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TOPICAL REVIEW

Carbon flux estimates are sensitive to data source: a comparison of field and lab temperature sensitivity data

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Abstract

A large literature exists on mechanisms driving soil production of the greenhouse gases CO₂ and CH₄. Although it is common knowledge that measurements obtained through field studies vs. laboratory incubations can diverge because of the vastly different conditions of these environments, few studies have systematically examined these patterns. These data are used to parameterize and benchmark ecosystem- to global-scale models, which are then susceptible to the biases of the source data. Here, we examine how greenhouse gas measurements may be influenced by whether the measurement/incubation was conducted in the field vs. laboratory, focusing on CO₂ and CH₄ measurements. We use Q₁₀ of greenhouse gas flux (temperature sensitivity) for our analyses because this metric is commonly used in biological and Earth system sciences and is an important parameter in many modeling frameworks. We predicted that laboratory measurements would be less variable, but also less representative of true field conditions. However, there was greater variability in the Q₁₀ values calculated from lab-based measurements of CO₂ fluxes, because lab experiments explore extremes rarely seen *in situ*, and reflect the physical and chemical disturbances occurring during sampling, transport, and incubation. Overall, respiration Q₁₀ values were significantly greater in laboratory incubations (mean = 4.19) than field measurements (mean = 3.05), with strong influences of incubation temperature and climate region/biome. However, this was in part because field measurements typically represent total respiration (Rs), whereas lab incubations typically represent heterotrophic respiration (Rh), making direct comparisons difficult to interpret. Focusing only on Rh-derived Q₁₀, these values showed almost identical distributions across laboratory ($n = 1110$) and field ($n = 581$) experiments, providing strong support for using the former as an experimental proxy for the latter, although we caution that geographic biases in the extant data make this conclusion tentative. Due to a smaller sample size of CH₄ Q₁₀ data, we were unable to perform a comparable robust analysis, but we expect similar interactions with soil temperature, moisture, and environmental/climatic variables. Our results here suggest the need for more concerted efforts to document and standardize these data, including sample and site metadata.

1. Introduction

Understanding the mechanisms that drive greenhouse gas (e.g. CO₂ and CH₄) production depends

on accurate measurements of the production of these gases. With the current trajectory of our changing climate, including rising temperatures and increasing precipitation fluctuations, we can expect accelerated

CO₂ and CH₄ flux from environmental systems, and it is important to understand mechanisms that drive these processes in order to build more robust predictive models. Such improvements are crucial, as the degree to which greenhouse gases from land ecosystems will feed back to the climate remains one of the least certain aspects of Earth System Models (ESMs) (Friedlingstein *et al* 2014).

Both field and lab experiments are used to understand temperature-driven changes in soil C and parameterize the models seeking to predict those changes. Field experiments provide an integrated site-level understanding of biogeochemical transformations, and—because of their similar scale to eddy covariance and remote sensing products—the potential to scale these processes and fluxes regionally and globally. However, their inherent complexity can make understanding mechanistic causality difficult; field measurements are often subject to low signal-to-noise ratios due to environmental and climatic fluctuations, or multiple interacting drivers that are difficult to unravel and control.

In contrast, laboratory soil studies occur in tightly controlled environments and are almost entirely experimental, rather than observational, which allows for clearer mechanistic understanding. However, laboratory experimental conditions may not accurately reflect *in situ* temperature and moisture variations (Kirschbaum 1995). In addition, and perhaps more importantly, sampling separates the soils from the pedosphere and thus laboratory incubations are inherently artificial, excluding the effect of roots, litter, and soil fauna, as well as processes such as nitrogen uptake and leaching (Williams *et al* 1998, Risk *et al* 2008). Sampling also introduces physical disturbances—such as cutting of roots and disrupting fungal hyphae—that alter the biological and biochemical conditions at the pore to core scale. As a consequence, laboratory incubations typically allow us to measure only heterotrophic respiration, Rh, whereas field experiments typically give us a measure of total soil respiration, Rs (i.e. autotrophic + heterotrophic), resulting in a further mismatch when directly comparing field and lab measurements of respiration (Bond-Lamberty *et al* 2004, Subke *et al* 2006). A troubling consequence is that measured variables and thus model parameterizations tend to systematically differ between these two approaches.

A complicating factor, but also a powerful potential way to examine these differences, is that models representing field and lab conditions tend to have different goals and structures. The predictive models that emerge from (and are needed by) field studies are generally simpler in structure, and tend to focus on larger-scale dynamics and processes (Manzoni and Porporato 2009). In contrast, the predictive models that emerge from lab studies tend to be more

mechanistic and limited in temporal and spatial scale. They are usually designed to serve very specific problems with explicit system simplifications, which may not be widely applicable, and their necessary parameters may not be measurable at a larger scale. Field-scale models, however, are also often parameterized using results from lab studies, resulting in large uncertainties in their predictive power. A typical example is modeling soil heterotrophic respiration processes in ESMs. Most land models in ESMs employ various empirical functions to represent the impacts of temperature and moisture changes on respiration rates. These empirical functions are mostly derived from lab based experimenters, e.g. (Moyano *et al* 2012, Sierra *et al* 2015), but have been frequently used to simulate field processes at regional or global scales. Model intercomparisons have shown large disagreement in simulated soil carbon dynamics (Wieder *et al* 2018), partly due to the variations in the functional format of temperature and moisture responses derived from lab experiments.

We propose that quantifying and explaining the gap between lab and field observations will reduce model uncertainties and provide a more systemic understanding of biogeochemical cycling, including how soils interact with temperature, moisture, and C inputs to drive transformations and fluxes in different ecosystems. Here, we specifically examine how greenhouse gas measurements may be influenced by whether the measurement/incubation was conducted in the field vs. laboratory, focusing on CO₂ and CH₄ measurements. We use Q₁₀ of greenhouse gas flux (temperature sensitivity) for our analyses, because of the ubiquity of this metric in biological and Earth system sciences and its importance to many modeling frameworks. Reported Q₁₀ values differ greatly between laboratory incubations (e.g. 1.6–2.7, Chen *et al* 2010), field observations (1.4–2.0, Zhou *et al* 2009), and earth system scale observations (1.4–1.5, Mahecha *et al* 2010, Bond-Lamberty and Thomson 2010b). This divergence causes significant problems for ESM parameterization and uncertainty quantification at ecosystem to global scales (Friedlingstein *et al* 2014).

Soil respiration and its Q₁₀ have been heavily studied for the last few decades, and numerous studies have identified key environmental and edaphic controls on the temperature sensitivity of soil respiration, including soil temperature and moisture (Kirschbaum 1995, Janssens and Pilegaard 2003, Carey *et al* 2016, Meyer *et al* 2018), texture/clay content (Zhang *et al* 2015), pH (Li *et al* 2020), carbon/substrate quality and availability (Hamdi *et al* 2013, Wang *et al* 2018), and land use (Meyer *et al* 2018). However, most of the synthesis studies focus either on field measurements e.g. (Raich *et al* 2002, Hibbard *et al* 2005, Xu-Ri *et al* 2019) or laboratory experiments (Kirschbaum 1995, Hamdi *et al*

2013), but a systematic and quantitative comparison between field and lab experiments is still missing.

We offer a unique, *quantitative* perspective of experimental biases introduced by incubation environmental conditions. This analysis of gas flux measurements at different scales will provide an opportunity to systematically understand the factors driving divergence of field and lab results.

2. Methods

2.1. Review criteria/search/screening

2.1.1. Data in published papers

The studies included in this analysis were identified by searching the Web of Science and Google Scholar databases until December 2021. The search terms used were ('CO₂' OR 'carbon dioxide' OR 'respiration' OR 'CH₄' OR 'methane') AND 'soil' AND 'Q₁₀'. We only included studies that reported Q₁₀ values. Some studies were syntheses/meta-analyses (e.g. Kirschbaum 1995, Hamdi *et al* 2013, Wang *et al* 2019, Chen *et al* 2020), and we also used these syntheses to identify additional sources of Q₁₀ data.

We recorded the Q₁₀ values, incubation temperatures/temperature ranges, site locations (latitude, longitude), and any experimental manipulations/treatments. We included only unmanipulated samples/controls in our analysis to avoid confounding effects of nutrient or substrate amendments, warming, burning, etc.

2.1.2. Published respiration databases

In addition, we also used data from publicly available (open access) soil respiration databases. The *Soil Respiration Database* (SRDB-V5) is a near-universal database of globally published field respiration measurements, particularly seasonal-to-annual respiration fluxes (Bond-Lamberty and Thomson 2010a, Jian *et al* 2020). This database includes 572 studies that reported Q₁₀ values, which were screened for studies that were in unmanipulated, natural (non-managed, including agricultural) ecosystems; these were then used directly in our current analysis without any further data manipulation, across all soil depths. The *Soil Incubation Database* (SIDb) is an open database containing time-series respiration measurements from 16 laboratory experiments (Schädel *et al* 2020, Sierra *et al* 2020). We extracted respiration flux data from this database and calculated Q₁₀ using the exponential equation (Cui *et al* 2020):

$$R_T = a \times e^{bT}$$

$$Q_{10} = \frac{R_{T+10}}{R_T}$$

where *a* and *b* are the fitted parameters for the model, R_T is the soil respiration rate at temperature *T* (Celsius), and R_{T+10} is the soil respiration rate at

temperature *T* + 10. A number of functions have conventionally been used to calculate Q₁₀ of soil respiration, with different parameters (Cui *et al* 2020)—we chose the exponential model because that was the most widely used function in the SRDB.

2.1.3. Screening

(a) Experimental manipulations—we included only unmanipulated samples/controls in our analysis. A list of manipulations reported in the SRDB is included in appendix A3. Where manipulations were part of the experimental design, we included only samples listed as 'control'. (b) Study durations—we included all studies, irrespective of study duration or time/season of data collection, as Q₁₀ has been previously been found to be independent of incubation duration (Reichstein *et al* 2005). (c) Measurement method—we did not filter data by measurement method, and we included all data and studies. However, we provide a comparison of the three common measurement types in appendix A6. Of the nearly 6000 data points for CO₂ Q₁₀ in this analysis, 4494 were measured using infra-red gas analyzers/IRGA (primarily LI-COR instruments, but also including other makes and models); 582 were measured by alkali absorption method; and 593 were by gas chromatography. Other measurement types included isotope ratio mass spectrometry, tunable diode laser absorption spectroscopy, or 'unknown' (not listed), but these measurements made up a very small portion (3%) of the data analyzed in this paper.

Based on these criteria, we identified a total of 744 studies for CO₂ Q₁₀ data and 47 studies for CH₄ Q₁₀ data (figures 1 and 2, table 1). Following the criteria outlined above, we extracted a total of 1230 datapoints (181 studies) from published papers, 4818 datapoints (1764 studies) from SRDB-V5, and 44 datapoints (16 studies) from SIDb.

2.2. Data processing

2.2.1. Incubation temperatures

Our compiled dataset contained flux data at various incubation temperatures, spanning a wide range of -15 °C–+60 °C (supplemental figure S1). Initial analysis was performed on the entire dataset, and these data were subsequently categorized into discrete classes to investigate the effect of incubation temperature on Q₁₀: <5, 5–15, 15–25, >25 °C (table 2).

2.2.2. Site climate and biome classification

Mean annual air temperature and precipitation for the study sites were obtained from the Center for Climate Research at the University of Delaware (Willmott and Matsuura 2001), and the sites were classified into one of five biome types (equatorial, arid, temperate, snow, and polar) based on the Köppen-Geiger climate classification (Kottek *et al* 2006, Appendix A2).

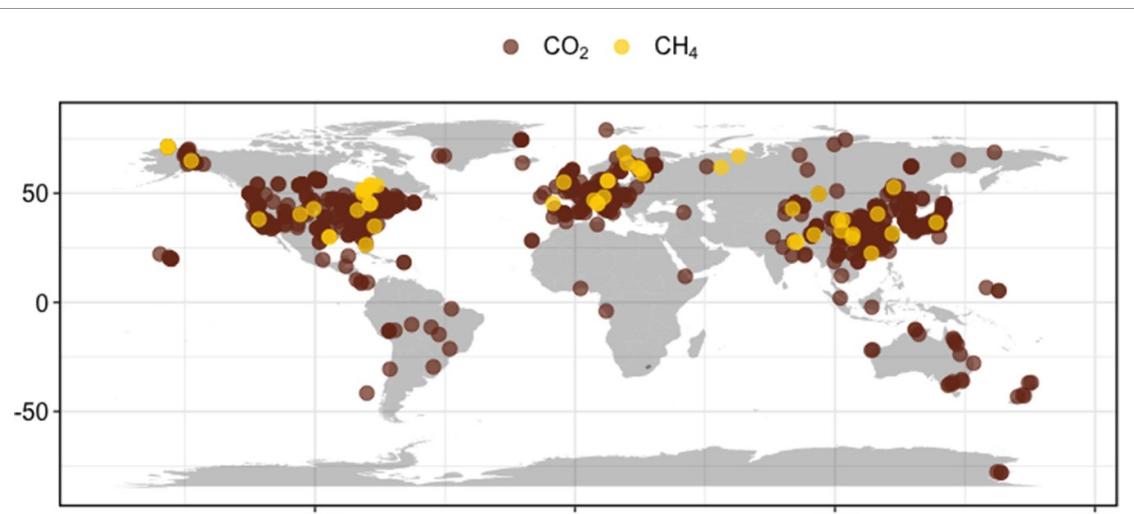


Figure 1. Spatial distribution of study sites. Red dots represent CO₂ measurements, yellow dots represent CH₄ measurements.

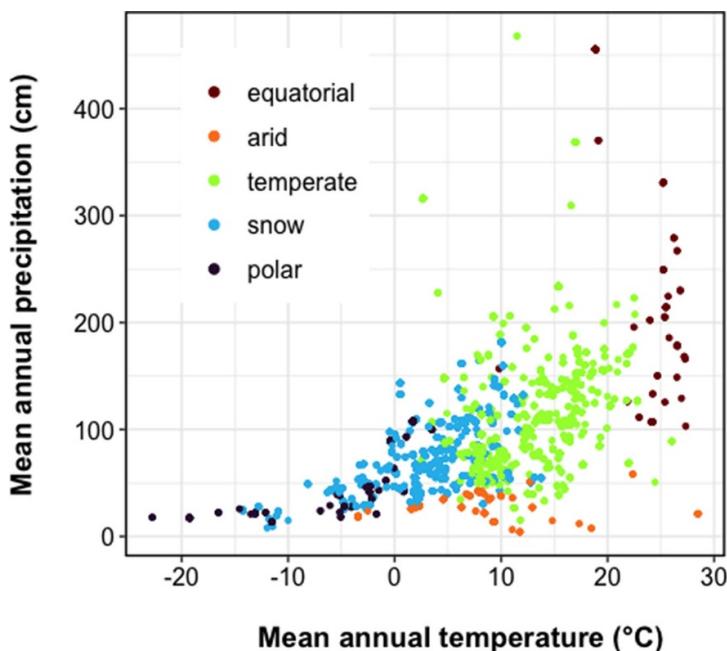


Figure 2. Distribution of study sites across different climatic regions (Köppen Climate Classification) (Kottek *et al* 2006). Of the 682 respiration studies assigned to a climate region, 4% were equatorial, 5% arid, 46.5% temperate, 38% snow, and 6.5% polar.

2.2.3. Partitioning of soil respiration

We used the 'RC' (root contribution) index provided within SRDB-V5 to identify data that were dominated by autotrophic vs. heterotrophic respiration. The RC index is defined as the ratio of annual Root to Rs, and is a unitless value ranging from 0 (no root contribution, or 100% heterotrophic/microbial) to 1 (no microbial contribution, 100% autotrophic/roots) (Bond-Lamberty *et al* 2004, Jian *et al* 2022). We used a cutoff of 0.5 to group our data into broad root/autotrophic dominated (RC > 0.5) vs. microbial/heterotrophic dominated (RC < 0.5) categories.

2.3. Statistical and data analysis

We used analysis of variance (ANOVA) to detect statistically significant differences between field and lab measurements. To account for unequal sample sizes between field and laboratory measurements, we employed a bootstrapping approach (10 000 iterations × sample size 10).

All data processing and analysis was performed using R version 4.1.1 (R Core Team 2021), primarily with packages *dplyr* v1.0.7 (Wickham *et al* 2021) and *tidyverse* v1.1.4 (Wickham *et al* 2021) for data cleaning/processing; and *ggplot2* v3.3.5 (Wickham 2016), *PNWColors* v0.1.0 (Lawlor 2020), and *soilpalettes*

Table 1. Number of studies and data points in this analysis.

	Field	Lab	Field	Lab
CH ₄ : number of datapoints		CH ₄ : number of studies		
Equatorial	NA	1	NA	1
Arid	2	12	2	1
Temperate	11	42	9	6
Snow	44	56	11	8
Polar	2	13	2	3
Not classified (lat-lon data not available)	2	8	2	3
TOTAL	61	132	26	21
CO ₂ : number of datapoints		CO ₂ : number of studies		
Equatorial	64	90	19	9
Arid	165	45	28	9
Temperate	1875	458	272	60
Snow	2568	160	235	28
Polar	120	113	29	18
Not classified (lat-lon data not available)	67	141	11	24
TOTAL	4859	1007	594	148

Table 2. Summary statistics of CO₂ Q₁₀ values. Asterisks represent significant differences between field and laboratory measurements, at $\alpha = 0.05$.

	CH ₄		CO ₂	
	Field	Lab	Field	Lab
Overall summary				
Mean	6.14	5.51	3.05	4.19*
Median (50th percentile)	4.10	3.10	2.66	2.35
1st percentile	0.92	1.05	1.13	1.00
25th percentile	2.41	1.73	2.03	1.90
75th percentile	5.31	5.75	3.40	3.00
99th percentile	56.88	34.69	10.54	49.94
By biome (mean values)				
Equatorial	NA	14.00	2.78	2.39
Arid	2.91	4.23	1.76	2.48*
Temperate	9.56	2.92	2.82	3.52
Snow	5.64	6.97	3.30	7.95*
Polar	3.01	8.12	3.37	5.69
By temperature range (mean values)				
5 °C–15 °C			2.93	3.33*
15 °C–25 °C			2.54	2.29*
>25 °C			3.07	2.08*

v0.1.0 (Patel and Bond-Lamberty 2022) for data visualization. All data and scripts are available on GitHub (https://github.com/kaizadp/field_lab_q10, 10.5281/zenodo.7106554) and archived on ESS-DIVE (10.15485/1889750).

3. Results and discussion

3.1. CH₄: no difference between field and laboratory measurements

The Q₁₀ values for CH₄ ranged from 0.80 to 83.00 and did not differ significantly between field and lab measurements (figure 3, ANOVA, $F = 0.183$, $P = 0.670$). The smaller sample size of the CH₄ data did not permit robust analyses based on temperature or climate grouping, as we did for CO₂ (see below). Because methane is such an important greenhouse

gas, we share our limited results here, and suggest that broader efforts to quantify and document methane emissions are needed.

3.2. CO₂: laboratory measurements were more variable than field measurements

Overall, Q₁₀ values for CO₂ ranged from 0.56 to 132 for field measurements (mean = 3.05) and from 0.50 to 344 for laboratory incubations (mean = 4.19) and differed significantly between the two experiment types (figure 4(A), ANOVA, $F = 18.9$, $P < 0.001$). Contrary to our expectations, laboratory measurements were significantly more variable than field measurements (F -test, $F = 38.547$, $P < 0.001$; coefficient of variation: field = 103%, lab = 409%). Despite these wide ranges and high variability, the median Q₁₀ values were generally similar for the two: 2.66

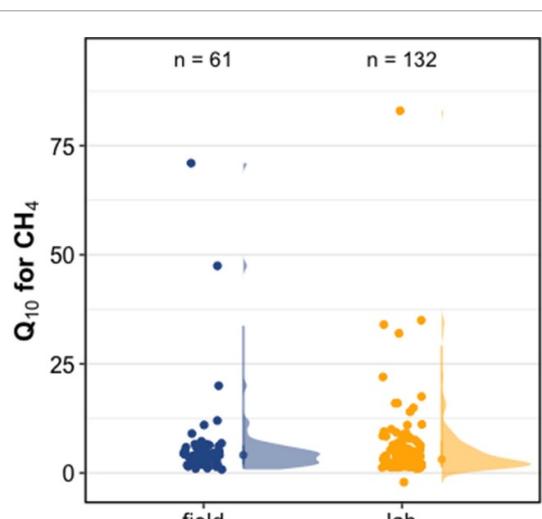


Figure 3. Q_{10} values for CH_4 measurements. The Q_{10} values were not significantly different for field vs. laboratory ($\alpha = 0.05$).

for field measurements vs. 2.35 for laboratory measurements. These median values are noticeably higher than generalized values in the literature; respiration Q_{10} is often assumed to be 1.5 or 2 (Raich *et al* 1991, Potter *et al* 1993, Ise and Moorcroft 2006, Foereid *et al* 2014).

3.3. Extreme values may represent laboratory artifacts

Incubation temperature has long been recognized as a strong driver of temperature sensitivity (Kirschbaum 1995, Chen and Tian 2005), due to the fundamental underlying biokinetics (Davidson and Janssens 2006), and we see a consistent pattern in figure 4(B). Q_{10} measurements at lower temperatures were typically 1–2 orders of magnitude greater than those at higher temperatures. Because these values represent ‘apparent’ temperature sensitivity (*sensu* Davidson and Janssens 2006), they have a long right-hand tail of seemingly extreme values.

In our analysis, most of the Q_{10} values > 30 (99.9th percentile in field measurements) were from snow and polar regions (with a few temperate), in laboratory experiments with nearly zero or sub-zero incubation temperatures (appendices A4 and A5). Many of these ‘extreme’ data were obtained from Mikan *et al* (2002), who reported drastically greater Q_{10} values for frozen ($Q_{10} = 63\text{--}237$) compared to thawed soils ($Q_{10} < 10$) in laboratory incubations of arctic tundra soils, suggesting shifting controls on respiration as soils are frozen. Water is an important driver of soil respiration, affecting spatial accessibility and substrate bioavailability (Bailey *et al* 2019, Patel *et al* 2021), including controls on substrate and enzyme diffusion (Ebrahimi and Or 2015, Zheng *et al* 2022). Freezing water below 0 °C limits the diffusion of substrates, nutrients, and enzymes

in soils, providing additional physical barriers for substrate access, compared to unfrozen soils. This can decouple the link between temperature sensitivity and substrate decomposition (Ostroumov and Siegert 1996). The Q_{10} values of frozen soils therefore do not accurately represent kinetic response to temperature, and instead are more likely to represent physical barriers to diffusion.

It is interesting to note that it was only the lab experiments that showed such high Q_{10} values for sub-zero incubation temperatures. Most field Q_{10} values were below 30, including for sub-zero temperatures, with only two measurements higher, at 105 and 131 (Nakane *et al* 1997, Monson *et al* 2006). This would suggest that the laboratory incubations introduced experimental artifacts that may have influenced the high Q_{10} values, including physical disturbance of sampling and sieving, disruption of roots and microbes, releasing fresh labile carbon into the system (Curtin *et al* 2014, Herbst *et al* 2016). Researchers must thus be cautious and aware of experimental and environmental artifact that can influence these values, when comparing data across different experiments.

3.4. Q_{10} by biome and ecosystem type

The spread in Q_{10} values was greatest for ‘cold-influenced’ biomes (i.e. temperate, snow, and polar), as high as 150 in temperate, 237 in snow, and 344 in polar regions (figure 5(A)). The median Q_{10} values were consistently between 1.5 and 2.5 across all five biomes, despite the wider ranges and greater variation for the cold-influenced regions. There was a significant difference between field and lab measurements in arid and snow regions (lab $>$ field, ANOVA, $P < 0.01$), but not in any of the other biomes. We suggest that the difference was greatest in these two biomes because they represent regions that are strongly constrained by environmental conditions (one is dry and one is cold), and thus even small shifts in water content or temperature during laboratory incubations would likely induce strong responses. For arid soils, in particular, soil respiration is decoupled from temperature and less sensitive to temperature changes, because drought reduces access to organic substrate—leading to lower Q_{10} values (Jassal *et al* 2008, Suseela *et al* 2012, Carey *et al* 2016). Liu *et al* (2016a) reported that soil respiration in arid areas was strongly influenced by increased precipitation, whereas more humid regions would be less sensitive to precipitation/moisture changes, and we can assume similar responses to laboratory incubations, as water is added to the experimental units.

For all biomes except arid, there was a significant difference in variability between field and lab measurements (*F*-test, $P < 0.001$). For equatorial regions, field measurements were more variable than lab. But for temperate/snow/polar, lab measurements were more variable than field, strongly influenced

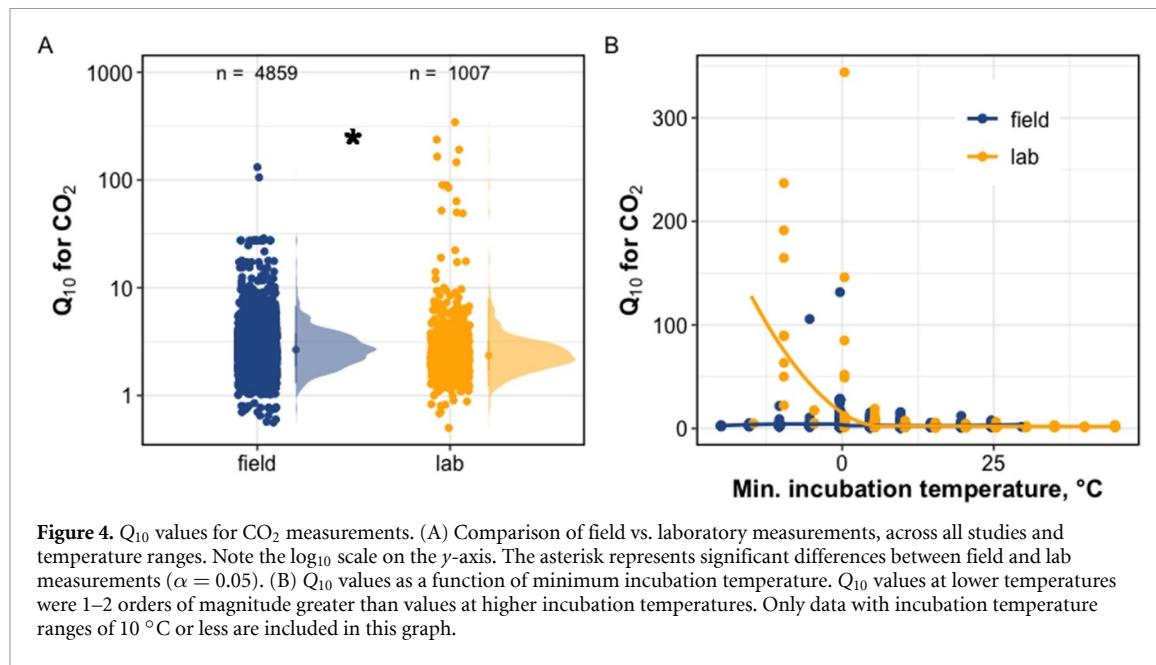


Figure 4. Q_{10} values for CO_2 measurements. (A) Comparison of field vs. laboratory measurements, across all studies and temperature ranges. Note the \log_{10} scale on the y -axis. The asterisk represents significant differences between field and lab measurements ($\alpha = 0.05$). (B) Q_{10} values as a function of minimum incubation temperature. Q_{10} values at lower temperatures were 1–2 orders of magnitude greater than values at higher incubation temperatures. Only data with incubation temperature ranges of 10°C or less are included in this graph.

by the extreme values. This is interesting because we expected field measurements to be more variable, in contrast to the tightly controlled conditions found in laboratory experiments. However, these data represent all the measurements across all incubation temperatures, including more ‘extreme’ laboratory incubations. In fact, the range of incubation temperatures for laboratory experiments was much broader than that seen in field measurements, indicating that the lab incubations may not always reflect the ‘normal’ field conditions (appendices A4 and A5). Additional experimental artifacts may also drive the variability in the laboratory measurements, including the physical disturbance of sampling and sieving, which could damage/cut roots and hyphae, introducing fresh carbon for metabolism. This may be a source of a carbon surge that is more temperature sensitive than the naturally turned over carbon in the field (Zimmermann and Bird 2012, Datta *et al* 2014, Sokol and Bradford 2018, Makita *et al* 2021). However, when excluding $Q_{10} > 30$, equatorial, snow, and temperate regions showed significant differences in variability between field and lab.

When grouped by ecosystem type (figure 5(B)), there were significant differences between field and lab measurements only for forest (field > lab) and wetland (lab > field). For wetland soils, this might be due to experimental artifact, as most respiration incubations are performed on partially saturated soils, as opposed to field conditions, where the soils are presumably saturated. Forest soils made up the majority of the data in this synthesis, and the differences in field vs. lab are likely due to the variable incubation/experimental temperatures, and the unequal distribution across biomes (field data points

were 42% temperate and 54% snow, whereas lab data points were 54% temperate and 10%–15% each of snow, polar, and equatorial).

3.5. Effect of incubation temperature

The results in figures 4 and 5 include data across all incubation temperatures from -15°C to $+60^{\circ}\text{C}$ (incubation temperature ranges provided in figure S1) and therefore do not provide an accurate comparison of field vs. laboratory measurements. Q_{10} measurements at lower temperatures are typically 1–2 orders of magnitude compared to higher temperatures (figure 4(B)) (Kirschbaum 1995, Mikan *et al* 2002, Chen and Tian 2005), and we therefore need to account for this when comparing Q_{10} values across different studies.

To account for these temperature effects, we split the data into groups based on incubation temperature ranges: 5°C – 15°C , 15°C – 25°C , and $>25^{\circ}\text{C}$ (figure 6(A)). We chose only studies where incubation temperature ranges were 10°C or less (for instance, 5 – 10 , 10 – 12 , and 5 – 15°C all fell under the group 5 – 15°C ; but 5 – 25°C was excluded). We chose these groups because they had the greatest number of datapoints, allowing for a more robust analysis (appendix A1). Another consideration was to prevent confounding effects of freezing (Mikan *et al* 2002)—we therefore chose 5 – 15°C , and not 0 – 10°C . For this analysis/figure, we only include data from incubations above 5°C (figure 6(A)), as we did not have sufficient data points below 5°C for a robust analysis.

When split into these temperature range groups (5 – 15°C , 15 – 25°C , and $>25^{\circ}\text{C}$), there were significant differences between field and laboratory measurements, although the trends differed by

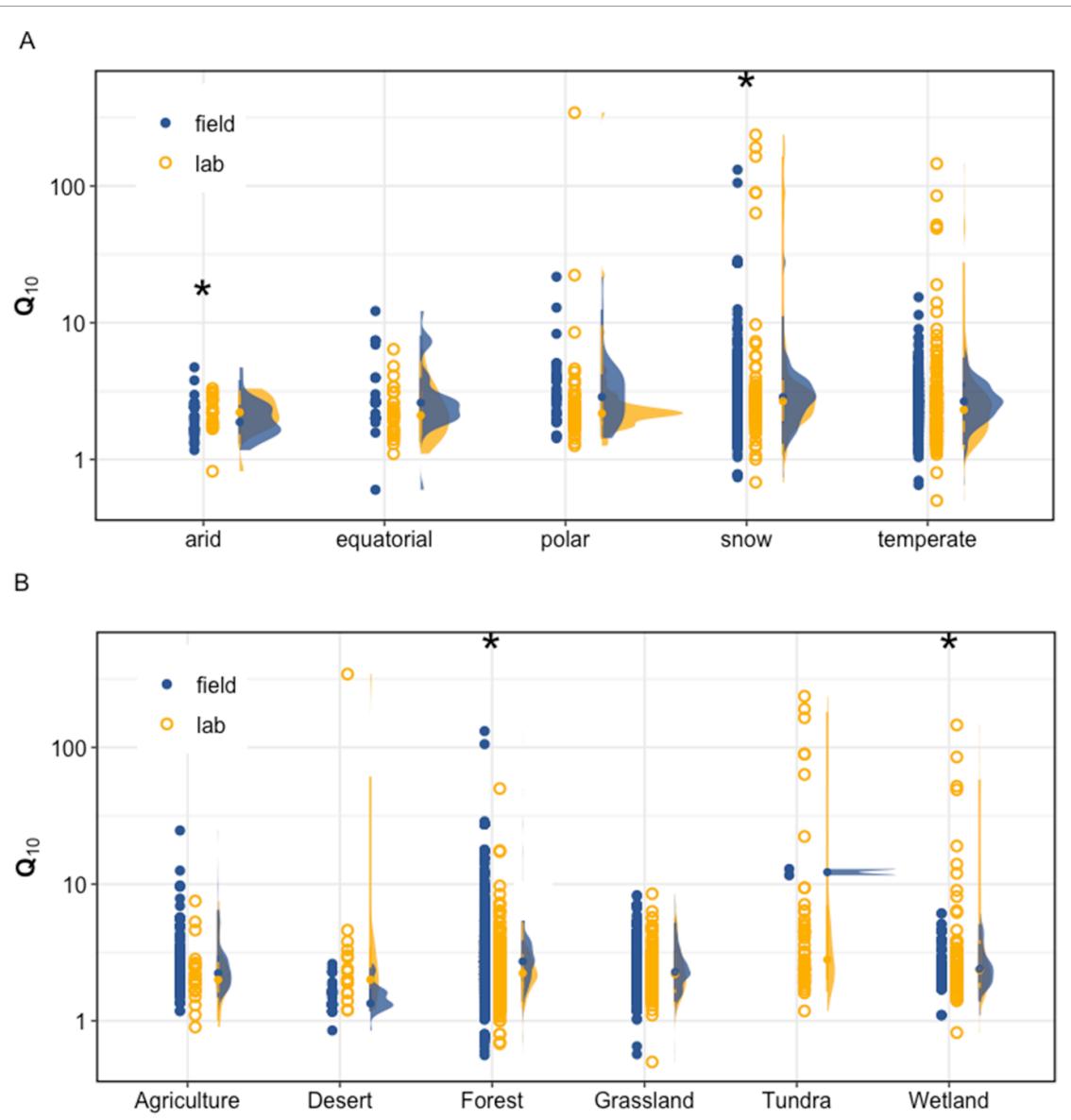


Figure 5. (A) Q_{10} values for CO_2 , by climate region. Asterisks represent significant differences between field and lab measurements ($\alpha = 0.05$). Sample numbers for each climate region can be found in table 1. (B) Q_{10} values for CO_2 , by ecosystem type. Asterisks represent significant differences between field and lab measurements ($\alpha = 0.05$). Sample sizes are as follows: agriculture: field = 255, lab = 23; desert: field = 41, lab = 17; forest: field = 3619, lab = 491; grassland: field = 632, lab = 112; tundra: field = 2, lab = 55; wetland: field = 102, lab = 72.

incubation temperature range: for $5\text{ }^{\circ}\text{C}$ – $15\text{ }^{\circ}\text{C}$, lab $Q_{10} >$ field Q_{10} ; whereas for $15\text{ }^{\circ}\text{C}$ – $25\text{ }^{\circ}\text{C}$, and $>25\text{ }^{\circ}\text{C}$, field $Q_{10} >$ lab Q_{10} (figure 6(A)).

These comparisons were done on unequal sample sizes (see figure 6(A)). Such sampling inequality complicates frequentist statistical tests, and we therefore performed a bootstrapping analysis on these data to compare data across equal sample sizes (figure 6(B)). The trends between field and laboratory data still held true after the bootstrapping analysis, with laboratory $Q_{10} >$ field Q_{10} for $5\text{ }^{\circ}\text{C}$ – $15\text{ }^{\circ}\text{C}$, and field $Q_{10} >$ laboratory Q_{10} for $15\text{ }^{\circ}\text{C}$ – $25\text{ }^{\circ}\text{C}$, and $>25\text{ }^{\circ}\text{C}$. It is interesting to note that despite the wide spread of Q_{10} values, the bootstrapped data remained only between 0 and 10, highlighting once again the overall rarity of the extreme values.

Why the different trends? Due to stronger temperature limitations on respiration at lower temperatures, it is likely that these soils were more sensitive or responsive to other sampling disturbances or incubation artifacts, increasing the variability across seemingly comparable experimental incubations. On the other hand, these responses could be muted or countered by other factors at higher incubation temperatures. Another reason for this variable pattern across temperatures could be respiration partitioning (autotrophic vs. heterotrophic vs. total soil respiration), as the shifting balance between autotrophic (R_a) and heterotrophic (R_h) respiration across temperatures is an important factor to be considered (Wei *et al* 2010, Rankin *et al* 2021, Lei *et al* 2022), as we discuss below.

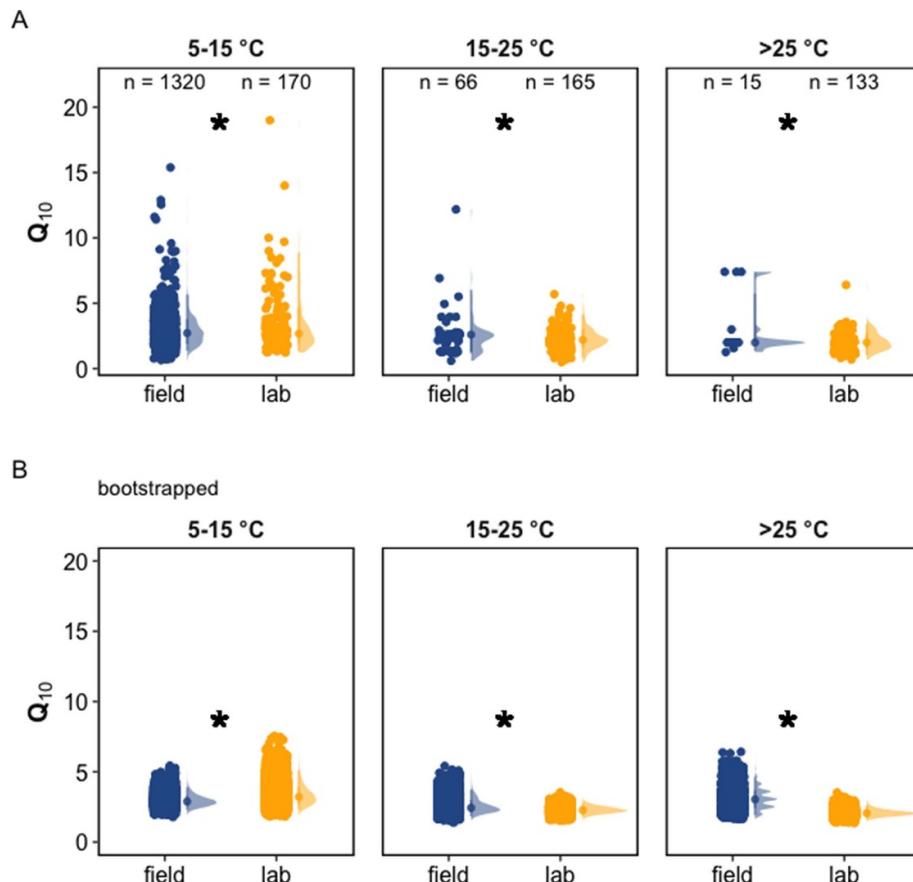


Figure 6. Q_{10} values for CO_2 by incubation temperature range. (A) Comparison of field vs. lab based on unequal sample sizes. (B) Comparison of field vs. lab based on bootstrapped data (10 000 points). Asterisks represent significant differences between field and lab measurements ($\alpha = 0.05$).

3.6. Heterotrophic soil respiration was comparable between field and lab

A complication when comparing field and laboratory respiration measurements is the measurement of heterotrophic vs. total soil respiration, R_s (Bond-Lamberty *et al* 2004, Subke *et al* 2006, Maseyk *et al* 2008, Liu *et al* 2016b, Bond-Lamberty *et al* 2018, Feng *et al* 2018). Soil surface CO_2 flux (total soil respiration) consists of respiration by roots (autotrophic respiration, R_a) and respiration by soil organisms (heterotrophic respiration, R_h). In contrast, laboratory incubations of CO_2 flux generally account only for heterotrophic respiration, because roots are often cut and removed for these experiments. Greenhouse experiments offer an alternative to laboratory experiments to address respiration partitioning—they can provide the experimental control needed, and the inclusion of plants in greenhouse incubations can provide estimates of total soil respiration. However, we do not have sufficient Q_{10} data from these studies for our analysis, and they are not included here.

Thus, a direct comparison of field vs. lab may not provide accurate comparisons, and we must account for differences due to respiration partitioning when we analyze data across different experiments. Most of the SRDB data represent total soil respiration in

the field, but some studies (e.g. Dhital *et al* 2010, Ruehr and Buchmann 2010, De Simon *et al* 2013, Yan *et al* 2015) partitioned total soil respiration into autotrophic and heterotrophic components. We used the ‘RC’ (root contribution) index provided within SRDB (Bond-Lamberty and Thomson 2010a) to compare data that were dominated by autotrophic ($RC > 0.5$) vs. heterotrophic ($RC < 0.5$) respiration (figure 7). Q_{10} values for autotrophic-dominated respiration were significantly greater than those for heterotrophic-dominated respiration (mean autotrophic = 3.13, heterotrophic 2.70; ANOVA, $F = 24.67$, $P < 0.001$, table 3). Interestingly, the distributions of R_h -dominated field data and laboratory data (R_h -only) showed a strong overlap, suggesting that, based on this limited dataset, heterotrophic respiration measurements may be similar across field and lab experiments.

The almost identical distributions of laboratory- and field-derived Q_{10} values for R_h (figure 7) provide strong support for using the former as an experimental proxy for the latter.

The contribution of R_a vs. R_h to total soil respiration is an important consideration for field measurements. Since root respiration is more sensitive to temperature changes, R_a is likely to have a stronger

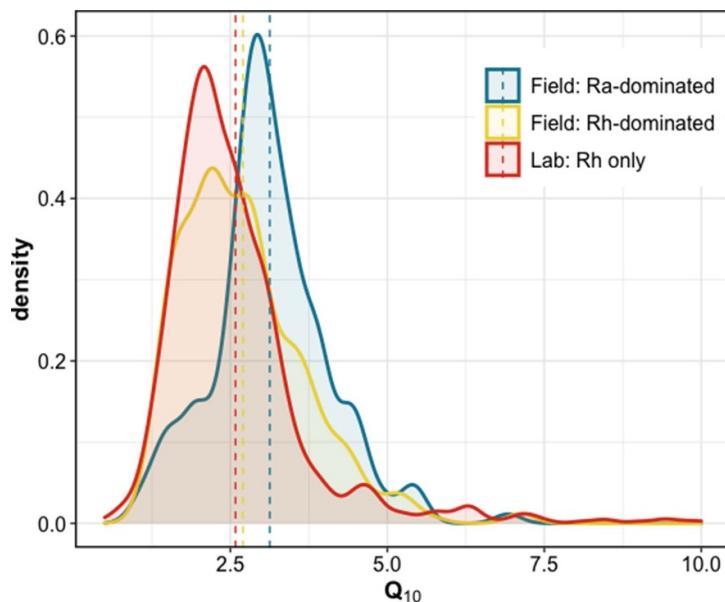


Figure 7. Density plot of Q_{10} for heterotrophic (Rh) vs. autotrophic (Ra) dominated respiration. Field-based data were classified as Ra-dominated or Rh-dominated based on the RC index (root contribution) from SRDB. All laboratory-based data reflect Rh. The dashed lines represent the means for the groups (field-Ra = 3.13; field-Rh = 2.70; lab-Rh = 2.58). The Ra-dominated field Q_{10} data were significantly different from Rh-dominated field and laboratory (Rh) Q_{10} data (ANOVA, $P < 0.001$). The Rh-dominated field Q_{10} data were not significantly different from the laboratory (Rh) Q_{10} data (ANOVA, $P = 0.764$).

Table 3. Summary statistics of field-derived CO_2 Q_{10} values, partitioned into Ra-dominated and Rh-dominated. The asterisk represents statistically significant differences between Ra- and Rh-dominated Q_{10} values.

	Ra-dominated	Rh-dominated
<i>n</i>	167	581
Mean	3.13	2.70*
Median (50th percentile)	3.06	2.56
1st percentile	1.17	1.30
25th percentile	2.66	2.00
75th percentile	3.53	3.22
99th percentile	5.42	5.39

phenological/seasonal pattern (Schindlbacher *et al* 2009), with ‘root growing periods’ inflating respiration rates because of increased fine root/fine tissue respiration during this period (Boone *et al* 1998, Epron *et al* 1999, Hanson *et al* 2003, Davidson *et al* 2006). Conversely, microbes are generally more insulated from aboveground temperature changes, and are therefore less likely to show strong seasonal patterns in Rh Q_{10} values. Yet another complication is that Rh:Rs has been rising significantly over the last few decades (Bond-Lamberty *et al* 2018, Lei *et al* 2021), reflecting enhanced soil organic matter (SOM) mineralization driven by climate changes, showing a shifting balance between autotrophic and heterotrophic respiration. Ra, however, has remained unchanged over this period (Lei *et al* 2021), and it is therefore important to understand the relationships between Ra, Rh, and Rs as we study the soil carbon cycling in a changing environment. Also important is that the proportion of plant roots (and therefore

Ra:Rs) scales with the successional stage of an ecosystem, implying that the age of the stand will also influence the respiration partitioning and hence the overall Q_{10} patterns (Wang *et al* 2010).

3.7. Field vs. lab measurements: perspective

After 16 years since the call of Davidson *et al* (2006) to ‘move beyond Q_{10} ’, and in spite of the wide recognition of its weaknesses (Gu *et al* 2004, Tang and Riley 2020), temperature sensitivity remains a central concept in lab, field, and modeling sciences of the earth system. As a parameter commonly used in existing models, it is easy to understand, and as an index, it allows us to compare measurements and data across different study types that may have different measurement methods.

Our objective was to identify the biases occurring in field vs. lab experiments that would guide optimization of measurements for specific uses, decreasing the aforementioned signal-to-noise ratio. We demonstrate that this is a very complicated question. Initial assumptions were that field measurements would be more variable than lab measurements, given the abundance of environmental factors that cannot be controlled. Lab measurements were predicted to be less variable, but less representative of true field conditions, owing to the absence of those same environmental factors. Surprisingly, our analyses revealed that there was greater variability in the Q_{10} values calculated from lab-based measurements of CO_2 fluxes. This initially surprising result makes sense on further reflection: lab experiments can explore extremes rarely seen *in situ*, and more critically, by design

isolate single experimental factors, removing other constraints. In contrast, field observations will always be subject to constraint by the most limiting factor—and only rarely will these factors ‘line up’ to produce extreme observations.

In spite of this, models typically have trouble replicating real-world extremes, because we need a better mechanistic understanding of the extremes themselves and the ecosystem carbon-cycle processes responding to these extremes (Reichstein *et al* 2013, Zscheischler *et al* 2014). This speaks to the value of *both* types of observations and ways of doing science. The real-world Q_{10} values at core-to-ecosystem scales are critical to evaluate models against (Todd-Brown *et al* 2018), but impossible (or very difficult) to draw mechanistic insight from. In contrast, the artificiality of incubations means that they should not be used for larger-scale, integrated (plant + soil) model benchmarking; but these studies are essential for probing mechanistic understanding (Wieder *et al* 2019). Together, these approaches highlight the critical role of ecosystem-scale manipulations (e.g. SPRUCE (Hanson *et al* 2017), FACE (Palmroth *et al* 2006), TEMPEST (Hopple *et al* submitted), BBWM (Patel *et al* 2019)) that provide experimental control but also integrated, real-world soil, plant, and microbial conditions. The overall variabilities of field vs lab-based measurements appear to depend on the geographic origin of the soils, with water being a key driver.

3.7.1. Environmental factors contributing to bias

Water content exerts strong physicochemical and biochemical controls on carbon availability (Moyano *et al* 2012, Ebrahimi and Or 2015, Yan *et al* 2016, Patel *et al* 2021), and strong correlations have been reported for respiration Q_{10} and soil moisture—both positive (Xu and Qi 2001, Craine and Gelderman 2011, Meyer *et al* 2018) and negative (Luan *et al* 2013, Meyer *et al* 2018), depending on the land use and vegetation type, SOM quality, and other soil properties. Reported soil moisture values for our compiled dataset ranged from 30% to 70% water holding capacity, up to 75% water-filled pore space, and as high as 340% gravimetric water content. However, not all studies reported soil moisture, and, as we demonstrate with these values, the moisture reported was in inconsistent units (Franzluebbers 2020), and we are therefore unable to perform a robust analysis of soil moisture effects here.

Seasonality and study duration can also influence respiration Q_{10} values, due to shifting patterns of temperature and moisture on an annual scale. For instance, winter Q_{10} values are generally larger than summer Q_{10} values (Rayment and Jarvis 2000, Janssens and Pilegaard 2003, Han and Jin 2018). Short-term measurements, especially in the field, are therefore subject to these seasonal variations, which must be considered when we interpret respiration

data. Further, short-term incubations (days) could have higher Q_{10} values compared to longer incubations, driven by experimental artifacts, which get smoothed out over time (Janssens and Pilegaard 2003, Wang *et al* 2014). This can be seen especially in the ‘extreme’ environmental conditions like dry or cold regions, where the microbes are likely more sensitive to small changes in temperature and moisture. For lab incubations, the time of year that the soils are sampled may also influence how comparable the data are to the field measurements. For our current analysis, we include data from all experiments, irrespective of duration and seasons.

3.7.2. Current gaps and future opportunities

This data synthesis highlights a number of crucial gaps in data and understanding, but also opportunities for both experimentalists and modelers studying soils and their temperature-sensitive GHG processes. First, we need information on soil depth and composition, including simple measurements such as organic vs. mineral soil, reported more regularly. Reporting the soil depth associated with Q_{10} is also crucial, as they have different responses to temperature fluctuations *in situ* or in the lab. Soil texture is another crucial piece of information (Ghezzehei *et al* 2019), and can, along with gravimetric water content, help to infer soil water tension and water retention properties. While we were unable to perform a comparable robust analysis for the CH_4 data, we expect similar interactions with soil temperature, moisture, and environmental/climatic variables, as we discuss above. Numerous studies have reported on CH_4 emissions over the last few decades, but our results here suggest the need for more concerted efforts to document and standardize these data, including sample and site metadata (Bond-Lamberty *et al* 2021).

In addition to these current limitations exist future opportunities. The work we present here highlights some of the challenges in interpreting data across different experimental/incubation types, as well as the need for more concerted and targeted experiments. Quantifying and understanding how and why field and lab measurements of GHG temperature sensitivity vary is crucial to better understanding the strengths and limitations of experimental designs.

Finally, our results have implications for the parameterization and assessment of ESMs. The sensitivity of terrestrial carbon pools to climate change is one of the largest sources of uncertainty in earth system modeling (Friedlingstein *et al* 2014, Bonan and Doney 2018), meaning that robust parameterization of fundamental processes in ESMs, and benchmarking of these models’ outputs, are crucial. This process is most effective when observations and modeling iteratively strengthen each other (Kyker-Snowman *et al* 2022). In our analysis, the consistency between field- and lab-based Rh Q_{10}

distributions (figure 7) provides confidence in the use of laboratory experiments to parameterize larger-scale models, and that models' emergent Rh temperature sensitivity can be reasonably compared to ecosystem-scale observations (Moyano *et al* 2013, Shao *et al* 2013). Such emergent behaviors likely provide the strongest scale-dependent response metric for evaluating ESMs (Collier *et al* 2018), for which assembled field and lab datasets will be crucial resources. This highlights the need for improved and expanded respiration measurements from under-represented/excluded regions (Xu and Shang 2016, Kim *et al* 2022). Most of the studies published focus on temperate regions, a common problem in soil field sciences, but it is in less represented high- and low-latitude regions that the climate and carbon cycle is changing most rapidly (Pörtner *et al* 2022).

Data availability statement

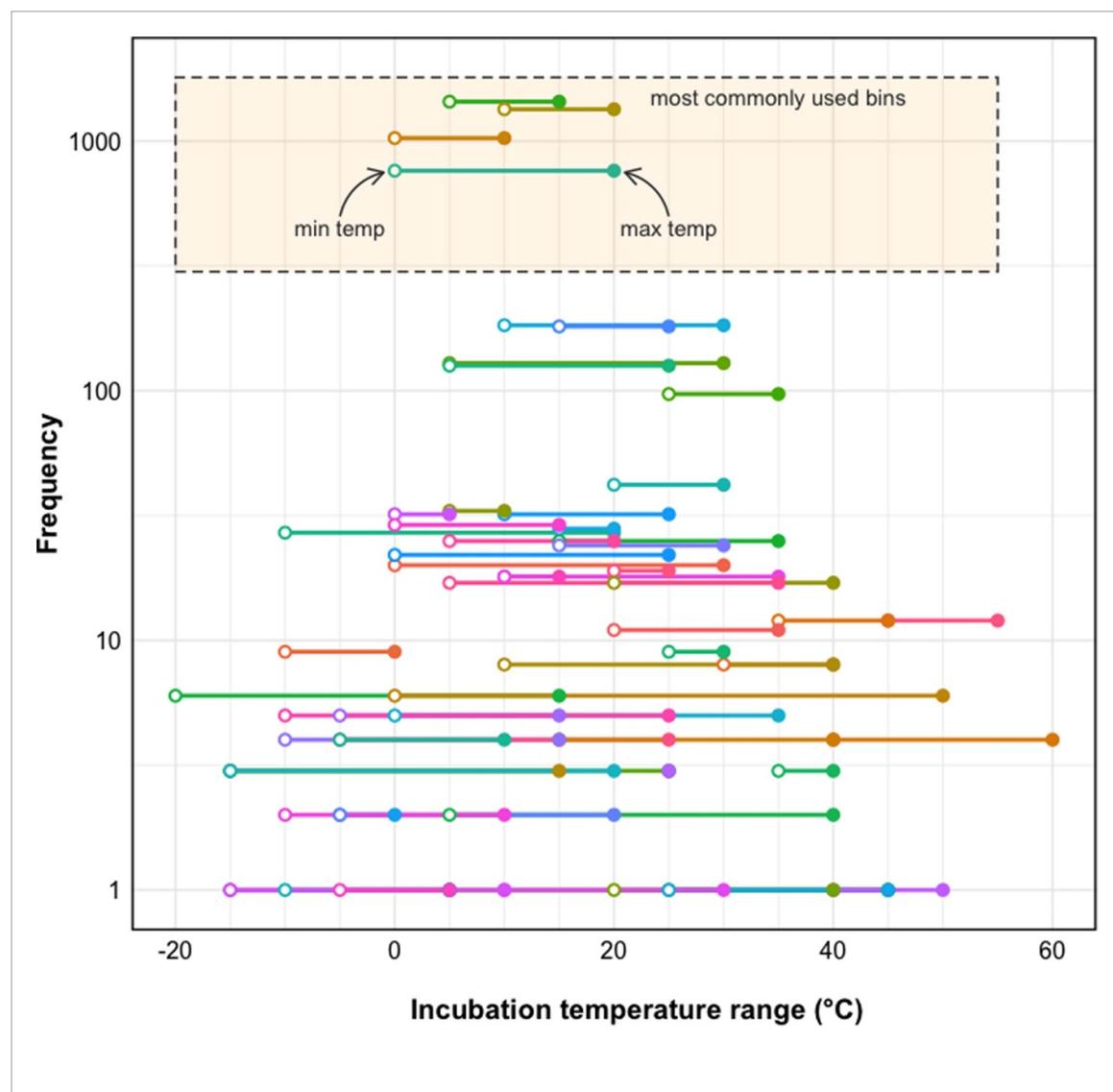
The data and R scripts that support the findings of this study are openly available at the following URL/DOI: https://github.com/kaizadp/field_lab_q10 (10.5281/zenodo.7106554) and archived at ESS-DIVE (doi:10.15485/1889750).

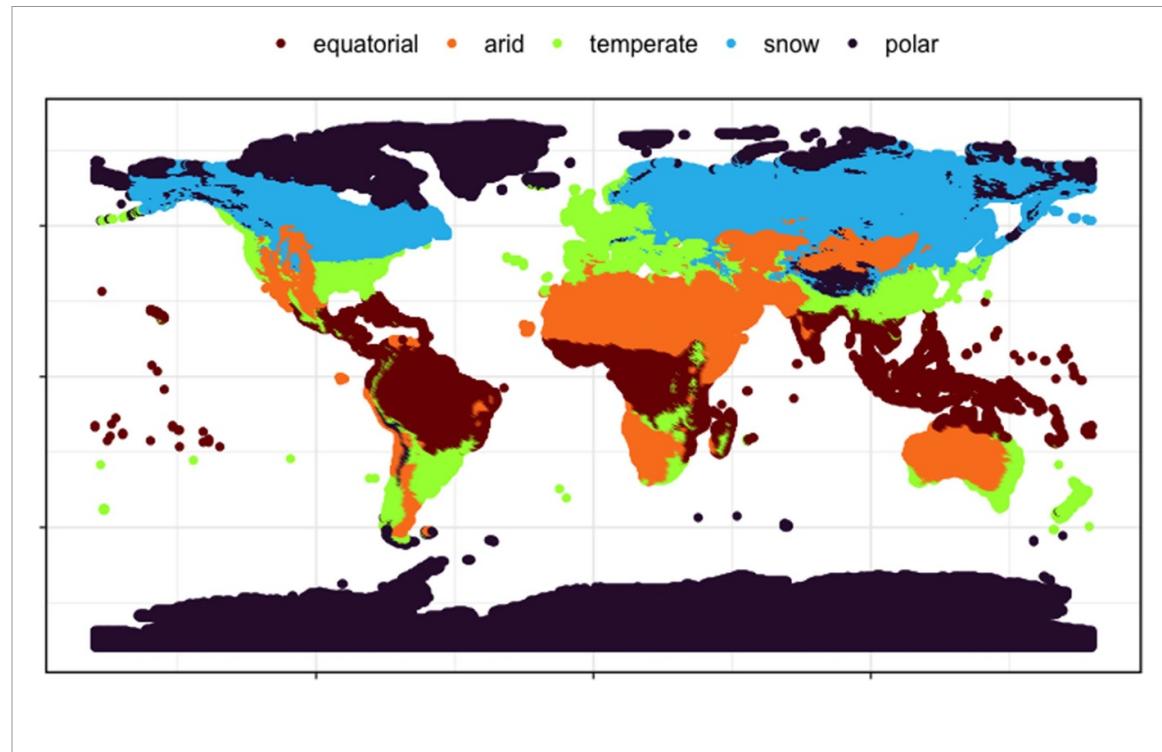
Acknowledgments

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Appendix A1. Temperature ranges used in the experiments, for either laboratory incubations or field measurements of CO₂

The x -axis represents the incubation temperature range (open circles = minimum temperature, solid circles = maximum temperature) and the y -axis represents the counts/frequency of data points for that temperature range. Note the \log_{10} scale on the y -axis. Each color represents a different temperature bin. While experiments were conducted at temperatures ranging from -20 to $+55$, most of the data points were for 5–15, 10–20, 0–10, and 0 °C–20 °C.



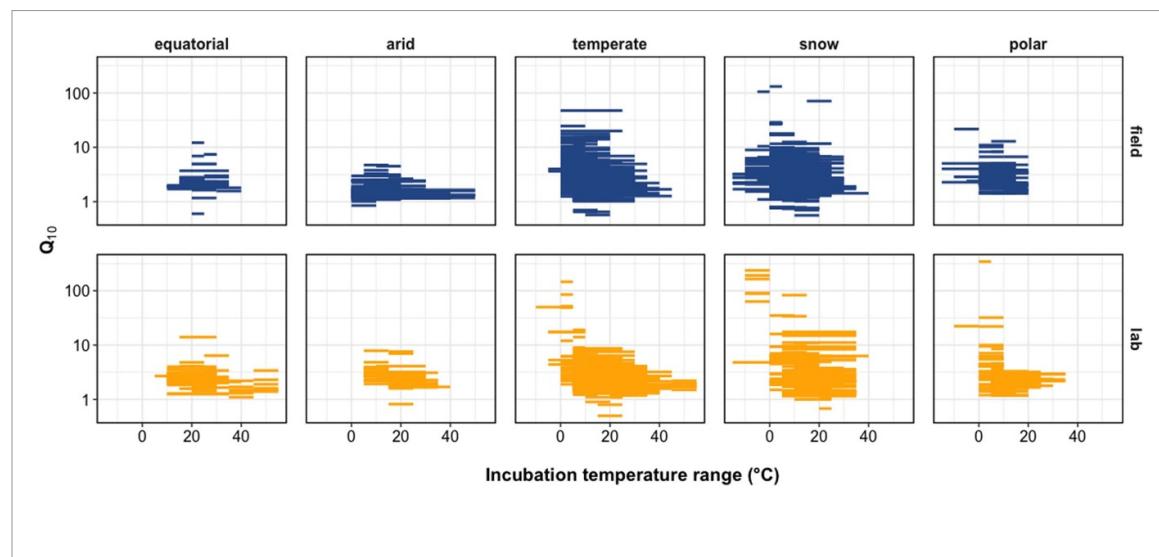
Appendix A2. Geographic distribution of the climate regions according to the Köppen-Geiger classification (Kottek *et al* 2006)**Appendix A3.**

List of manipulations (data pulled and cleaned from SRDB)

Acidification	Grazing	Throughfall reduction
Burned	Harvest	Trench
C/N manipulations	Irrigation	Ultraviolet radiation
Clearcut	Mowed	Understory removal
CO ₂	No-till	Vegetation control
Cover crop	Ploughed	Warmed
Defoliation	Root excluded	Weed control
Drought	Rotation	Wetted
Fertilized	Snow manipulations	Woody adelgid infestation
Flood	Species added	
Fungicide	Stump removal	
Girdling	Thinned	

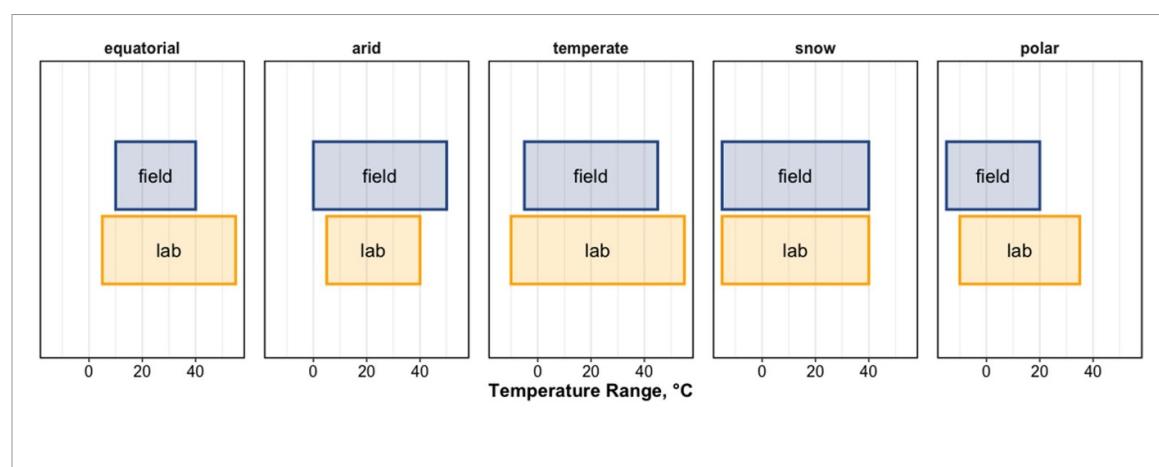
Appendix A4. Q_{10} for CO₂ as a function of the incubation temperature ranges

The temperature ranges are represented as segments along the x -axis, denoting minimum-to-maximum temperatures. Note the log₁₀ scale for the y -axis. These graphs provide a visual representation of the range of Q_{10} values, including where the extreme values were found. Most of the Q_{10} values >30 were found in laboratory incubations of temperate and snow biome soils, where incubation temperatures were below 0 °C. In contrast, for the field experiments, even sub-zero incubations resulted in Q_{10} values generally below 10 °C.



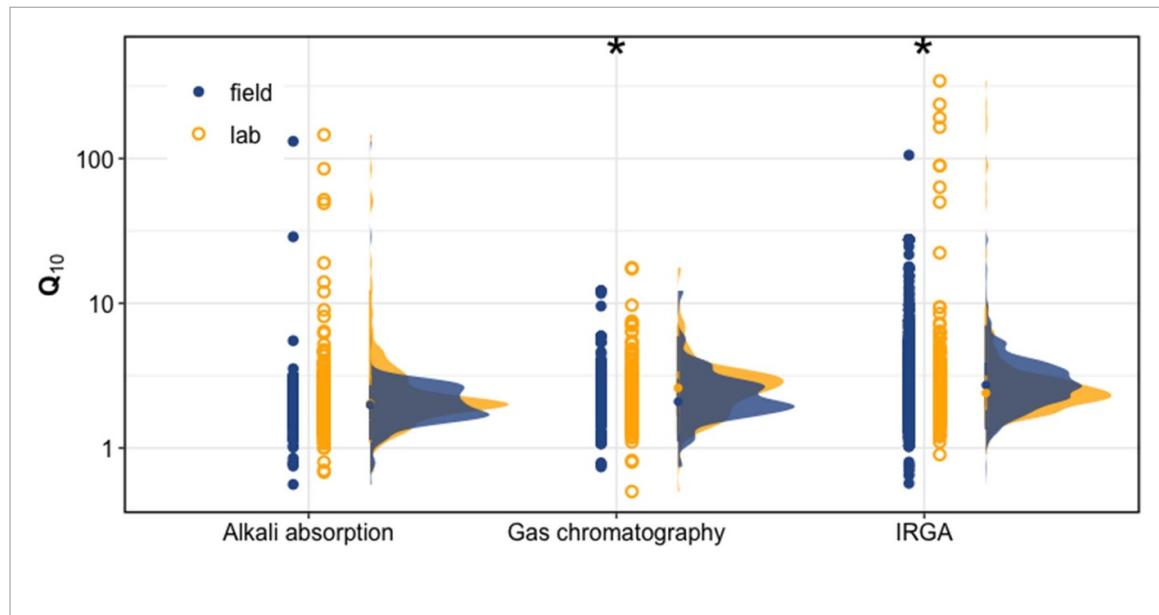
Appendix A5. Temperature ranges for field and lab incubations, within each biome

The temperature ranges are represented as boxes with minimum-to-maximum temperatures along the x -axis. For the purpose of this analysis, we assume that the field temperatures represent the natural temperature ranges experienced in the field. Thus, we see that for some regions (equatorial and temperate), the laboratory incubations were conducted at temperatures below those experienced in the field, and therefore might show abnormally high Q_{10} values.



Appendix A6. Field vs. lab comparisons of CO₂Q₁₀ ranges for different measurement types

We include only the three most common methods: (a) infra-red gas analyzers (IRGA), $n = 4494$; (b) gas chromatography, $n = 593$; and (c) alkali absorption, $n = 582$. Asterisks represent statistically significant differences between field and lab measurements at $\alpha = 0.05$.



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