underscore the necessity of considering multiple environmental variables in predicting CO_2 emissions those ecosystems. The results of the study contribute to the improvement of emission factors and models specific to the temperate region to improve the accuracy of emission estimates related to wetlands. These not only contribute to a more accurate national carbon budget, but also highlight the mitigation potential of conserving and restoring these ecosystems as part of national climate strategies.

Future perspectives include improving predictive models by integrating more comprehensive datasets encompassing a wider range of environmental variables, such as data on soil chemistry, vegetation cover and hydrological dynamics, as well as extended observation periods.

Acknowledgments

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