

Large underestimations of warming-induced soil carbon emissions from oversimplistic Q_{10} indicator

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ABSTRACT

The sensitivity of soil microbial respiration to climate warming is a major source of uncertainty in predicting soil carbon (C) emissions to the atmosphere and their feedback to climate change. One key issue is the persistent misuse of Q_{10} , the factor by which respiration rate is multiplied for a 10 °C increase in temperature, as an indicator of the temperature sensitivity. Despite ample empirical and theoretical evidence that Q_{10} is temperature-dependent, most publications on the topic continue to measure and conceptualise Q_{10} as being independent of temperature. Here, we analyse a published dataset of temperature incubations of soil microbial respiration across a global latitudinal gradient and project the resulting sensitivities onto global maps under four climate change scenarios. We reveal that omitting to account for the temperature dependence of Q_{10} leads to an underestimation of global soil C emissions from 2015 to 2100 ranging from 5.5 ± 2.4 PgC to 10.4 ± 6.9 PgC across different climate change scenarios. Moreover, beyond uncertainties in predictions of global soil C emissions, modelling inaccuracies are geographically skewed, with large underestimations at high latitudes (of up to 34 MgC ha^{-1}) and overestimations in warmer regions (of up to 12 MgC ha^{-1}). The disparate regional patterns have large implications for land stewardship, as management efforts could overlook soil C losses in vulnerable septentrional areas while unnecessary interventions could be recommended in tropical regions where soil C sequestration may not be as pressing.

1. Introduction

Soils globally contain approximately 1700 billion tons (or petagrams, Pg) of carbon (C), which is more than the atmosphere and global vegetation combined (Friedlingstein et al., 2022). This large pool is dynamic: soil C is continually lost to the atmosphere as carbon dioxide (CO_2) due to the activity of roots and soil heterotrophic microorganisms decomposing soil organic matter (commonly referred to as soil heterotrophic respiration), while C inputs from plants replenish the soil by capturing atmospheric CO_2 via photosynthesis. Under normal conditions, annual inputs balance the losses and maintain soil C in a steady state (Chapin et al., 2011). However, climate warming is disrupting this balance. If rising temperatures stimulate soil C release more than C inputs, net losses to the atmosphere will occur. This can propel global soils and atmosphere into a positive, self-reinforcing feedback loop that exacerbates climate warming (Bradford et al., 2016; Soong et al., 2021).

Despite hundreds of studies having explored this pressing issue, the direction and scale of this so-called land-climate feedback remain contentious (Nottingham et al., 2022; van Gestel et al., 2018). The core uncertainty arises from gaps in understanding the temperature sensitivity of soil heterotrophic respiration (Bradford et al., 2016; Conant et al., 2011), aggravated by inconsistent and occasionally ambiguous concepts and methodologies (Sierra, 2012).

One such ambiguity is the persistent misuse of the temperature coefficient (Q_{10}) as a measure of the temperature sensitivity. The Q_{10} serves as a measure of the proportional change in respiration rate in response to temperature variation, known as *relative* temperature sensitivity. It is usually measured as the ratio between two rates at any temperatures that are 10 °C apart, or derived from an exponential equation fitted to temperature response data (see Section 3). Both methods have the inherent implication that Q_{10} and relative sensitivity would be independent of temperature (see Supplementary Materials).

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There is, however, clear empirical and theoretical support for a temperature dependence of Q_{10} (Conant et al., 2008; Davidson and Janssens, 2006; Del Grosso et al., 2005; Hamdi et al., 2013; Kirschbaum, 1995; Moinet et al., 2018, 2021; Schipper et al., 2014), dating back as far as the early 20th century (Slaton, 1906). The exponential equation and the Q_{10} were even recognized as mere empirical convenience by their inventor, van't Hoff (Lloyd and Taylor, 1994), who also laid the theoretical basis (van't Hoff and Jacobus, 1884) later used by Arrhenius (1889) and Eyring (1935) to develop their eponymous equations which grounded empirical observations in thermodynamics theory.

Conceptual issues associated with temperature-independent Q_{10} estimates and temperature sensitivity have been highlighted before (Alster et al., 2020; García-Palacios et al., 2021; Schipper et al., 2014). And yet, we conducted a literature survey and reveal that nearly 86 % of papers published in the last five years (212 out of 245 papers) use temperature-independent Q_{10} values as a measure of temperature sensitivity (see Supplementary Materials). Overall, despite efforts to clearly layout pitfalls and support rigorous and consistent terminology (Davidson and Janssens, 2006; Kirschbaum, 1995; Schipper et al., 2014; Conant et al., 2011; Sierra, 2012), much confusion remains. The persistent use of temperature-independent Q_{10} values likely reflects the historical simplicity of the exponential model and the lack of widespread understanding of its limitations. To reduce future misuse, efforts should focus on clarifying conceptual definitions and engaging users on the mechanistic underpinnings and implications of different formulations. The present paper is an attempt to contribute to such endeavors.

Our objective is twofold: (i) clearly illustrating the conceptual difference between two commonly used Q_{10} estimation methods, as an effort to clarify the concepts surrounding the temperature sensitivity of soil microbial respiration in a new light; and (ii) quantify the consequences of overlooking the temperature dependence of Q_{10} on projections of global soil C emissions under four different climate scenarios.

The study presented hereafter builds on the dataset (Sáez-Sandino, 2023) compiled by Sáez-Sandino et al. (2023), which includes soil heterotrophic respiration rates (R) from a soil incubation experiment at four discrete temperatures from 0 to 30 °C. Additionally, the dataset includes diverse soil physical, chemical, and biological properties collected from 99 soil samples worldwide, spanning a wide range of mean annual temperature (MAT) from -7 to 30 °C. To address our first objective, we first compare the empirical exponential equation, which implies temperature-independent Q_{10} , with the Lloyd & Taylor equation (Lloyd and Taylor, 1994), a widely used and more theoretically grounded Arrhenius-based equation. Then, we analyse the resulting Q_{10} estimates and clearly laying out the conceptual flaw associated with the exponential equation. In our effort of clarification, we also extend our comparison to some of the main equations used in the literature to describe the temperature response of microbial respiration and provide an explainer including mathematical formulations to derive Q_{10} , relative and absolute sensitivities (Supplementary material). To address our second objective, we project parameters from both equations on a world map to simulate changes in soil C emissions from 2015 to 2100 across four climate change scenarios, and finally quantify the modelling inaccuracies associated with the use of the exponential equation.

2. Material and methods

2.1. Dataset

We downloaded the dataset (Sáez-Sandino, 2023) used and described in detail by Sáez-Sandino et al. (2023). The data comprise soil heterotrophic respiration rates (R) from a short-term (10 h) soil incubation experiment in which respiration rates were estimated at four discrete temperatures (0, 10, 20 and 30 °C) following the Microresp protocol (Campbell et al., 2003). The data also comprise diverse environmental and soil physical, chemical and biological properties. The original data presented and used in Sáez-Sandino et al. (2023) includes

soil samples from 332 ecosystems. Here, we used the subset of 99 soil samples for which both environmental and soil properties as well as temperature responses of respiration are provided (Sáez-Sandino, 2023).

The subset of 99 samples spans a wide range of environmental conditions, biomes, and pedoclimatic conditions. Available ecosystem properties for each sample comprise: mean annual temperature (MAT, range -6.7 to 29.2 °C), mean annual precipitations (MAP, range 17–2161 mm y⁻¹), plant species richness (range 0–61 species) and plant cover (range 0–97.8 %). Available soil properties comprise: soil organic carbon content (SOC; range 0.4–378.1 gC kg⁻¹ soil), soil microbial biomass as estimated from the glucose-induced respiration method (B_m , range 0.10–0.63 µgC g⁻¹ soil h⁻¹), soil C: N (based on total soil C and total soil N, range 3.4–29.0), total soil phosphorus (range 0–4440 mgP kg⁻¹ soil), pH in water (range 3.77–9.54), fine texture (Silt + Clay, range 0.5–88.2 %), electrical conductivity (range 22–9690 dS m⁻¹), the proportion of total carbon contained in mineral-associated organic carbon (MAOC, range 12.1–91.4 %) and particulate organic carbon (POC = 100 – MAOC).

Detailed information about the methods employed to measure all these variables can be found in Sáez-Sandino et al. (2023). Briefly, at each site, plant cover was measured during field surveys along three transects using the line interception method (Maestre et al., 2012). The total number of perennial species found at each transect was used as a measure of plant species richness. MAT and MAP were calculated based on the Worldclim database v2 (Fick and Hijmans, 2017). The soil sample from each site was collected as a bulked and homogenised sample of composite subsamples taken randomly under the main perennial vegetation from the 0–100 mm soil layer. Total C, N, P, electrical conductivity, texture, pH in water were measured using standard methodologies. MAOC and POC were separated based on size fractionation. Information is also provided on the biochemical recalcitrance of soil organic matter (percentages of alkanes, aromatics, polysaccharides and amides) that is based on diffuse reflectance mid-infrared Fourier transform spectroscopy (DRIFT). Finally, for a subset of samples (for 61 out of the subset of 99 samples, and 187 out of the total 332 samples), additional information on microbial community biomass and composition are provided that is based on the PLFA (PhosphoLipid Fatty Acids) method.

2.2. Temperature responses

For each individual soil sample, we fitted two different equations to the response of soil heterotrophic respiration (R) to temperature. The empirical exponential equation, as used by Sáez-Sandino et al. (2023) (Equation (1)), and the Lloyd & Taylor equation (Lloyd and Taylor, 1994) (Equation (2)).

$$R_{exp} = R_0 e^{\beta T} \quad (1)$$

T is the measurement temperature in °C, R_0 is a basal respiration rate at 0 °C in µgC g⁻¹ soil h⁻¹, and β is the slope of the (logarithmic) relationship in °C⁻¹.

$$R_{L\&T} = R_{10} e^{\left(E_0 \left(\frac{1}{56.02} - \frac{1}{T - 227.13} \right) \right)} \quad (2)$$

T is the measurement temperature in K, R_{10} is the decomposition rate at 10 °C and E_0 (K) is related to the steepness of the increase and is loosely related to the activation energy concept of Arrhenius.

2.3. Q_{10} analyses

Q_{10} can be estimated from Equations (1) and (2) with Equations (3) and (4), respectively as:

$$Q_{10,exp} = e^{10\beta} \quad (3)$$

$$Q_{10,L\&T} = e^{\frac{10E_0}{(T-227.13)(T-217.13)}} \quad (4)$$

where T is the temperature in K and β and E_0 are the parameters from Equations (1) and (2).

To illustrate the discrepancies between estimation methods, we first calculated Q_{10} for all samples following Equation (3). Then, we calculated Q_{10} for all samples using Equation (4) at five different temperatures ($-7, 0, 10, 20, 30$ °C), covering the range of MAT observed in the data. We also calculated Q_{10} using Equation (4) for two samples selected for their contrasting MATs, but this time, along a continuous temperature scale ranging from -7 to 30 °C.

2.4. Temperature response parameters analyses

We analysed the relationship between each estimated parameter R_0 , β , R_{10} and E_0 and the environmental and soil variables using backwards stepwise multiple regression analyses. The summary output of the best models describing R_0 , β , R_{10} and E_0 were extracted. For further analyses, we selected only SOC and B_m (see Section 2.7). Estimated regression coefficients and standard errors around those estimates between SOC and B_m on one hand, and R_0 , β , R_{10} and E_0 on the other hand, are provided in Table S1.

2.5. Map processing

Our projections were based on a range of publicly available global maps of SOC and microbial biomass (used to project the parameters R_0 , β , R_{10} and E_0 on maps using the regression coefficient in Table S1), as well as bulk density (used for converting emissions on a per land area basis). We downloaded maps of SOC content (in dg kg^{-1}), bulk density (in cg cm^{-3}) from SoilGrids 2.0 (Poggio et al., 2021) at 0–50 and 5–150 mm depth intervals. Maps were aggregated through averaging to the 0–150 mm interval and units were converted to g kg^{-1} and g cm^{-3} for SOC and bulk density, respectively.

Microbial biomass was obtained by summing up the maps of bacterial and fungal biomass from Bastida et al. (2021) (in $\text{nmolPLFA g}^{-1}\text{soil}$, normalised with $\log_{10} X + 1$) after back-transforming the individual maps with $10^x - 1$. The data we used for the regression analyses to estimate the effect of microbial biomass on the estimated temperature response parameters were collected using the glucose-induced respiration method and expressed in $\mu\text{gC g}^{-1}\text{soil h}^{-1}$. Thus, we converted the map to $\mu\text{gC g}^{-1}\text{soil h}^{-1}$ using the subset of 187 samples for which both substrate induced respiration and PLFA were used to determine microbial biomass. We made a linear correlation between the values of microbial biomass as quantified from the two methods and used the estimated parameters to convert the $\text{nmolPLFA g}^{-1}\text{soil}$ from the map to $\mu\text{gC g}^{-1}\text{soil h}^{-1}$. It is worth noting that the positive correlation between the two methods (Fig. S2) is significant ($p < 0.0001$), but weak ($R^2 = 0.19$). Further regression analyses revealed a positive correlation with SOC as well. Combined, SOC and microbial biomass from PLFA explained 50 % of the variability in microbial biomass measured using the glucose induced respiration method. Regression coefficients for both SOC and PLFA were used to convert the microbial biomass map.

We also used maps of MAT from 2015 to 2100 as predicted by five global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) under four the Shared Socioeconomic Pathways (SSPs) representing weak, moderate, strong, and very strong radiative forcing and referred to as SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 (V. Eyring et al., 2016). We accessed the ACCESS-CM2 (Australia), BCC-CSM2-MR (China), GFDL-ESM4 (USA), IPSL-CM6A-LR (France) and MRI-ESM2-0 (Japan) GCMs. These models were selected for their high spatial resolution and to represent a diversity of country and providers. We averaged the monthly temperature maps of each GCMs to produce GCM-specific yearly averages, and averaged the annual temperature maps across the five CGMs. All maps were projected to the

World Geodetic System 1984 (EPSG:4326) and resampled with bilinear interpolation to conform with a grid cell size of $0.08333333 \times 0.08333333^\circ$ (about 10 km at the equator).

2.6. Projections

First, we used the estimated parameters in Table S1 (and shown in Fig. S1) to project R_0 , R_{10} , β and E_0 on a world map using the SOC and microbial biomass maps processed as described above. From those parameters, we calculated $Q_{10, \text{exp}}$ and $Q_{10, L\&T}$ (Equations (3) and (4)) to visualise discrepancies between the two estimation methods on a map (Fig. S4).

Then, we initialised our simulations for the four CMIP6 climate change scenarios using 2015 as a starting year. To do so, we used the MAT maps in 2015 and R_{10} and E_0 maps to calculate initial values of R (R_{initial}) using the Loyd & Taylor equation (Equation (2)). Maps of R_{initial} ($\mu\text{gC g}^{-1}\text{soil h}^{-1}$) were converted to $\text{MgC ha}^{-1}\text{y}^{-1}$ to a depth of 150 mm using the bulk density map.

After initialisation, we simulated cumulative soil C emissions to the 2100 horizon under the four different climate warming scenarios. Following our own recommendations, we avoided the direct use of Q_{10} and preferred making use of the relative temperature sensitivity as defined in the supplementary equations. For each year between 2015 and 2100, we estimated R using the relative sensitivity derived from the exponential ($R_{\text{year, exp}}$, Equation (5)) and the Lloyd & Taylor ($R_{\text{year, L\&T}}$, Equation (6)):

$$R_{\text{year, exp}} = R_{\text{initial}} e^{\left(\beta(\text{MAT}_{\text{year}} - \text{MAT}_{2015})\right)} \quad (5)$$

where MAT_{year} is the temperature predicted for the specific year and MAT_{2015} is the temperature in 2015, in °C.

$$R_{\text{year, L\&T}} = R_{\text{initial}} e^{\left(E_0 \left(\frac{1}{(\text{MAT}_{2015} - 227.13)} - \frac{1}{(\text{MAT}_{\text{year}} - 227.13)} \right)\right)} \quad (6)$$

where MAT_{year} is the temperature predicted for the specific year and MAT_{2015} is the temperature in 2015, in K.

Then, for each climate change scenario, we made maps of the difference between soil C emissions estimated from the exponential equation and emissions estimated from the Lloyd & Taylor equation ($R_{\text{year, exp}} - R_{\text{year, L\&T}}$), and aggregated the maps through calculating the cumulated sum of the difference at the year 2100. We obtained four maps (one per climate change scenario, Fig. 3)

2.7. Statistical analyses

All analyses were conducted in R (version 4.2.2). Equations (1) and (2) were fitted to each respiration-temperature response curve using non-linear least square regressions. Mean estimated parameters were then extracted and analysed as functions of the environmental and soil properties provided in the dataset using backward stepwise regression analyses. First, correlations between explanatory variables were checked using Pearson's correlation coefficients. When pairs of variables were correlated with a coefficient higher than 0.6, one of the variables was discarded. Doing so, we excluded alkane percentage (correlated with SOC), amide percentage (correlated with polysaccharide) and MAP (correlated with soil pH). SOC and microbial biomass were also correlated between them, but in view of their importance in the analysis of Sáez-Sandino et al. (2023), they were kept in the present analysis. Then, we calculated variance inflation factors to test for collinearity among the remaining explanatory variables in our models. None of the values were greater than 10, so all variables were kept in our full models (James et al., 2013). The full models included SOC, B_m , soil C: N, total soil P, pH, fine texture, electrical conductivity, aromatics percentage, polysaccharide percentage, MAOC: POC ratio, MAT, plant cover and plant richness. The stepwise regression was conducted using Akaike's

information Criterion (AIC). The summary output of the best models was checked, which revealed that not all variables were significantly correlated with the temperature response parameters. Microbial biomass and SOC were the only variables presenting significant correlations with all temperature response parameters ($p < 0.05$, Fig. S1). Soil C: N was correlated significantly with R_0 ($p = 0.04$). Only regression coefficients with SOC and microbial biomass were used in further analyses.

Calculations to make maps of parameters and projections of soil carbon emissions were made as described above. To estimate the uncertainty in those projections related to the uncertainty in the estimated regression coefficients between SOC and B_m on one hand, and R_0 , β , R_{10} and E_0 on the other hand, we performed 100 Monte Carlo simulations by randomly sampling 100 sets of parameters R_0 , β , R_{10} and E_0 within a Gaussian distribution with the mean and standard errors of each regression coefficient estimates (Table S1). From these, we produced 100 maps for each temperature-response parameters, made 100 maps of $R_{initial}$ using the Lloyd & Taylor equation (Equation (2)) and made as many maps of $Q_{10, exp}$ as estimated from Equation (3) and of $Q_{10, L\&T}$ as estimated from Equation (4). From the 100 maps of $R_{initial}$, we ran as many simulations for each of the four climate change scenarios and for both the empirical exponential (Equation (5)) and Lloyd & Taylor (Equation (6)) estimation methods. We produced maps of standard deviations around the mean of those 100 simulations for $Q_{10, exp}$ and $Q_{10, L\&T}$ (Fig. S5) and for the cumulated difference (2015–2100) between carbon emissions estimated using the exponential and those estimated using the Lloyd & Taylor equations ($R_{year, exp} - R_{year, L\&T}$) for each climate change scenario (Fig. S6).

Finally, we estimated global soil carbon emissions and the error associated with the use of the exponential equation. For each of the 100 sets of temperature response parameters, each year and each climate change scenario, we calculated the difference in global emissions between exponential and Lloyd & Taylor methods by summing the difference in emissions for all pixels on the map divided by their size in hectare. Then, for each climate change scenario, we calculated the cumulative sum of the mean of the 100 Monte Carlo iterations over time between 2015 and 2100, from which we obtained the mean values and standard deviation.

3. Results and discussion

3.1. Similarities in estimated parameters

The exponential and Lloyd & Taylor equations are very similar in formulation, with a pre-exponential factor (R_0 for the exponential and

R_{10} for the Lloyd & Taylor equation) and an exponential parameter (β for the exponential and E_0 for the Lloyd & Taylor equation).

We find that R_0 and R_{10} are strongly positively correlated to each other (Fig. 1b), and somewhat less strongly than β and E_0 (Fig. 1a). Moreover, all parameters are largely explained by the same soil properties, namely the soil organic carbon (SOC) content and soil microbial biomass (Fig. S1). In all cases, SOC and microbial biomass are the strongest predictors and the only soil properties showing significant correlations with the parameters estimates. One exception is R_0 , which also shows a weak but significant positive correlation with the C: N ratio of the soil. An additive model that includes SOC and microbial biomass explains 79 % of the variability in R_{10} and 58 % of the variability in R_0 across the 99 samples (Fig. S1a and c). The same linear models explain 43 and 40 % of the variability for E_0 and β , respectively (Fig. S1b and d).

Similarities in formulation and estimated parameters may make the choice of equation appear trivial. Further, the parameters β and E_0 are both related to the slope of the relationship between respiration and temperature, and thus to the temperature sensitivity. Their strong correlation may suggest that the choice of equation has little influence on the outcome of analyses aimed at understanding the temperature sensitivity of soil processes, such that conducted by Sáez-Sandino et al. (2023) and others (Tian et al., 2022; Yan et al., 2017; Yu et al., 2023; Wang et al., 2023; Qin et al., 2019). This, however, is misleading.

3.2. Discrepancies in Q_{10} estimates

Estimations derived from the Lloyd & Taylor equation, as opposed to those derived from the empirical exponential equation, capture the temperature dependence of Q_{10} (Fig. 2a). At low temperatures, Q_{10} estimates from the Lloyd & Taylor equation are high, and then decrease with increasing temperature, as shown previously (Lloyd and Taylor, 1994; Moinet et al., 2021, 2020; Moinet and Millard, 2020; Schipper et al., 2014). Consequently, Q_{10} estimates are higher than those derived from the exponential equation at low temperatures, similar for intermediate temperatures, and lower at high temperatures (Fig. 2a). Sáez-Sandino et al. (2023) acknowledged that Q_{10} is dependent of temperature, and yet chose to derive temperature-independent Q_{10} from the empirical exponential equation with the aim of analysing Q_{10} *a posteriori* as a function of MAT. However, as illustrated in Fig. 2a, comparing two samples from the datasets with contrasting MATs (3.9 and 17.6 °C), this approach is ill-suited. Indeed, Q_{10} values estimated from the exponential equation are similar for both samples and close to 2 (1.87 and 2.05, for MATs of 3.9 and 17.6 °C, respectively), while the Q_{10} values estimated from the Lloyd & Taylor equation are further apart (2.45 and 1.95, for MATs of 3.9 and 17.6 °C, respectively).

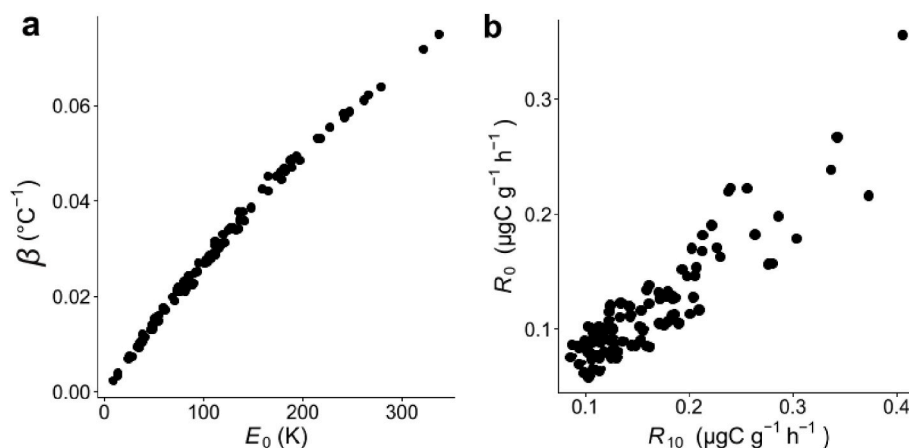


Fig. 1. Correlations between the estimated parameters of the exponential equation (R_0 and β) and the Lloyd & Taylor equation (R_{10} and E_0) for all 99 soil samples of the data set. In panel a, the exponential parameters β and E_0 are plotted against each other. In panel b, the pre-exponential parameters R_0 and R_{10} are plotted against each other.

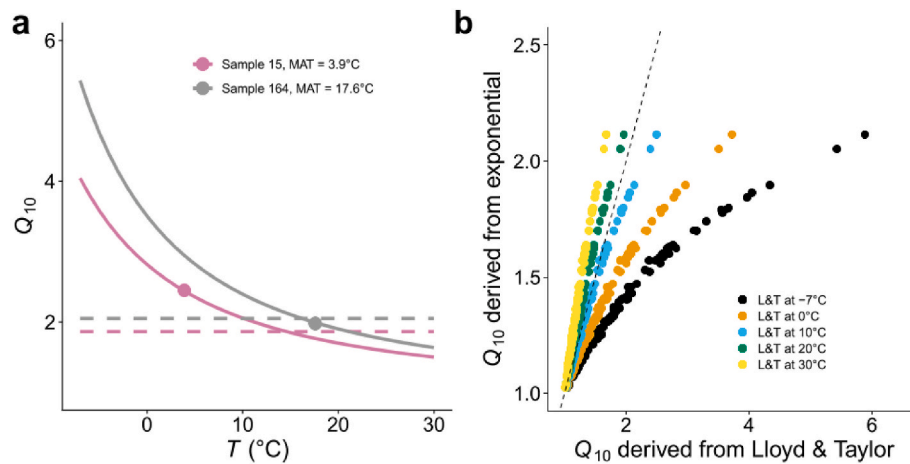


Fig. 2. Q_{10} values as estimated from the Lloyd & Taylor and the exponential equations. In panel a, the Q_{10} values for the exponential (dotted lines) and Lloyd & Taylor (plain lines) equations are plotted against temperature (T). Two individual samples from the datasets are used as examples (coloured points). Sample 15 (pink lines and point) was taken from a location with an MAT of 3.9 °C whereas sample 164 (grey lines and point) was taken from a location with an MAT of 17.6 °C. The two points on the plain lines represent the Q_{10} of each sample at their respective MATs. It appears that the Q_{10} of sample 15, with low MAT, is largely underestimated by the exponential equation (the point is much higher than the dotted line), while that of sample 164, with high MAT, is marginally overestimated by the exponential equation (the point is slightly lower than the dotted line). In panel b, the temperature-independent Q_{10} estimated from the exponential equation is plotted against Q_{10} as estimated from the Lloyd & Taylor equation at -7, 0, 10, 20, and 30 °C for all 99 soil samples of the dataset. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

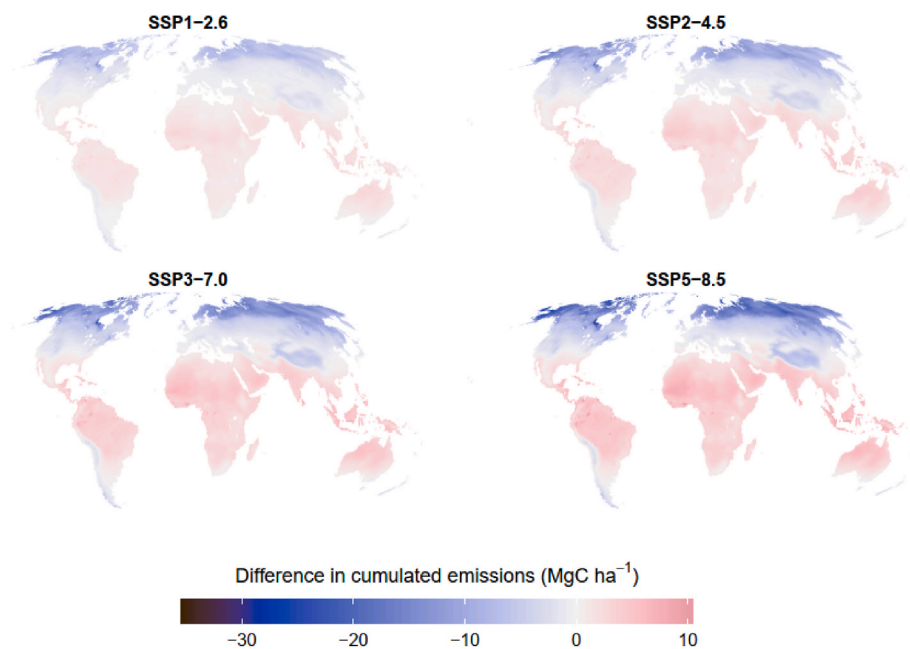


Fig. 3. Maps of differences between emissions as estimated from the exponential equation and those estimated from the Lloyd & Taylor equation, cumulated over the 2015–2100 period, and for the four CMIP6 climate change scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5. Estimates from the Lloyd & Taylor equation are deducted from those from the empirical exponential equation such that positive values (shades of red) signify overestimations from the exponential equation and negative values (shades of blue) signify underestimations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

We further illustrate the discrepancy by calculating Q_{10} estimates from the Lloyd & Taylor equation across a range of temperatures corresponding to the observed MAT range in the dataset, and then comparing these estimates, for each data point, to the temperature-independent Q_{10} values derived from the exponential equation (Fig. 2b). This visualisation reveals an interesting pattern: the discrepancy in Q_{10} estimates is largest for high Q_{10} values. It also confirms that at intermediate temperatures close to 10 °C, the equations are in broad agreement (especially for low Q_{10} values). However, with increasing temperatures above 10 °C, the temperature-independent Q_{10} derived

from the exponential equation provides an increasingly large overestimation of the relative sensitivity. Reciprocally, with decreasing temperatures below 10 °C, it provides an increasingly large underestimation.

This may suggest that choosing the wrong equation could lead to overestimated soil C losses in the tropics and underestimated losses at high latitude, where most soil C is stored, as suggested long ago (Kirschbaum, 1995; Raich and Schlesinger, 1992). However, while observations of Q_{10} and any measure of relative temperature sensitivity are crucial in biogeochemical modelling, they are insufficient to decisively

conclude on absolute quantities of C emitted (Davidson and Janssens, 2006; Sierra, 2012). As a proportional change in respiration rate per unit change in temperature, the relative temperature sensitivity must be analysed with respect to the *absolute* respiration rate to conclude on the magnitude of C emissions (see Supplementary Materials).

3.3. Large and geographically skewed inaccuracies

To infer on the absolute rates of C emissions and the magnitude of inaccuracies associated with the empirical exponential equation and its associated temperature-independent Q_{10} estimates, we projected the parameters estimated from the Lloyd & Taylor and exponential equations on a map using the regression coefficients with the strongest predictors (See Fig. S1 and Table S1). We produced a map of respiration rates for the year 2015, chosen as the starting point for our simulations. To this common initial soil C emissions map, we applied the relative temperature sensitivities as estimated from the exponential and Lloyd & Taylor equations to simulate climate warming-induced increases in soil C emissions for four scenarios from the Coupled Model Intercomparison Project Phase 6 (CMIP6) to the horizon 2100. To quantify the potential inaccuracies associated with the use of the empirical exponential equation, we show the cumulated differences between C emissions as estimated from Lloyd & Taylor and those estimated from the exponential equation, both as maps (Fig. 3) and as global emissions (Fig. 4). Our quantification confirms the trends suggested by the analyses of Q_{10} : overall, the exponential equation and temperature-independent Q_{10} leads to underestimations of C emissions at high latitude, of up to 34 MgC ha⁻¹ in the most pronounced case, and comparatively moderate overestimations at low latitudes (Fig. 3).

In addition, it can be noted that C emissions are underestimated along the east coast of South-America and north of India, close to the

Himalayas, presumably due to low MATs in those mountainous areas. The trends appear similar for all four climate change scenarios, but the magnitude of both under- and over-estimations increases as warming increases in more pessimistic climate change scenarios. It is worth noting that for some temperate regions, like in Europe, central Asia and North-America, the two methods (empirical exponential and Lloyd & Taylor) are in broad agreement in the most optimistic SSP1-2.6 scenario. However underestimations from the exponential equation appear in more pessimistic scenarios, for SSP2-4.5, and particularly for SSP3-7.0 and SSP5-8.5 (Fig. 3). Those trends are robust to the uncertainty related to the regression coefficients (Table S1) used to project temperature response parameters on the map, as estimated by the standard deviation around the mean from 100 Monte Carlo simulations (Fig. S6).

As for global soil C emissions cumulated over the 2015–2100 period, the projection inaccuracy associated with the use of the exponential equation ranges from 5.5 ± 2.4 PgC for the SSP1-2.6 scenario to 10.4 ± 6.9 PgC for the SSP5-8.5 scenario (mean $\pm$ standard deviation of 100 Monte Carlo simulations) (Fig. 4). These cumulated values may seem modest in comparison to the current annual anthropogenic CO₂ emissions of 10.8 PgC (Friedlingstein et al., 2022). But to give more perspective, a study of global soil respiration measurements suggested that soil C emissions rose by 1.9 PgC in the 19 years between 1989 and 2008 and attributed this increase to rising air temperature (Bond-Lamberty and Thomson, 2010). Nineteen years into our simulations (year 2034), our estimated inaccuracies associated with the use of the exponential equation range from 0.51 ± 0.26 to 0.76 ± 0.29 PgC, representing 27–40 % of the 1.9 PgC estimate from (Bond-Lamberty and Thomson, 2010).

3.4. The way forward

It is critical to note that our objective was not to predict absolute C emissions in different climate scenarios, but rather to quantify the potential inaccuracies associated with the use of the empirical exponential equation. Mapping respiration rates to the whole world from relatively few scattered points is subject to large uncertainties. Therefore, these results must be interpreted as a theoretical comparison under controlled assumptions, not as a full representation of soil carbon dynamics under future climates.

Overall, we show that conceptualising and quantifying Q_{10} and the relative temperature sensitivity as independent of temperature could lead to large and unevenly distributed inaccuracies in predicting climate warming-induced soil C emissions. Our comparative assessment using the Lloyd & Taylor equation is only a preliminary advancement towards a better accounting of the temperature sensitivity. Much has been developed since the original Lloyd & Taylor equation, with for example the development of the macromolecular rate theory (MMRT) (Schipper et al., 2014; Hobbs et al., 2013) or the enzyme-assisted Arrhenius equation (EAAR) (DeLong et al., 2017), and it must be recognized that the Lloyd & Taylor equation presents critical limitations. While the model introduces a temperature-dependent Q_{10} in alignment with Arrhenius kinetics, it implicitly assumes homogeneity in substrate properties and overlooks key processes that regulate substrate accessibility. As Sierra (2012) and Conant et al. (2011) highlight, soils store carbon in a spectrum of chemical forms and associations, each subject to distinct controls. Many of these, such as sorption-desorption dynamics, enzymatic depolymerization, or aggregate formation and destabilization, have temperature sensitivities that remain poorly quantified.

Much scientific literature aims at improving our understanding of how temperature sensitivity varies as functions of these processes, for example studying the role of substrate supply, microbial community physiology and microbial adaptation to long term warming in explaining the temperature sensitivity (Moinet et al., 2021; Karhu et al., 2014; Dacal et al., 2019; Alster et al., 2022, 2023), or variations in space along gradients in soil physico-chemical properties such as those related to the biochemical recalcitrance and the protection of C in the soil matrix

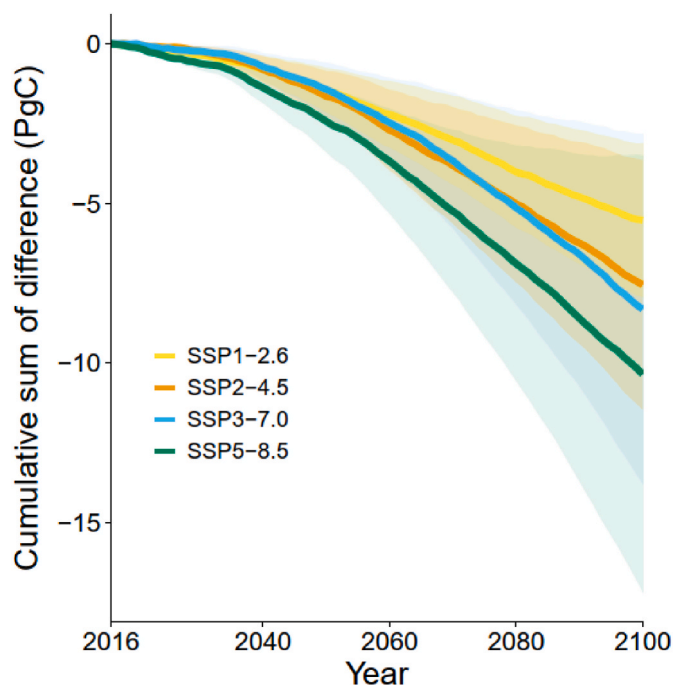


Fig. 4. Cumulative difference between global emissions as estimated from the exponential equation and those estimated from Lloyd & Taylor equation, over time and for the four CMIP6 climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). Estimates from the Lloyd & Taylor equation are deducted from those from the exponential equation such that negative values signify underestimations of the exponential equation. The lines represent the cumulative sum of the mean global soil carbon emissions from 100 Monte Carlo simulations. The shaded areas represent the standard deviation around this mean.

(Davidson and Janssens, 2006; Moinet et al., 2018; Conant et al., 2011; Sáez-Sandino et al., 2023; García-Palacios et al., 2024; Lugato et al., 2021; Liáng et al., 2023). Filling these knowledge gaps is critical indeed, as accurate predictions of the global land-climate feedback and of local changes in soil C depend on it. However, a significant portion of this literature overlooks the wealth of papers aiming at clearly laying out pitfalls, supporting rigorous and consistent terminology, and progressing the development of robust theories supporting empirical observations of temperature responses (Davidson and Janssens, 2006; Kirschbaum, 1995; Lloyd and Taylor, 1994; Schipper et al., 2014; Alster et al., 2020; DeLong et al., 2017; Arcus et al., 2016).

Abandoning temperature-independent Q_{10} estimates and the empirical exponential fit is an easy win with potentially high gains, but it remains insufficient. Bradford et al. (2016) recommended to integrate recent knowledge on the temperature sensitivity in predictive biogeochemical models. We agree with their recommendation and further emphasize that empirical studies should also embrace recently developed equations which are strongly rooted in thermodynamic theory, and engage with theoretical developments in the field.

As Davidson and Janssens (2006) pointed out: “it is important to remember that instantaneous temperature responses of decomposition of current C stocks reflect the relative abundances of organic C substrates of differing kinetic properties”. We can extend this observation to the relative abundance of different fractions with different physical and chemical protection mechanisms. Interestingly, in this light, the spatial patterns observed in our mapping exercise are consistent with observations that carbon stocks in cold climates are more sensitive to warming than those in warm regions, due to both climatic effects on turnover (Koven et al., 2017) as well as differences in stabilisation capacity (Hartley et al., 2021; Georgiou et al., 2024). In particular, these studies highlight that soils in colder or coarser-textured environments contain a larger proportion of unprotected carbon, which is more vulnerable to warming. Ultimately, as suggested for example by Schipper et al. (2019), we may need to abandon attempts at a single unified temperature response curve and instead fit different equations to different pools or processes, reflecting their distinct physical and chemical protection mechanisms.

3.5. Conclusion

After decades of research on the topic, the temperature sensitivity of soil microbial respiration remains debated. The sheer complexity of the topic is partly to blame, but lack of consideration for terminology and persistent use of outdated methods also hinder progress in the field. However well described the problematic use of Q_{10} has been in the past, the fact that 85 % of recently published papers overlook the scale-dependence of the temperature response testifies to the need for a clear reminder of the main limitations of Q_{10} . We stress here clearly that temperature independent Q_{10} estimates are erroneous and should not be used, particularly when comparing samples from contrasting climatic zones. Further, our quantification of potential inaccuracies associated with its use reveal large and geographically skewed errors in projections. These are too large to be ignored, and misleading with respect to land stewardship, as management efforts could overlook soil C losses in high latitude areas while unnecessary interventions could be recommended in tropical regions where soil C appear less vulnerable to climate warming.

CRedit authorship contribution statement

Gabriel Y.K. Moinet: Writing – original draft, Visualization, Formal analysis. **Karen Morán-Rivera:** Writing – review & editing, Methodology. **Antoine Moinet:** Writing – review & editing, Methodology. **Alexandre M.J.-C. Wadoux:** Writing – review & editing, Visualization, Methodology.

Data availability statement

All analysed data in this study are publicly available. The microbial respiration data and soil properties data for this study are available at: <https://doi.org/10.6084/m9.figshare.20776243> (ref. 24).

Spatially aggregated maps for organic carbon and bulk density are available at: https://files.isric.org/soilgrids/latest/data_aggregated/

Maps of mean annual temperature and precipitation were obtained from: <https://worldclim.org/data/worldclim21.html>.

Bacterial and fungal biomass maps were obtained from: <http://s://figshare.com/s/b75f1c08ceca22aa551b>.

CMIP6 climate projection were downloaded from the Climate Data Store: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6>.

Declaration of competing interest

The authors declare no conflict of interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.soilbio.2025.109839>.

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