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CO_2 emissions from dredged sediment as a function of moisture, temperature, and oxygen

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Abstract. Estuaries represent a crucial compartment in the global carbon cycle, with high rates of organic matter formation, burial and degradation. Sedimentary processes control the balance between long-term burial of carbon and CO_2 and CH_4 emissions upon OM degradation, for which estuaries are a global hotspot. The profound and globally intensifying perturbation of estuarine sediment by anthropogenic activities such as harbor dredging has a far-reaching but poorly understood impact on sedimentary carbon cycling processes in estuaries and by extension potentially on global carbon budgets. Hence, understanding carbon emissions from dredged sediments under varying environmental conditions is critical for assessing their environmental impact and informing large-scale sediment reuse strategies. This study investigates the effects of moisture, temperature, and oxygen availability on CO_2 emission rates from dredged sediments collected from the Port of Rotterdam, the largest port in Europe. Results are compared with soil CO_2 emissions from a global database of nearly 400 laboratory incubations under different conditions. Our sediment incubation showed that CO_2 emissions increased 1.5–8.1 times with higher moisture levels, 3.8–6.0 times with elevated temperatures, and 4.5–6.4 times with oxygen exposure. Applying machine-learning tools (XGBoost) to a global database of soils and sediment incubations suggested that moisture and temperature responses observed in our experiment are widespread in both soils and sediments. However, functions that described these responses differed significantly from those used in global biogeochemical carbon-cycle models, indicating a need to revisit these functions. Oxygen displayed a relatively stronger effect in sediments, likely due to better preservation of labile organic matter (OM) in anoxic conditions and its rapid oxidation upon re-exposure to oxygen. A model incorporating organic matter with different degradation rates showed that while labile OM fueled high initial rates of CO_2 emission, more recalcitrant OM was a much more abundant OM pool (> 80 %) that dominated cumulative CO_2 emissions on longer timescales. Overall, our experiment and meta-analysis on a global soil dataset suggest the importance of environmental controls on carbon emissions and that dredged sediments are an organic-rich, potent source of CO_2 upon oxidation after dredging, which should be considered in sediment management and reuse practices.

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1 Introduction

Within the global carbon cycle estuaries represent a crucial link between the terrestrial and marine realms characterized by high rates of organic matter formation, burial and degradation. The balance between long-term burial of carbon, CO_2 and CH_4 emissions as a function of OM degradation are partly controlled by sedimentary process in estuaries. Anthropogenic activities such as harbour dredging have far-reaching but poorly understood impacts on sedimentary carbon cycling in these estuaries and may affect global carbon budgets. This important also as globally perturbation of estuarine sediment is intensifying because of coastal and harbour management practices. Large-scale dredging is often essential for water-rich countries as neglecting the siltation of water bodies may have adverse socioeconomic consequences (Paranaíba et al., 2023). It is estimated that 600 million m^3 of sediment is dredged annually in China, Europe, and the United States, a large proportion of which is associated with major shipping ports (Amar et al., 2021). In many cases, regular dredging is necessary to maintain adequate water depth for navigation with sediment being supplied continuously, which makes dredging a persistent and costly operation. Meanwhile, managing the large amount of dredged sediment poses a major challenge, as storing or disposing of these materials can be difficult and expensive (Yoobanpot et al., 2020). Consequently, there is a growing emphasis on nature-based solutions that reuse dredged sediments within local systems, reducing costs as well as supporting natural development (Brils et al., 2014). The practices of sediment reuse and potential benefits are documented in many studies, particularly in relation to production of raw materials (e.g. stabilized sediment as soil) to support projects such as habitat restoration and land reclamation (CEDA, 2019; Paranaíba et al., 2023).

A key consideration in beneficial reuse of dredged sediment is its potential environmental impact (e.g. through release of contaminants; Wu et al., 2024b) and also impact on the carbon associated with the sediment (SedNet, 2021). Sediments play a vital role in sequestering and storing carbon for very long times (Holmquist et al., 2024). Certain marine sedimentary environments (e.g. mangrove, seagrass meadow) store disproportionate large amounts of organic carbon on a per-area basis compared to terrestrial habitats (Hilmi et al., 2021). When sediment is removed from the aquatic system and placed in a new environment (often terrestrial context), it can boost the release of carbon as CO_2 previously stored in organic matter (OM) in the sediments. Studies have shown that exposure of originally reducing sediments from anoxic environments to atmospheric oxygen can enhance organic matter (OM) decomposition rates by up to an order of magnitude (Dauwe et al., 2001; Wu, Nierop, et al., 2024). Over time, dredged sediment placed on land undergoes various biogeochemical changes, such as dewatering and so-called ripening (Paranaíba et al., 2023). How these processes impact carbon stability remains as a subject of ongoing research (Besseling et al., 2021; Vermeulen et al., 2003).

Carbon emissions from reused sediment involve complex biogeochemical processes shaped by the dredging-induced perturbation of ambient environmental conditions. Besides oxygen, temperature and moisture are widely recognized as key environmental factors controlling CO_2 emissions from sediments and soils (Fang et al., 2022; Lacroix et al., 2019). While

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traditional Arrhenius kinetics predicts that decomposition rates increase monotonically as temperature rises, many studies report an optimum temperature, beyond which emission rate declines, with the threshold (25–45 °C) varying across soil types and climates (Alster et al., 2023; Kirschbaum, 1995; Liu et al., 2018; Sierra et al., 2017). Moisture content governs decomposition rates by regulating the transport of nutrients and oxygen: OM degradation and the resulting CO_2 emission rates are limited by nutrient supply to the OM-degrading bacteria at low moisture levels and limited by oxygen availability for respiration at high moisture levels, with CO_2 fluxes peaking at intermediate moisture levels (Fairbairn et al., 2023; Fang et al., 2022). However, the dependence of carbon emission rates from native soils on temperature and moisture may not be applicable to dredged sediment, because of distinct properties like redox state, OM substrate and extant microbial communities. Improved understanding of carbon dynamics and CO_2 production in dredged sediments requires quantitative insight into the effects of temperature and moisture. Such insight is crucial for effectively reusing sediment in a way that minimizes carbon emissions while preserving the benefits of sediment valorisation. With increasingly frequent extreme climate events (e.g. droughts, heatwaves, flooding) that may directly impact reused sediments, assessing sediment carbon stability under varying moisture and temperature conditions has become even more urgent (Frank et al., 2015).

Here, we investigate the effects of moisture, temperature and oxygen availability on carbon dynamics in sediments dredged from Europe's largest port—the Port of Rotterdam (PoR). Laboratory incubation experiments were conducted to quantify the carbon emission rates under various moisture, temperature, and oxygen conditions. We compared these findings with a compiled dataset of nearly 400 laboratory soil incubations extracted from 24 studies from 156 locations worldwide. Using a machine learning approach, we observe that carbon emission rates in dredged sediments exhibit similar dependencies on moisture, temperature, and oxygen as found in soils. By applying a two-pool OM model, we further estimated that dredged sediments generally show shorter carbon turnover times than many of the soils in the compiled dataset. By bridging insights from dredged sediments and other soil types, this study improves our understanding of sediment and soil carbon dynamics under different environmental conditions.

2 Materials and methods

2.1 Sediment collection, preparation and incubation

Fresh sediments were collected in 2021 from the Port of Rotterdam, where 10–15 million m^3 of wet sediment is dredged annually (Kirichek & Rutgers, 2020). Surface sediment (up to 50 cm) from six locations (Figure S1) was retrieved with a gravity corer (diameter 9 cm), immediately transferred into 5-L polypropylene buckets on deck, and stored in the fridge at 4 °C. These samples were further processed at the Royal Netherlands Institute for Sea Research (NIOZ, Texel) within a week.

Sediments were subsampled for grain size, total organic carbon (TOC) and nitrogen (TN) analyses (detailed in SI), while the remaining sediments used for incubation were preserved at −20 °C. Prior to incubation, sediment was freeze-dried, gently

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crushed, and sieved (2 mm). Around 10 g of sediment was transferred into 330-mL borosilicate bottles and the moisture level was adjusted with artificial rainwater (composition in Table S1) to 20%, 40%, 60%, 80%, and 100% water-filled pore space (WFPS) according to Fairbairn et al. (2023). Two sets of rewetted sediments at these five moisture levels were incubated at 20 °C, either under air (oxic) or N_2:H_2 (95:5 v/v, anoxic) atmospheres. To assess the effect of temperature, additional oxic incubations were conducted at 10 °C and 30 °C for three moisture levels (20%, 60%, and 100% WFPS). When headspace gas was not measured, bottles were covered with parafilm to minimize evaporation and prevent gas buildup, with oxic and anoxic experiments kept under air or in a Coy anaerobic chamber (N_2:H_2, 95:5 v/v) respectively. All treatments were performed in triplicate.

The CO_2 and CH_4 fluxes were measured on days 2, 6, 9, 16, 23, 30, and 37. During each measurement, bottles were sealed with butyl-rubber septa and aluminium screw caps for 3 hours. Gas samples (150 µL) were collected at the start and end of the 3-h period and analysed with gas chromatography (Agilent 8890 GC). Calibration was performed using certified reference gases (Scott specialty gases, Air Liquide). Gas fluxes were calculated from the accumulation of CO_2 and CH_4 in the sealed bottles over 3 hours (see Supporting Information, SI). Moisture levels were maintained weekly, with absolute deviations from the target values mostly below 5%.

2.2 Incubation dataset compilation

We compiled a dataset of soil laboratory incubation experiments under various conditions from literature and public datasets such as the Soil Incubation DataBase (SIDB; Schädel et al., 2020). In total, we obtained 386 records of soils from 156 locations (Figure S2) from 24 publications with normalized carbon emission rates (µg C g TOC^{-1} day^{-1}) or cumulative carbon emissions (µg C g TOC^{-1}). All here included incubation experiments met the following criteria: (1) the incubation conditions were constant throughout the experiments; (2) OM mineralization rates were reported in TOC-normalized format or can be directly calculated from the reported data; (3) incubation duration was longer than a week; (4) soils were incubated without any substrate addition (except for moisture adjustments). All relevant data were directly extracted from the publications, except in seven studies where data presented in figures were extracted using WebPlotDigitizer (Burda et al., 2017).

The compiled dataset (see SI) includes incubation temperature ranging from −10 °C to 40 °C, moisture level between 0% and 100% WFPS, and incubation durations from 7 to 1000 days. Soil moisture level was often reported as percentage of water holding capacity in the original studies. We converted it to WFPS using water holding capacity (g H_2O g $soil^{-1}$), soil bulk density (g cm^{-3}), and particle density (assumed to be 2.65 g cm^{-3}), detailed in SI. Additionally, we included in the database reported soil properties including TOC content (wt.%), TN content (wt.%), C/N ratio, soil pH, soil texture (sand, silt, and clay fractions, %) when available. Climate variables, such as geographical location (latitude and longitude), mean annual precipitation (MAP, mm) and temperature (MAT, °C), and the ecosystem type of the sample location (e.g. forest, grassland, tundra), were either gathered from the original publications (see SI) or global database WorldClim (Fick & Hijmans, 2017).

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2.3 Carbon emission rate prediction model

We developed a predictive model for the average carbon emission rate throughout the incubation (R, mg C g TOC^{-1} day^{-1}) using the XGBoost algorithm (Jiang et al., 2023). Logarithmic transformation was applied to R prior to modeling. The model was trained by randomly selecting 80% of the full dataset and tested with the remaining 20% of the dataset. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE) for both training and test datasets.

Eight environmental factors and soil properties (i.e. incubation temperature, incubation moisture level, oxygen availability, TOC, C/N ratio, pH, sand fraction, and MAT) were selected as explanatory variables (often termed as 'features') for the predictive model. The selection was based on recursive feature elimination (RFE), following the approach of (Xiang et al., 2023), to remove less important variables and maximize the goodness-of-fit between predicted R and observed R. The model was constructed and operated using the 'sklearn' library in Python (version 3.12.4). Detailed code and explanation for feature selection and the model construction can be found in the Supporting Information.

The XGBoost model outputs were interpreted using SHAP (Shapley Additive Explanations), which quantifies each variable's contribution to the model predictions as SHAP values. The SHAP value of each variable describes the extent of that variable that increases or decreases the prediction relative to a baseline. This baseline, called the base value, is the average of all log-transformed predictions made by the model. For each individual sample, the relationship between SHAP values, base value, and predicted R can be expressed as:

$$\log(\,predicted\ R) = base\ value + \sum_{i}^{n} SHAP\ value_i \quad (1)$$

On the linear scale, the predicted rate R in our study can be expressed as:

$$predicted\ R = 10^{base\ value} \cdot 10^{SHAP\ value_T} \cdot 10^{SHAP\ value_M} \cdot 10^{SHAP\ value_{O_2}} \cdot \prod 10^{SHAP\ value_{others}} \quad (2)$$

Following (Sierra et al., 2017), the effects of variables such as temperature (T), moisture (M), and oxygen (O_2) can be treated as decomposition modifiers that scale the predicted baseline carbon emission rate. In this approach, each environmental factor modifies the emission rate individually, reflecting its individual effect. The predicted carbon emission rate (R) can thus be written as:

$$predicted\ R = 10^{base\ value} \cdot f(T) \cdot f(M) \cdot f(O_2) \cdot \prod f(others) \quad (3)$$

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2.4 Two-pool model and carbon turnover time estimation

The degradation of soil and sediment OM was assumed to follow first-order reaction kinetics (Arndt et al., 2013). To represent this process, we used a two-pool model that partitions soil/sediment organic carbon into reactive and refractory carbon pools, i.e. fast and slowly degrading, with different decomposition rate constants (Xiang et al., 2023). The degradation rate can therefore be expressed as:

$$\frac{dC}{dt} = -k_1 \cdot C_1(t) - k_2 \cdot C_2(t) \quad (4)$$

which can be integrated to:

$$C(t) = -k_1 \cdot C_1(0) \cdot e^{-k_1 \cdot t} - k_2 \cdot C_2(0) \cdot e^{-k_2 \cdot t} \quad (5)$$

$$C(0) = C_1(0) + C_2(0) = \gamma_1 \cdot C(0) + \gamma_2 \cdot C(0) \quad (6)$$

where $C(t)$ is the total organic carbon (g) during the experiment at time t (in days), partitioned into the fast pool $C_1(t)$ and slow pool $C_2(t)$; $C(0)$ is the initial amount of soil/sediment organic carbon (g); γ_1 and γ_2 are the initial fractions of fast pool and slow pool (unitless) with their sum equaling 1; k_1 and k_2 are the corresponding degradation rate constants (day^{-1}) for fast and slow pools.

We applied the two-pool model to each time series of carbon emissions from both our experiments and the compiled dataset (see Section 2.2). When the cumulative carbon release was not directly reported, we calculated it by integrating the area under the emission rate curve for each incubation period. The modelling was performed in Rstudio using the 'SoilR' package and solved numerically with the 'FME' package (Sierra et al., 2012; Soetaert & Petzoldt, 2010). Model parameters were constrained within ranges reported in the literature: k_1 was set at 0.00001–10 day^{-1}, k_2 at 0.0000001–0.01 day^{-1}, and γ_1 at 0–1 (Arndt et al., 2013; Jian et al., 2018; Wijsman et al., 2002; Xiang et al., 2023). From the best-fit parameters, we estimated carbon turnover time τ (year) using the equation from (Feng et al., 2016).

$$\tau = \frac{\gamma_1}{k_1} + \frac{\gamma_2}{k_2} \quad (7)$$

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2.4 Statistical analyses

We performed a one-way ANOVA followed by Turkey post-hoc tests to assess differences in carbon emission rates under different moisture levels at 20 °C. Additionally, a two-way ANOVA was conducted to evaluate potential two-way interactions between moisture level and oxygen level as well as between moisture level and temperature in explaining carbon emission rates. Bonferroni adjustment was further applied to control the familywise error resulting from multiple pairwise comparisons. The analyses were conducted in RStudio using the 'rsttix', 'ggpubr', and 'emmeans' packages.

3 Results and discussion

3.1 Carbon emission rates in sediments and soils

The incubation experiment with dredged sediment conducted in this study demonstrated a strong impact of moisture, temperature and oxygen on OM decomposition rates (Figure 1). The CO_2 emission rate, calculated as total CO_2 emission averaged over the incubation time and normalized to TOC content of the sediment, increased with higher moisture levels, elevated temperatures, and the presence of oxygen. One-way ANOVA showed that moisture level substantially affected carbon emission rates ($p \leq 0.0001$, Figure 1a), although no significant difference was found between 20% and 40% WFPS. The lack of an impact at low moisture levels suggests an inhibitory effect, potentially resulting from low microbial activity related to still limited nutrient mobility at these low moisture levels (Fairbairn et al., 2023), already at WFPS < 40 %. Due to the same constraint, elevated temperature (Figure 1b) or exposure to oxygen (Figure 1c) did not show significant enhancement on carbon emission rates at 20% WFPS, whereas they showed strong effects at higher moisture levels. Interestingly, the highest CO_2 emission rate occurred at 100% WFPS, exceeding the typical optimum of 50–60% WFPS (Fairbairn et al., 2023). We propose two processes that could account for this discrepancy: (1) native microbes in sediment may be adapted to high water contents and thus were most active under water-saturated condition; (2) as the incubated sediments were fine-grained (D50 < 20 µm), aggregates occurring in the sediment could limit substrate (e.g. OM, nutrients) supply. This will shift the optimal moisture to near saturation, as moisture enhances the desorption of substrates from mineral surfaces and promotes diffusion (Yan et al., 2016).

Generally, a higher temperature within the range of 10–20 °C leads to more CO_2 release due to enhanced enzyme activity and increased microbial population, witnessed by a sharp increase from 10 °C to 20 °C under 60% and 100% WFPS (Figure 1b). However, the absence of significant differences between 20 °C and 30 °C suggests a possible thermal optimum within this range, in line with meta-studies based on investigating various soils and sediments (Čapek et al., 2019; Swails et al., 2022). However, other studies reported temperature continuously stimulated microbial activity even above 35 °C(Liu et al., 2018; Sierra et al., 2017), suggesting that other factors such as enzyme activity (e.g. related to microbe types, adaption) and substrate

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availability may have affected microbial respiration at temperatures > 20 °C. Detailed mechanistic studies, using e.g. DNA extraction and labelled different substrate classes, could investigate this in future research.

We observed that CO_2 emission rates under oxic conditions were 4–6 times higher than under anoxic conditions (Figure 1c), implying redox condition plays a critical role in influencing carbon emission rate, mostly likely via regulating OM degradation pathways. Due to the higher Gibbs free energy yield, oxygen availability for respiration facilitates the breakdown of organic substrates. Previous research on OM properties and degradation in similar PoR sediments has shown that the introduction of oxygen into these sediments, associated with human perturbation, increased carbon emission rates by a factor of 4–7 (Wu, Nierop, et al., 2024). We did not detect CH_4 accumulation in anoxic incubations, likely due to the high abundance of alternative electron acceptors (e.g., iron (oxy)hydroxides) in PoR sediments (Wu, Reichart, et al., 2024). Alternatively, if these electron acceptors were depleted, methanogenesis may still proceed too slowly to result in detectable CH_4 accumulation within the three-hour incubation period. Our results highlight that organic-rich, reducing sediments host a pool of relatively labile OM that is rapidly degraded upon the introduction of oxygen; sediment dredging therefore rapidly reintroduces C that was destined for long-term removal as sedimentary OM into the atmosphere as CO_2. The fact that these very consistent differences were observed under condition in which all larger fauna was removed implies that differences in activity of mega- and meiofauna under contrasting oxygenation are not the main reason for the difference in organic matter degradation.

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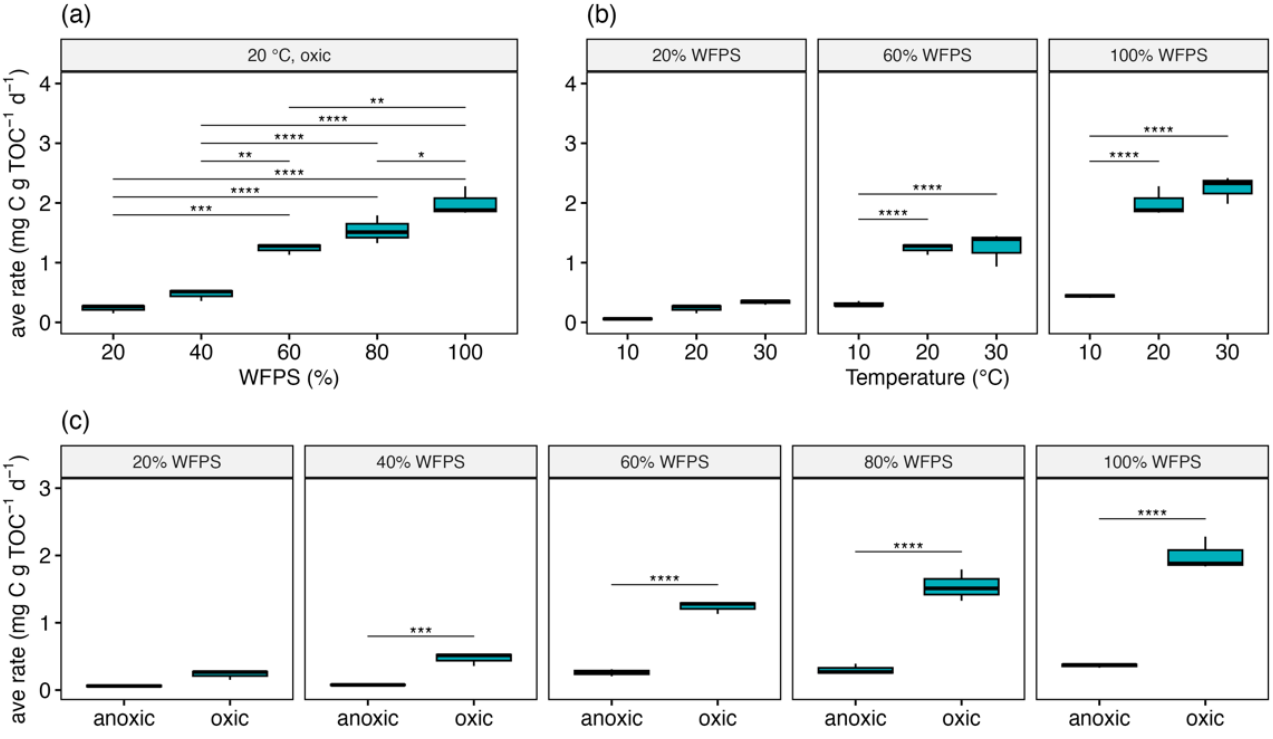

Figure 1. Average CO_2 emission rates of dredged sediments over the 37-day incubation period under different conditions. (a) Oxic incubation at 20 °C under different moisture levels. (b) Oxic incubation at three temperatures under three moisture levels. (c) Oxic and anoxic incubations at 20 °C under different moisture levels. Asterisks denote ANOVA statistical significance: $p \leq 0.05$ (*), $p \leq 0.01$ (**), $p \leq 0.001$ (***), $p \leq 0.0001$ (****).

To place these findings in a broader context, we compared the measured carbon emission rates from dredged sediments with those from a global database of over 400 laboratory incubation experiments from 18 studies (Figure 2). We observed a large variability in carbon emission rates in the compiled global dataset, ranging from 0.0032 to 4.3 mg C g TOC^{-1} day^{-1}. The CO_2 emission rates from the dredged sediments studied here, except under anoxic conditions, are in the upper part of this range (0.2–2.2 mg C g TOC^{-1} day^{-1}). This reinforces the notion that, due to the initially strongly reducing conditions under which OM in harbor sediment existed, it is relatively reactive towards oxygen compared to OM in many soils (Figure S3).

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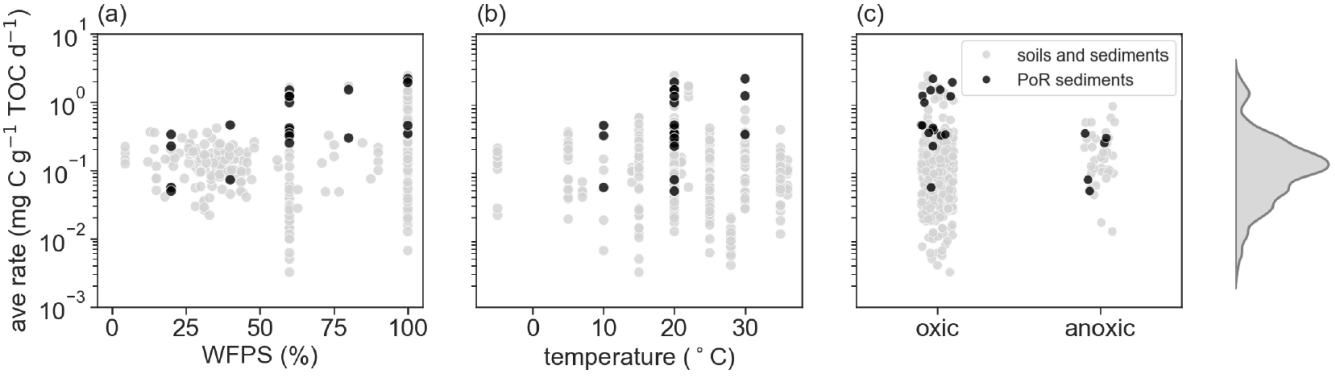

Figure 2. Average CO_2 emission rates from dredged PoR sediments (incubated in this study, in black) versus compiled soils and sediments (literature, in grey) under varying (a) moisture levels (WFPS, %), (b) temperatures (°C), and (c) oxygen levels (oxic or anoxic). The panel on the right shows the overall distribution of average carbon emission rates.

While clear trends were observed in the controlled incubation experiments for dredged sediments, the compiled global soil dataset showed no pronounced trend in relation to moisture level, temperature, or oxygen availability (Figure 2). This lack of a clear trend is likely due to the large spread/scatter in data, which reflects the diverse incubation conditions used, various experimental designs, and different soil biogeochemistry across studies. Factors beyond moisture, temperature, and oxygen, such as OM composition, microbial dynamics, or experimental setup, have a much bigger impact on emission rates. As a result, the interactions between these factors and emission rates are not clearly discernible in Figure 2, further complicating the identification of the potential underlying patterns of changes in carbon emission driven by moisture, temperature, and oxygen. In the next section, we leverage machine learning techniques to disentangle the complex interactions among environmental variables and unravel their effects on soil carbon emission dynamics.

3.2 Global patterns of organic matter degradation driven by moisture, temperature and oxygen

Building on the results from our sediment incubations, we analysed the compiled global dataset using the XGBoost algorithm to assess whether the trends observed in dredged sediments hold across broader soil environments. The machine learning model achieved a good predictive performance (R^2 = 0.76, Figure S4), suggesting it successfully captured the general trends of CO_2 emission rates as function of moisture, temperature, and oxygen.

3.2.1 The impact of moisture level on OM degradation and CO_2 emission rates

Consistent with our finding for dredged sediments, moisture appeared as a key driver in the meta-study (Figure 3a): we observed an almost linear increase in CO_2 emission rate between 0 and 80% WFPS, implying substrate (e.g. OM, nutrients) diffusion is the main limiting factor in this range. Above 80% WFPS, the CO_2 emission rate appeared to decline. We interpret this as the onset of a waterlogging effect, where oxygen diffusion becomes restricted and microbial respiration is suppressed. When normalized to the optimal conditions (f(M)/f(M_{opt}), the impact of moisture is more pronounced (Figure S5a). A pore-

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scale mechanistic model developed by Yan et al. (2018) demonstrated a M_{opt} higher than 75% WFPS in many soils due to the reduced pore connectivity, higher clay content, and heterogeneous soil structure. Additionally, elevated moisture was reported to stimulate carbon loss from mineral soils by reductively dissolving iron mineral and associated OM (Huang & Hall, 2017). The high M_{opt} value in our meta-study aligns with these studies, highlighting that these pore-scale effects and iron reduction may occur across a broad spectrum of soils (Georgiou et al., 2022). Conventional moisture functions in Earth system models often assume the optimum moisture at 50–60% WFPS(Kucharik et al., 2000; Parton et al., 1993; Rubol et al., 2013), which might overlook the complexities introduced by soil structure and microscale processes and thereby underestimate CO_2 emission from soils (and dredged sediment) under high-moisture conditions.

3.2.2 Temperature dependence of OM degradation rates

The predicted temperature function f(T) showed three distinct ranges: (1) a range with limited temperature-dependent changes in CO_2 emission rates below 10 °C, likely reflecting a low microbial enzymatic activity; (2) a sharp increase in emission rate between 10 °C to 20 °C; (3) no discernible rise between 20 °C and 35 °C (Figure 3b). This predicted pattern indicates that microbial processes driving OM degradation accelerate most rapidly above 10 °C but approach an enzymatic optimum between 20 °C and 35 °C, which is consistent with the incubated dredged sediments (Figure 1b) as well as other studies reporting an apparent thermal optimum around 27 °C (Čapek et al., 2019; Swails et al., 2022). Notably, many biogeochemical models using Arrhenius-type functions (e.g. Q10, Demeter, LandT, RothC in Figure S5b; Burke et al., 2003) continue to predict rising respiration above 30 °C (see SI), potentially overlooking the enzymatic threshold. In contrast, sigmoid-shaped functions (e.g., Century, Daycent, KB in Figure S5b) with a temperature optimum at 35 °C align more closely with our data, implying they may better capture microbial respiration behaviour across a broader temperature range (Burke et al., 2003; Sierra et al., 2015). Currently, the reported temperature functions differ in their reference temperature for normalization (i.e. where f(T) equals '1'), which complicates quantitative comparisons (Sierra et al., 2015).

3.2.3 CO_2 emissions as function of oxygen availability

The oxygen effect in the global dataset was isolated by machine learning data analysis with XGBoost. Unlike other environmental variables (e.g. temperature and moisture), which showed no strong soil-type-specific responses, the model predicted the most pronounced oxygen effect in sediments and wetland soils—systems characterized by reducing conditions and limited oxygen penetration. In these samples, CO_2 emission rates were 1.1–1.7 times higher under oxic conditions compared to anoxic conditions (Figure 3c). In contrast, forest soils, which are generally more aerated, showed minimal response to oxygen (i.e. increasing by 1.0–1.1 times). The greater impact of oxygen in sediments and wetland soils likely reflects the preservation of relatively labile OM under long-term anoxic condition, highlighting the role of depositional environment and redox state in governing the sensitivity of OM degradation to oxygen availability. (Arndt et al., 2013; Moodley et al., 2005)

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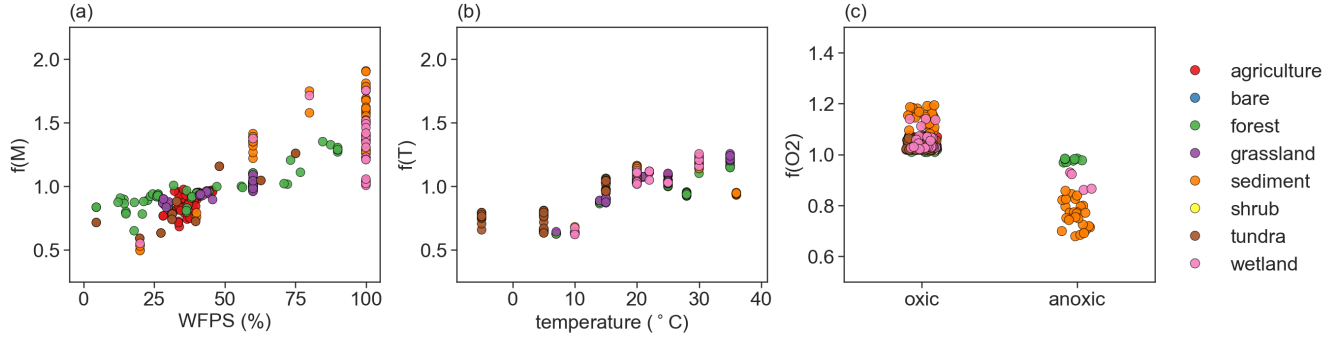

Figure 3. SHAP-based effects of (a) moisture, (b) temperature, (c) oxygen availability on XGBoost-predicted CO_2 emission rates. Effects were expressed as decomposition modifiers, f(M), f(T), and f(O_2), defined in Equation 3. The normalized moisture effect, f(M)/f(M_{opt}), is presented in the Supporting Information Figure S5, along with commonly used moisture [f(M)/f(M_{opt})] and temperature [f(T)] functions from Earth systems models. SHAP values are presetented in Figure S6. Note that y-axis scales differ between panels.

3.2.4 Emerging key parameters from machine learning

In addition to moisture, temperature and oxygen, the XGBoost identified sand content as a key predictor of carbon emission rates. Increasing sand content leads to a lower carbon emission rate, indicated by a declining decomposition modifier (Figure 4a). This aligns with the meta-study by Xiang et al. (2023), suggesting that coarser soil texture reduces water-holding capacity and nutrient availability, thereby limiting microbial activity. However, our sediment samples showed the opposite trend—sand-rich sediments (sand content: 58–69%) exhibited slightly higher emissions than sediments with sand content < 15% (Figure S7a). This discrepancy may arise from the dual role of fine grains: while finer soils support higher nutrient availability, they also provide more mineral surface area for the formation of mineral-associated organic matter (MAOM), this way protecting OM from microbial access and decomposition (Schweizer et al., 2021; Zhou et al., 2024). Determine which process is more important remains challenging as quantitative data on MAOM is not available.

The impact of OM composition on carbon emission rate was evident both globally and in our dredged sediment samples. The C/N ratio, a widely used bulk indicator of OM quality, reflects the relative contribution of N-rich compounds (e.g. proteins in algal material) and C-rich substrates (e.g. lignin in vascular plants; Todd-Brown et al., 2013). Globally, SHAP analysis revealed a 'V'-shaped relationship between predicted carbon emission rates and C/N ratios from 5 to 25 (Figure 4b), with a minimum around C/N ratio of 12. This ratio often represents the most processed and least reactive material, while deviations in either direction suggest fresher, more degradable OM—consistent with diagenetic convergence toward ~12 in estuarine systems (Middelburg & Herman, 2007; Wu, Nierop, et al., 2024). Additionally, emission rates were higher at low C/N (~5) than at high C/N (~25), indicating greater degradability of N-rich OM. Our sediment samples further support this predicted pattern: sediments near the North Sea exhibited 2–4 times higher emission rates than sediments at the riverine setting (Figure S7b), likely reflecting fresher, algal-derived OM with low C/N ratios (5–7) on the marine side, and more recalcitrant, terrestrial OM with higher C/N ratios (up to 24) upstream (Lamb et al., 2006; Wu, Nierop, et al., 2024). However, at a C/N ratio above 25,

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the influence of C/N ratio on carbon emission rates exhibits substantial variability, which remains unexplained by the current dataset.

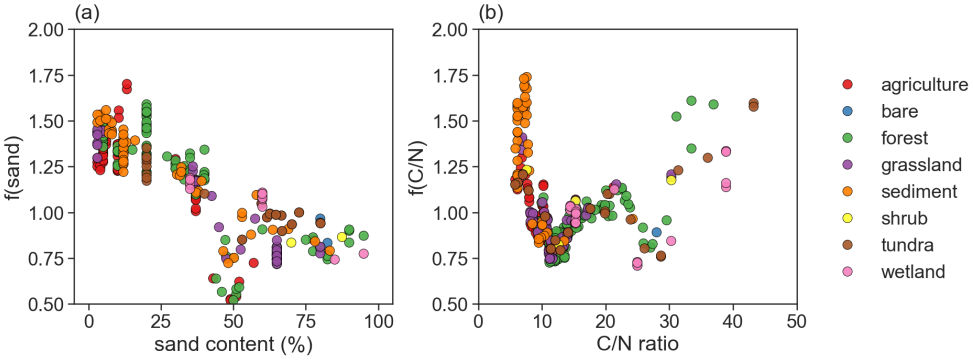

Figure 4. Effects of (a) sand content and (b) C/N ratio on XGBoost-predicted CO_2 emission rates. Effects were expressed as SHAP-based decomposition modifiers, f(sand) and f(C/N), see Section 2.3. SHAP values are presented in Figure S6.

Although the machine learning approach efficiently discerned the effects of multiple environmental drivers on carbon emission rates, it appears to underestimate the magnitude of certain effects in our dredged sediments. For instance, oxygen was predicted to enhance emission rates by at most two-fold (Figure 3c), compared to the 4–6-fold increase measured experimentally (Figure 2c). Similar underestimations occurred for moisture (a maximum 4-fold model prediction vs. 10-fold in laboratory observations) and temperature (2.5-fold vs. 10-fold). These discrepancies were likely derived from log-transformations applied during machine learning, which compresses large observational differences. Subsequent conversion of predictions back to linear scale might have reduced accuracy. Nevertheless, the model exhibited a satisfactory R^2 of 0.76 overall and allowed the evaluation of the isolated impact of environmental variables on soil carbon emissions in a complex global dataset with various interacting parameters. Given their strengths in handling large and complex datasets, machine learning approaches hold high application potential. Integrating these tools with mechanistic interpretations can enhance both field studies and modelling efforts in understanding the impact of environmental changes on terrestrial carbon dynamics.

3.3 Predicting soil and sediment carbon release and turnover time

Understanding the rate of carbon turnover is crucial for predicting the long-term OM stability and CO_2 emissions from soils and sediments. However, the average carbon emission rate measured during incubations (7–1000 days) may not reflect overall carbon turnover time, as carbon release typically declines over time. To better capture long-term dynamics, we applied a two-pool kinetic OM degradation model to our laboratory data and compiled a global incubation dataset, assuming fast- and slow-degrading carbon pools (see Section 2.4). While modelling more pools offers more details, we used a two-pool approach to limit model complexity and parameter uncertainty (Guan et al., 2022).

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The model results showed that decomposition rate constants for both the fast (k1) and slow (k2) pools span several orders of magnitude (Figure 5a), with k1 on average 2–3 orders of magnitude higher than k2. These ranges were similar to those reported in the literature (Figure 5a). The fast pool, according to the model, typically accounts for less than 10% of TOC (Figure 5b), agreeing with Xiang et al. (2023). High carbon emission rates in PoR sediments (Figure 2) appear to result primarily from large degradation rate constants (particularly k1), suggesting that the OM preserved under reducing environments is more reactive. Although reducing soils (e.g. wetlands) are argued to better preserve labile OM (Arndt et al., 2013), modelled fast pool sizes are similar between PoR sediments and other soils. This may reflect the wide range of rate constants (five orders of magnitude) assumed in the two-pool model, which obscures relatively small differences in pool size between soil types. Nonetheless, the model results support that oxygen-free environment favors the preservation of reactive OM. Combining conceptual models with physicochemical fractionation methods (e.g. particle size, density, or molecular characterization) may provide a more comprehensive picture of carbon stability (Schädel et al., 2020).

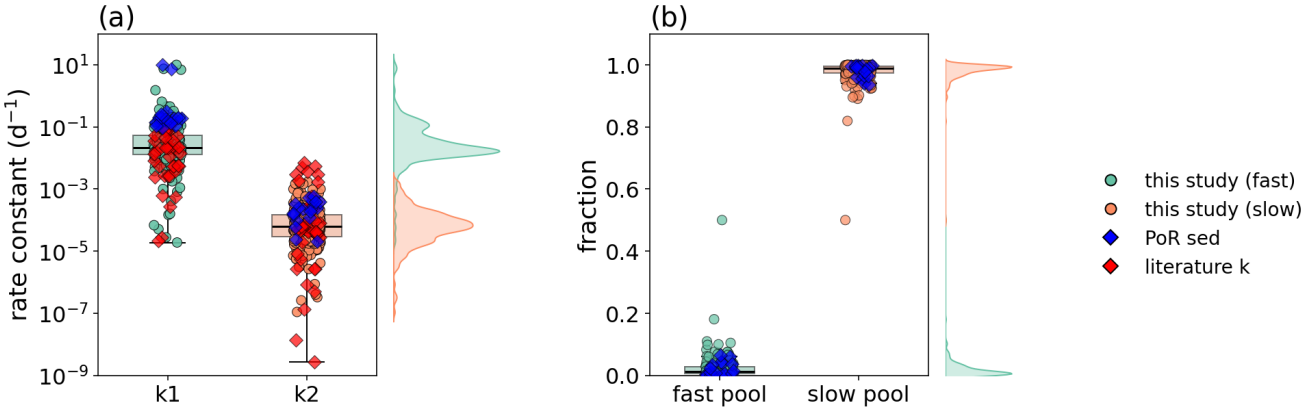

Figure 5. Modelled parameters of OM decomposition using the two-pool model. (a) Decomposition rate constants for the fast pool (k1) and slow pool (k2). (b) Estimated organic carbon fractions for fast and slow pools. Results of the PoR sediments are indicated as blue diamonds. Red diamonds in (a) represent the reported decomposition rate constants in the literature (Arndt et al., 2013). The panel on the right displays the overall distribution of k1, k2 and fractions of fast and slow pools. The two-pool model could not be solved for some incubations. All values are available in the Supporting Information.

Based on the modelled k1 and the fast-degrading OM pool size, we estimate the turnover time of the fast pool to be generally less than three days, meaning its rapid depletion in the beginning phase of most incubations. Consequently, CO_2 emissions over most of the incubation period (7–1000 days) were primarily driven by the degradation of the slow pool. This is further supported by the ratio between total CO_2 emitted and CO_2 derived from labile OM; > 90% of the incubations exhibited greater absolute cumulated CO_2 emission from the slow-degrading OM pool compared to the fast-degrading OM pool (Figure S8). Thus, the average carbon emission rate measured across the incubation predominantly reflects the release from the slow pool, while the fast pool is quickly depleted and not captured in many studies. The much stronger correlation between the average

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carbon emission rate and k2 (R = 0.81, Pearson), rather than k1 (R = 0.12, Pearson), further confirmed this interpretation (Figure 6).

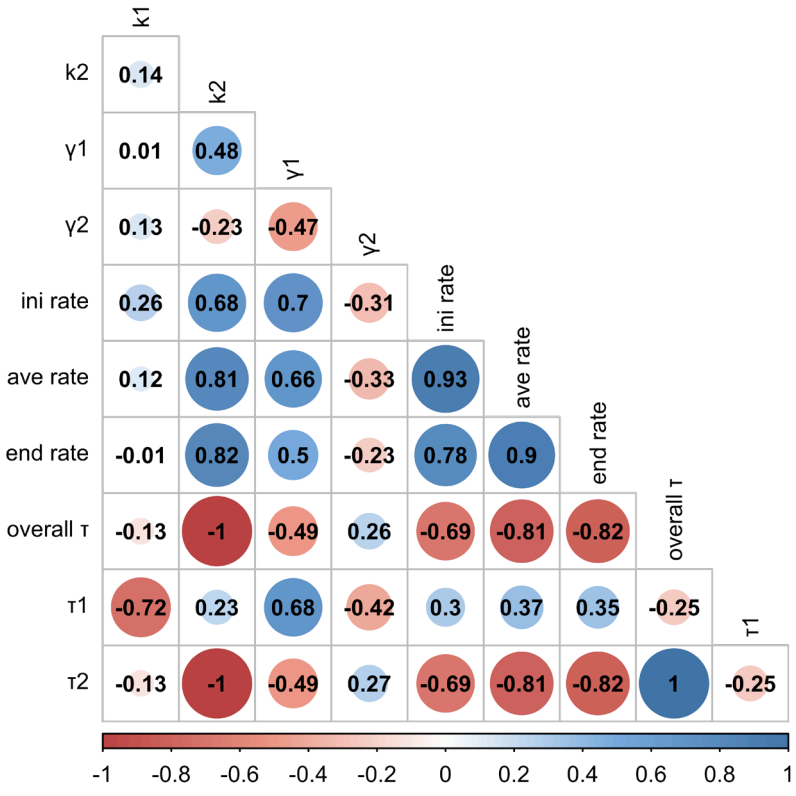

Figure 6. Correlation matrix of modelled parameters (k1, k2, γ1, γ2), measured carbon emission rates (initial, average, and end rates), and estimated carbon turnover times (overall τ, τ1, τ2) after log-scale transformation. Values represent Pearson correlation coefficients. k1 and k2 are decomposition rate constants, γ1 and γ2 represent the fast and slow carbon pools, and ini, ave, and end rates correspond to the first, average, and final CO_2 emission measurements. Turnover times (overall τ, τ1, τ2) are derived from the modelled parameters.

With fast carbon pools typically turning over being a few days, the overall carbon turnover time in our investigated sediments and compiled soils is governed by the slow pool, mostly ranging between 10 and 100 years (Figure 7). These estimates are of the same order of magnitude as those from Todd-Brown et al. (2013), indicating turnover times of 10–40 years in the top 1 m global soil calculated from soil organic carbon stock and net primary production. However, Ren et al. (2024) reported longer turnover times (89–696 years) based on a three-pool model incorporating a passive pool with smaller decomposition rate constant, applied to laboratory incubation data. These differences suggest that methodological choices can influence turnover time estimates. Additionally, it is important to mention that turnover times calculated from laboratory incubations may not

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fully represent differences from those under the field conditions. Feng et al. (2016) demonstrated that tracking carbon isotopes (^{13}C and ^{14}C) during decomposition in the field yields up to ten times higher turnover times compared to estimates based on laboratory incubations. However, field studies do not allow disentangling environmental conditions which are under natural circumstances inherently correlated. Therefore, incubation-based estimates under controlled conditions offer a valuable benchmark for quantifying carbon sensitivity to the individual environmental drivers, helping to better understand and diagnose soil OM-climate feedback (Zhou et al., 2024).

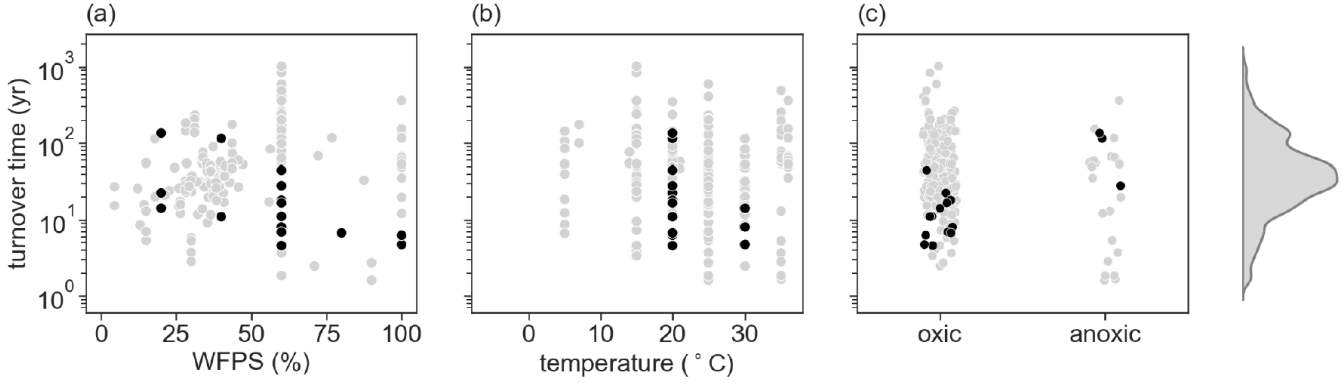

Figure 7. Estimated overall carbon turnover time based on the two-pool model in dredged sediments (black) and compiled soils and sediments (grey) under varying (a) moisture levels (WFPS, %), (b) temperatures (°C), and (c) oxygen conditions (oxic or anoxic). The panel on the right displays the overall distribution of turnover times. Turnover time could not be calculated for some samples where the two-pool model could not be resolved. All data are provided the Supporting Information.

Since the average carbon emission rate measured over the incubation primarily reflects the slow carbon pool, the relatively high emission rates observed in our dredged sediments under oxic conditions indicate a more reactive slow pool and thus shorter turnover compared to many soils. Environmental factors such as temperature, moisture, and oxygen availability affect turnover time (Figure 7) in ways consistent with their influence on average carbon emission rates (Figure 2, 3), with warmer, wetter, and oxic conditions accelerating decomposition. Whereas the relatively small labile OM pool fuelled high initial rates of CO_2 emission, more recalcitrant OM was a much more abundant OM pool dominating cumulative CO2 emissions on longer timescales. Moreover, the decomposition kinetics detailed in our analysis demonstrate the potential of using the average carbon emission rate over the entire incubation period (at least a few weeks) as a proxy for estimating long-term carbon stability across diverse soils.

4 Outlook

This study revealed trends in CO_2 emissions from dredged sediment and global soils as a function of moisture, temperature, and oxygen availability. Notably, dredged sediments exhibited similar response patterns to these environmental factors when

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compared to different soil types. However, discrepancies between our findings and those reported in the literature, particularly regarding the effect of moisture and temperature, as well as their optima for OM degradation, show the need to re-evaluate moisture and temperature functions in biogeochemistry models. Many models currently rely on moisture and temperature functions derived from limited datasets, which may oversimplify their effects on carbon release, reducing their applicability across different settings (Burke et al., 2003). Therefore, process-based models incorporating microscale processes, such as aggregate formation, are needed. These models may better represent the carbon release mechanisms under changing conditions and improve the predictability of carbon dynamics on longer time scales.

Vast amounts of dredged sediments are produced annually worldwide. The organic carbon in the PoR sediments showed higher carbon emission rates and greater reactivity than many reported soils, possibly due to better preservation of labile OM. Their pronounced sensitivity to oxygen suggests the importance of implementing suitable sediment management strategies to mitigate carbon loss. Practices such as anaerobic storage can reduce CO_2 emissions, although these might promote CH_4 production (Malet et al., 2023). While our experiment showed that sediment drying can substantially limit CO_2 emissions (potentially by restricting OM and nutrient transport), field-scale sediment management presents additional challenges. Dewatering methods, such as geotextile bag filtration, can lead to sediment compaction and the formation of an anaerobic environment, thereby increasing overall greenhouse gas emissions (Das et al., 2023; Wu, Nierop, et al., 2024). Additionally, atmospheric drying can induce sediment cracking, enabling trapped gases (particularly CH_4) to escape from deeper layers (Paranaíba et al., 2023). These discrepancies between controlled laboratory settings and field scenarios emphasize the complexity in translating laboratory findings to field-scale sediment management strategies. Investigation that integrates physical, chemical, and biological processes is needed to develop effective and field-based sediment management practices.

To offset the stimulated sediment carbon emission caused by perturbation and oxygenation during sediment management activities, it is essential to explore the benefits of sediment reuse in long term. For instance, Mchergui et al. (2014) demonstrated that carbon sequestration could occur after three years in a restored wetland using dredged sediment—a much shorter timeframe than the estimated carbon turnover in most soils and sediments (i.e. 10–100 years). Similarly, applying 5–7 cm of dredged sediment onto salt marsh was shown to promote rapid revegetation, enhance CO_2 uptake, and reduce CH_4 emissions (Puchkoff & Lawrence, 2022). These findings suggest that while disturbed sediment may initially enhance CO_2 release, integrating nature-based solutions into sediment management could offer a viable pathway to facilitate long-term carbon sequestration, transforming dredged sediment from a carbon source into a carbon sink.

5 Conclusions

Our sediment incubation experiments illustrated trends in moisture, temperature, and oxygen effects on carbon emission rates, consistent with results from a global meta-analysis of soil and sediment incubations using a machine learning approach. The

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optimal moisture for CO_2 emission rate in both our experiment and the global soil incubation dataset was found at a higher level (> 85% WFPS) than previously assumed (50–60 % WFPS). The optimal temperature for dredged sediment was between 20 °C and 30 °C, aligning with patterns observed in the global dataset. Additionally, the extent of the impact of oxygen availability on carbon emission rates was largely controlled by the original, in-situ redox conditions for the soils or sediments. Dredged sediments from the PoR exhibited relatively high carbon emission rates under oxic conditions compared to various soils, suggesting effective preservation of reactive OM in water-logging environments and thus requiring proper sediment management strategies in terms of carbon footprint. Despite some mentioned limitations (e.g. the lack of porewater and microbial information), our data uncovered important implications of major environmental factors in regulating carbon emissions from soils and sediments. Applying these findings could further improve the parameterization of biogeochemical models at a large scale to yield more robust estimates of land-atmosphere carbon fluxes, advancing our understanding of carbon-climate feedback under changing climate conditions.

Code and data availability

Data and code to reproduce the modelling results in this study are available in the NIOZ data archiving system, DAS, at https://dataverse.nioz.nl/dataset.xhtml?persistentId=doi:10.25850/nioz/7b.b.mj (Wu et al., 2025). The original soil incubation data are in the file 'Compiled_raw_data.xlsx'. The input data for the XGBoost and the generated soil decomposition kinetics data from the two-pool model are provided in the file 'Compiled_processed_incubation_dataset.csv'.

Supporting Information

Supporting Information can be found in the online version of this article.

Author contribution

Conceptualization: Guangnan Wu, Peter Kraal, Gert-Jan Reichart; **Data curation:** Guangnan Wu; **Formal analysis:** Guangnan Wu; **Funding acquisition:** Peter Kraal; **Investigation:** Guangnan Wu; **Supervision:** Peter Kraal, Gert-Jan Reichart; **Writing – original draft:** Guangnan Wu; **Writing – review & editing:** Peter Kraal, Gert-Jan Reichart, Guangnan Wu.

Competing interest

The authors declare no competing interest.

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