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TOPICAL REVIEW

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

Kaizad F Patel1,∗, Ben Bond-Lamberty2, Jinshi Jian3,4, Kendalynn A Morris2, Sophia A McKever1, Cooper G Norris1, Jianqiu Zheng1 and Vanessa L Bailey1

1 Pacific Northwest National Laboratory, Biological Sciences Division, Richland, WA, United States of America
2 Pacific Northwest National Laboratory, Joint Global Change Research Institute, College Park, College Park, MD, United States of America
3 State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Northwest A&F University, Yangling 712100, People’s Republic of China
4 University of Chinese Academy of Sciences, Beijing 100049, People’s Republic of China
5 Institute of Soil and Water Conservation, Northwest A & F University, Yangling, Shaanxi 712100, People’s Republic of China
∗ Author to whom any correspondence should be addressed.
E-mail: kaizad.patel@pnnl.gov

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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
CO$_2$ and CH$_4$ 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 CO$_2$ and CH$_4$ measurements. We use $Q_{10}$ 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 $Q_{10}$ 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 $Q_{10}$ 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 un manipulated, 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 (Gui 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 \(Q_{10}\) of soil respiration, with different parameters (Gui 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 to \(+60\) °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).
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 tidyr 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 |
|-------|-----|-------|-----|
| CH₄: number of datapoints | CH₄: 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 |

| CO₂: number of datapoints | CO₂: 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 α = 0.05.

| Field | Lab | Field | Lab |
|-------|-----|-------|-----|
| CH₄ | | | |
| 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* |

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, P = 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
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} = 63–237) 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 decomposition (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...
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 $+60$ °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 incubation temperatures. 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 >$25$ °C (figure 6(A)). We chose only studies where incubation temperature ranges were $10$ °C or less (for instance, $5$–$10$, $10$–$12$, and $5$ °C–$15$ °C all fell under the group $5$ °C–$15$ °C; but $5$ °C–$25$ °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 $5$ °C–$15$ °C, and not $0$ °C–$10$ °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 ($5$ °C–$15$ °C, $15$ °C–$25$ °C, and >$25$ °C), there were significant differences between field and laboratory measurements, although the trends differed by
incubation temperature range: for 5 °C–15 °C, lab $Q_{10}$ > field $Q_{10}$, whereas for 15 °C–25 °C, and >25 °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 °C–15 °C, and field $Q_{10}$ > laboratory $Q_{10}$ for 15 °C–25 °C, and >25 °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 (Ra) and heterotrophic (Rh) 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.
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, Rs (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, Ra) and respiration by soil organisms (heterotrophic respiration, Rh). 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 Rh-dominated field data and laboratory data (Rh-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 Rh (figure 7) provide strong support for using the former as an experimental proxy for the latter.

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

![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 (\(\alpha = 0.05\)).](image-url)
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 $Q_{10}$ 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 |
|------------------|--------------|--------------|
| $n$              | 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 (Palermo 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 (Raymont 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).

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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    |
| CO₂           | 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 CO$_2$ 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 log$_{10}$ 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 CO$_2$ Q$_{10}$ 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 $\alpha = 0.05$.

**ORCID iDs**

Kaizad F Patel [https://orcid.org/0000-0001-6437-7809](https://orcid.org/0000-0001-6437-7809)
Ben Bond-Lamberty [https://orcid.org/0000-0001-9525-4633](https://orcid.org/0000-0001-9525-4633)
Jinshi Jian [https://orcid.org/0000-0002-5272-5367](https://orcid.org/0000-0002-5272-5367)
Kendalynn A Morris [https://orcid.org/0000-0002-0388-6965](https://orcid.org/0000-0002-0388-6965)
Sophia A McKeever [https://orcid.org/0000-0003-2870-7713](https://orcid.org/0000-0003-2870-7713)
Jianqiu Zheng [https://orcid.org/0000-0002-1609-9004](https://orcid.org/0000-0002-1609-9004)
Vanessa L Bailey [https://orcid.org/0000-0002-2248-8890](https://orcid.org/0000-0002-2248-8890)

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