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Collar Properties and Measurement Time Confer Minimal Bias Overall on Annual Soil Respiration Estimates in a Global Database

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Key Points:
- Annual soil respiration (R_S) was negatively correlated with collar insertion depth, collar height, and collar coverage area
- We found no correlation of measurement duration or measurement frequency with annual R_S
- Overall, collar properties, measurement duration, and measurement frequency confer minimal bias to annual R_S
- The results provide strong support for compiling site-scale R_S measurements to support synthesis analysis, as well as global R_S modeling

Supporting Information:
- Supporting Information S1

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Abstract Measuring the soil-to-atmosphere carbon dioxide (CO_2) flux (soil respiration, R_S) is important to understanding terrestrial carbon balance and to forecasting climate change. Such measurements are frequently made using measurement collars permanently inserted into the soil surface. However, differences in measurement duration and frequency, as well as collar properties, may lead to biases in the estimation of annual R_S. Using a newly updated global R_S database (SRDB-V5), we investigated the annual R_S bias associated with five methodological factors: collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency. We found that annual R_S was negatively correlated with collar insertion depth, consistent with the idea that collar insertion cuts roots and thus reduces R_S. Annual R_S was also negatively related with collar height and collar coverage area, perhaps because uniform head-space mixing is difficult to achieve in larger volume chambers; however, these effects were quantitatively small (bias of ~2% to 10% of mean R_S). We found no correlation of measurement duration or measurement frequency with annual R_S. These findings suggest that variation in R_S methodology generally introduces minimal bias overall. Therefore, compilations of minimally adjusted annual R_S measurements provide a reliable resource for synthesis studies, global annual R_S modeling, and investigation of how soil carbon responds to climate change.

Plain Language Summary Soil-to-atmosphere carbon dioxide (CO_2) is the second largest component in the terrestrial carbon cycle; thus, our ability to balance the terrestrial carbon budget and forecast climate change relies upon accurate measurements of this process. Collars permanently installed in the soil are commonly used to measure soil-to-atmosphere CO_2. However, differences in collar properties, measurement duration, and measurement frequency may lead to biases in the estimation of annual soil-to-atmosphere CO_2 amount. While many studies on the methodology for measuring soil-to-atmosphere CO_2 have been conducted, a comprehensive evaluation of the influence of collar properties and measurement duration on annual soil-to-atmosphere CO_2 variability has not been investigated before. In this study, we use a global data set to analyze soil-to-atmosphere CO_2 measurement bias related to collar properties and measurement duration. We found that annual soil-to-atmosphere CO_2 amount negatively correlated with collar height and insertion depth but showed no significant relationship to measurement duration and measurement frequency. Overall, collar properties and measurement duration contributed minimal bias. The results provide strong support for compiling site-scale soil-to-atmosphere CO_2 measurements to support synthesis analysis, as well as global soil-to-atmosphere CO_2 modeling.

1. Introduction

After photosynthesis, the soil-to-atmosphere carbon dioxide (CO_2) flux (soil respiration, R_S) is the second largest carbon flux between terrestrial ecosystems and the atmosphere. At the global scale, annual CO_2 emissions from R_S are approximately 10 times greater than current fossil fuel emissions (Bond-Lamberty & Thomson, 2010a, 2010b). Soils represent a major global carbon stock that is sensitive to climate change and the ecosystem feedback through R_S is critical to the prediction of future atmospheric CO_2 concentrations. Thus, thousands of measurements of this flux have been made in different climate conditions and ecosystems across the globe in the past decades. Efforts to measure R_S date back to the early 1900s when alkali was set in a CO_2-free flask to measure CO_2 released from soil samples to evaluate soil biological activity (Stoklasa & Ernest, 1905) and to quantify R_S in the field (Lundegårdh, 1927). Starting in the 1950s, the advent of the infrared gas analyzer (IRGA) spurred a proliferation of more accurate R_S measurements; subsequently, fixed or portable chambers were combined with the IRGA system for instantaneous or continuous R_S measurement (Haber, 1958). Beginning in the 2000s, solid-state CO_2 sensors buried in different soil layers allowed for CO_2 concentrations from which to derive R_S fluxes (Hirano et al., 2000; Riveros-Iregui et al., 2008; Tang et al., 2003). More recently, Forced Diffusion Soil CO_2 Flux Sensors have been used to measure R_S (Risk et al., 2011). In addition, other techniques such as eddy covariance (EC) (Speckman et al., 2015) and isotope labeling (Hall et al., 2017) have also been used to estimate R_S.

With the development of these methods, the spatial and temporal variabilities of R_S have been monitored and studied at many sites across the globe. As no single method has been adopted as the gold standard, scientists around the globe use a variety of disparate methods to measure R_S in different climates and plant communities. In the global soil respiration database (version 5, SRDB-V5) (Jian & Bond-Lamberty, 2020; Jian, Vargas, et al., 2020), we compiled annual R_S data that were collected using different measurement methods; however, the potential sources of error introduced to annual R_S estimates due to measurement methodology has not been assessed. Without this analysis it is unknown whether annual R_S requires standardization prior to inclusion in synthesis and modeling activities.

Many R_S measurement methods require inserting permanent collars into the soil (Luo & Zhou, 2010). The variability in collar-related protocols (e.g., collar coverage area, height, and/or installation depth) may in theory bias measurements. For example, many studies have shown that annual R_S is negatively related with collar height and area because it is harder to achieve uniform air mixing for bigger collars and thus larger chamber volumes (Brændholt et al., 2017). However, larger chambers are more spatially representative and likely have lower variability among subsamples, increasing plot-scale annual R_S estimate accuracy (Ryan & Law, 2005). In addition, collar insertion may also cause plant root excision (Heinemeyer et al., 2011), thereby excluding a subset of roots that would otherwise contribute to R_S (Silvola et al., 1996; Wang et al., 2005).

At the site scale, several studies have shown that increasing collar insertion depth reduces R_S; however, the magnitude of this decrease is quite variable. For example, Jovani-Sancho et al. (2017) compared R_S rate from six collar insertion depth (5, 10, 15, 25, 35, and 45 cm) in a peatland and found that the insertion depth of 5 cm could reduce total R_S by ~40% compared to 0-cm insertion (based on regression results). Heinemeyer et al. (2011) compared R_S measurements with multiple collar insertion depths from grassland, forest, and peatland and found that ~5-cm insertion reduced total R_S by 15%, with the greatest reductions observed in peatland, which has shallow-rooted system, followed by forest and grassland. The large R_S reduction in peatland may also be because collar insertion results in long-term surface water buildup within the collar after rain events, affecting soil gas fluxes. In a palm plantation, Batubara et al. (2019) found that R_S from 60-cm insertion collars were 29% lower than that from 20-cm insertion collars due to the root excision. Furthermore, "deep collars" have been used to estimate soil heterotrophic respiration in lieu of more-difficult trenching approaches (Vogel & Valentine, 2005). Even though the influence of collar insertion on R_S measurements has been investigated at the site level, the annual-scale bias has not been evaluated. Larger-scale and longer-timespan analyses are increasingly essential as multi-site data sets are compiled and applied to syntheses and modeling, highlighting the need to assess potential sources of error associated with measurement methodology.

Annual estimates of R_S may also be biased from variation in measurement frequency (when using point measurement methods) and measurement duration and timing (when using instantaneous methods; measurement duration will be referred to as measurement timing hereon). Most R_S measurements are collected during the day and not continuously over 24 hr, although this is changing (Bond-Lamberty et al., 2020). In SRDB-V5, approximately 85% of annual R_S values are derived from point measurements during the day (not 24 hr continuously measured) (Figure 1b). For those measurements not monitored continuously, R_S was usually measured once (or several times) during daylight hours in the absence of precipitation, and then mean daily R_S calculated prior to scaling to an annual estimate. However, this simplification may cause a

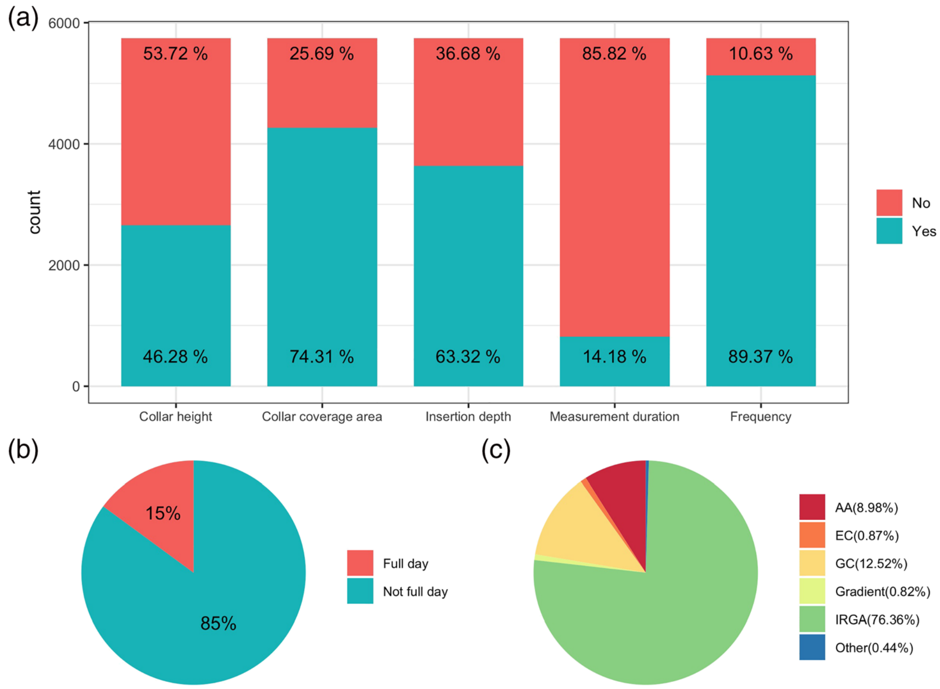

Figure 1. (panel a) Percentage of annual soil respiration (R_S) in SRDB-V5 with collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency reported. With the total 5,741 annual R_S in SRDB-V5, there are 2,657 (46.3%), 4,266 (74.3%), 3,635 (63.3%), 814 (14.2%), and 5,131 (89.4%) annual R_S also reported collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency information, respectively. (panel b**)** Percentage of annual R_S in SRDB-V5 with full day coverage (continuous daily measurement) and without full day coverage. (panel c) Annual R_S in SRDB-V5 measured by different methods, AA-alkali absorption, EC-eddy covariance, GC-gas chromatography, IRGA-infrared gas analyzer, and other-methods not reported.

bias from −29% to +40% (Cueva et al., 2017) because R_S could show substantial diurnal variation within a day that is not represented in annual R_S estimates.

However, choosing appropriate time windows to measure R_S can minimize the measurement error caused by R_S diurnal variability. Davidson et al. (1998) found that measurements made from 9:00 to 12:00 (local time, same hereafter) were mostly representative of the daily mean R_S in a temperate forest. However, in a shrubland located at semiarid Mediterranean, California, measuring from 9:00 to 11:00 caused a bias of −29% to +40% compared with the diurnal mean R_S flux (Cueva et al., 2017). The results from three mid-Atlantic deciduous forests showed that R_S rate from mid-morning and late afternoon (15:00–16:00) were most close to the daily mean R_S (Bond-Lamberty et al., 2019). At the global scale, Jian, et al. (2018b) found that diurnal variation contributed less than 6% of bias to scale daily R_S estimates; moreover, Jian, et al. (2018b) showed that midmorning is a representative time window to capture diurnal mean R_S because soil and air temperature reach diurnal mean between 9:00 to 12:00. In addition, ~92% of annual R_S values are not measured everyday (results not shown), R_S was usually measured once every week (or month or season), and then the overall mean value taken as the annual R_S rate (sometimes a modeling approach was used to calculate annual R_S rate). Cueva et al. (2017) found that the most common sampling frequency in the SRDB is about 28–45 days (approximately once a month), but whether this frequency yields comparable annual R_S values for sites with varying environmental conditions is unknown.

This study investigated the relationship between annual R_S and collar properties, measurement duration, and measurement frequency in a global R_S database. Our objectives are to (1) evaluate whether collar height, collar insertion depth, and collar coverage area affect annual R_S measurement bias; (2) investigate whether R_S measurement duration and the measurement frequency affect annual R_S; and (3) determine whether those collar properties, measurement duration, and measurement frequency bias are related to environmental conditions. A comprehensive analysis of whether collar properties and measurement duration bias annual R_S is essential to determining whether compiled data collected using different protocols require adjustment or standardization prior to use in syntheses and model analyses.

2. Materials and Methods

2.1. Data Source

Our analysis used 5,741 site-year (971 sites) annual R_S estimates from the newest version of a global soil respiration database, SRDB-V5 (Jian & Bond-Lamberty, 2020; Jian et al., 2020). Together with annual R_S, 46%, 74%, 63%, 14%, and 89% of measurements also reported collar height (the maximum distance above the soil surface), collar coverage area, collar insertion depth, measurement duration, and measurement frequency information, respectively (Figure 1a); approximately 85% of annual R_S were not measured 24-hourly continuously (Figure 1b); and the majority of annual R_S were measured by IRGA, GC, and AA methods (together accounting for more than 97% of the data), with the rest R_S measured by EC (0.87%), Gradient (0.82%), and other (0.44%) (Figure 1c).

2.2. Statistical Analysis

Piecewise regression (i.e., the *segmented* package under R) (R Core Team, 2019) was used to detect break points and significant changes in slope. We conducted linear regression modeling (i.e., the *lm* function) using R (R Core Team, 2019) to test whether annual R_S correlated separately with collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency after controlling for potentially confounding factors. To test whether vegetation and biome type affect the above relationships, vegetation type, biome type, or root respiration to R_S ratio (R_{root}:R_S) was included as a variable in the linear model. In addition, we analyzed the relationship between climate factors (i.e., mean annual temperature, MAT, and mean annual precipitation, MAP) and methodological factors (i.e., collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency) to investigate the influence from MAT and MAP. Finally, we used scatter diagrams to visualize whether the relationship between annual R_S and methodological factors was affected by MAT and MAP.

Collar insertion depth related R_S measurement biases were also investigated by comparing annual R_S and R_{root}:R_S from different measurement methods. EC, Equation, and Gradient methods to measure R_S do not require collar installation and root excision, and therefore, annual R_S is expected to be higher than that derived from methods which involve root excision (AA, GC, and IRGA). Studies have shown that 15–50% of R_S reduction could be due to roots excision from collar insertions (Batubara et al., 2019; Heinemeyer et al., 2011). Similarly, the R_{root}:R_S ratio from methods with collar insertion should be lower than that from methods without collar insertion. Finally, we expect sites with greater root biomass to have higher R_{root}:R_S ratios and, consequently, exhibit greater reduction in annual R_S with increasing collar insertion depth.

Annual R_S with extreme collar height, collar coverage area, insertion depth, measurement duration, and measurement frequency were excluded in the linear regression. We excluded any data with collar height >50 cm (n = 36 out of 2,657, ~1%) and collar insertion depth >20 cm (n = 23 out of 3,635, ~0.6%) in the linear modeling because only a very few measurements were made under those conditions. Following the same logic, we excluded annual R_S measurements with collar coverage area >4,000 cm^2 (n = 24 out of 4,266, ~0.5%), and measurement frequency >150 (days per measurement, n = 35 out of 5,131, ~0.7%) in the linear regression. We used the Cook's distance to detect whether the linear regressions were influenced by outlier points (Williams, 1987). Any points with Cook's distance >0.5 were identified as potential influential points. We then re-fit the regression excluding potential influential points, and if the regression results significantly changed, the potential influential points were removed from the regression.

Annual R_S values were not evenly distributed across collar height, collar coverage area, collar insertion depth, measurement duration, and measurement frequency. For instance, within all 4,266 annual R_S measurements with collar coverage area information, collar coverage areas of 78.5 and 314 cm^2 account for 20% and 16%, respectively, because 10- and 20-cm-diameter collars are most commonly used. To handle this issue, we aggregated annual R_S by collar coverage area and then weighted the linear regression by sample

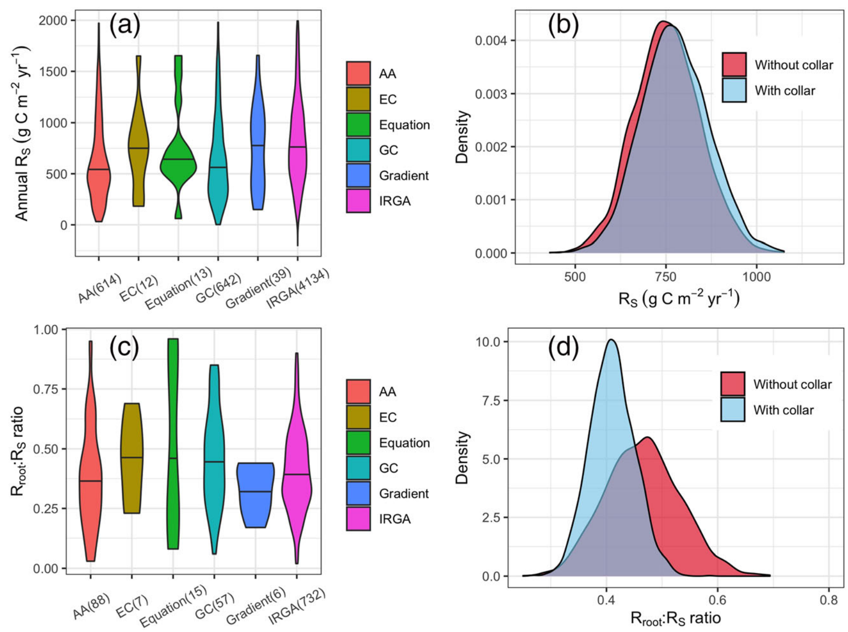

Figure 2. Violin plot of annual soil respiration (R_S) separated by different measurement methods and root respiration to R_S ratio (R_{root}:R_S ratio) separated by different measurement methods (a and c). We used bootstrap method to compare and test whether annual R_S and R_{root}:R_S ratio from AA, GC, and IRGA methods (with collar installation, b and d) significantly differ from the measurements by EC, Equation, and Gradient methods (without collar installation). AA: alkali absorption, EC: eddy covariance, GC: gas chromatography, and IRGA: infrared gas analyzer.

size. The same data processing was executed for the collar height, collar insertion depth, measurement duration, and measurement frequency analyses.

We investigated whether measurement methods (e.g., EC, IRGA, and Gradient) cause annual R_S estimation bias. As the sample size is different among measurement methods, a nonparametric Wilcoxon rank sum test was performed to test whether annual R_S measured 24 hr continuously significantly differ from the annual R_S not measured continuously. We also used a bootstrap resampling approach to resample and compare the mean of annual R_S and R_{root}:R_S ratio from different measurement methods, and to compare annual R_S from different groups (e.g., annual R_S with 24-hr continuous coverage or without 24-hr continuous coverage). Bootstrap resampling is now widely used for measuring confidence intervals, percentile points, and proportions in many areas (Jian et al., 2018; Jian et al., 2018a; Oladyshkin et al., 2013). An advantage of bootstrap resampling is that it does not require strong distributional assumptions and thus allows the researcher to compare data not following normal distribution (Haukoos & Lewis, 2005). In this study, we used the bootstrap resampling method randomly generated 10,000 subsamples of the annual R_S (or R_{root}:R_S ratio) under a specific condition (e.g., annual R_S measured by methods without collar insertion), and the mean of the 10,000 subsamples followed a normal distribution and thus can be compared among different groups (see results in Figure 2). All analyses were performed using R version 3.6.1 (R Core Team, 2019).

3. Results

We found that annual R_S measured by the methods with collar installation (775 ± 92 g C m^{-2} yr^{-1}, mean ± standard deviation from the bootstrap resample, same hereafter) were similar to methods without collar installation (753 ± 90 g C m^{-2} yr^{-1}, Figures 2a and 2b). However, the mean R_{root}:R_S ratios measured by the methods with collar installation (0.41 ± 0.04) was lower than that measured by the methods without collar installation (0.47 ± 0.07, Figures 2c and 2d), supporting the hypothesis that collar insertion affects R_S measurements to some degree.

Collar height and collar coverage area were negatively correlated with annual R_S measurements ($p < 0.05$), but their effect was quantitatively small (Figure 3 and Table 1). For every 10-cm increase in collar height, we

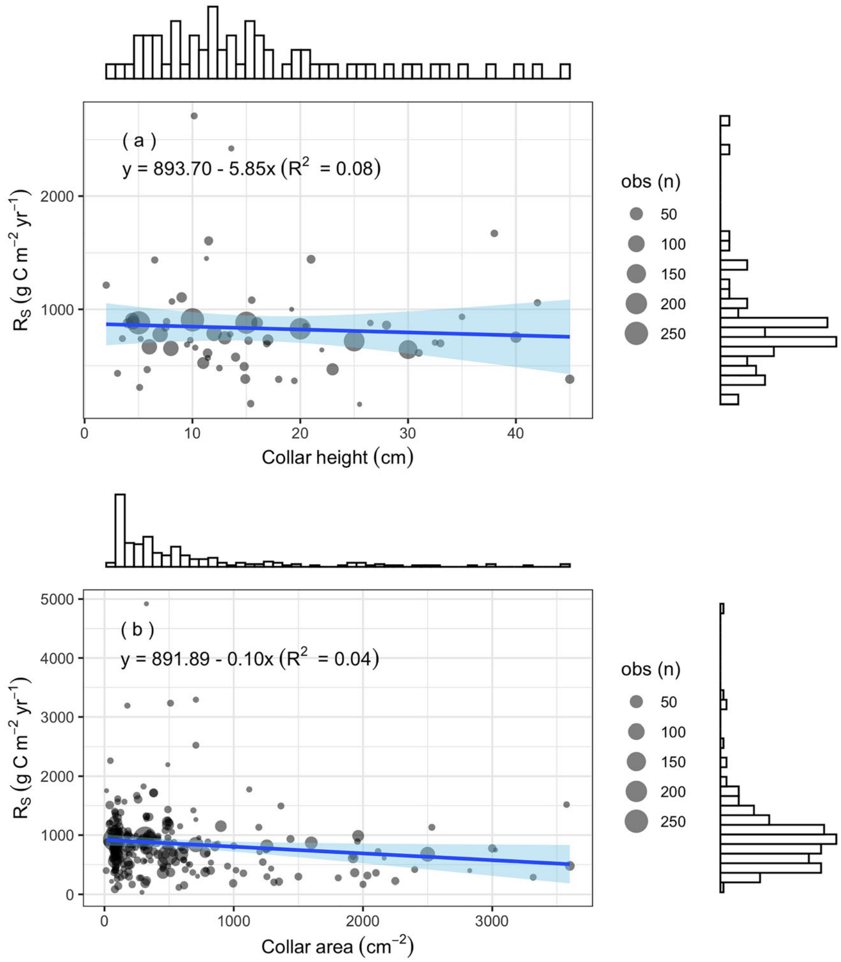

Figure 3. (panel a) Relationship between annual soil respiration (R_S) and collar height. (panel b) Relationship between annual soil respiration (R_S) and collar coverage area. The dot size represents the number of observations under different collar heights and areas. The top and right panels are marginal distributions of the underlying data. The linear regression (with 95% confidence interval in light blue, as determined by the *geom_smooth* function with method = "*lm*" under R) is shown in blue with significance level of $p < 0.05$.

Table 1
Statistical Parameter Summary of Linear Regressions Between Annual Soil Respiration (R_S) and Collar Height, Collar-Covered Surface Area (Collar Coverage Area), Collar Insertion Depth, Measurement Duration, and Measurement Frequency

Model	Intercept (g C m^{-2} yr^{-1})	Slope (g C m^{-2} yr^{-1})	Comment
Annual R_S ~ Collar height	893	-5.85^{**}	Figure 3a
Annual R_S ~ Collar coverage area	891	-0.10^{***}	Figure 3b
Annual R_S ~ Collar insertion depth	862	−3.11	A single model for all vegetations
Annual R_S ~ Measurement duration	843	2.97	Figure 5a
Annual R_S ~ Measurement frequency	800	1.31	Figure 5b

Note. The models were weighted by the number of observations. Note that model parameters in Table 1 were derived from regressions including all vegetation types combined, corresponding with trendlines shown in Figures 3 and 5. Parameters for annual R_S-collar insertion depth regressions by vegetation type are not shown.
**Means $p < 0.05$. ***Means $p < 0.01$.

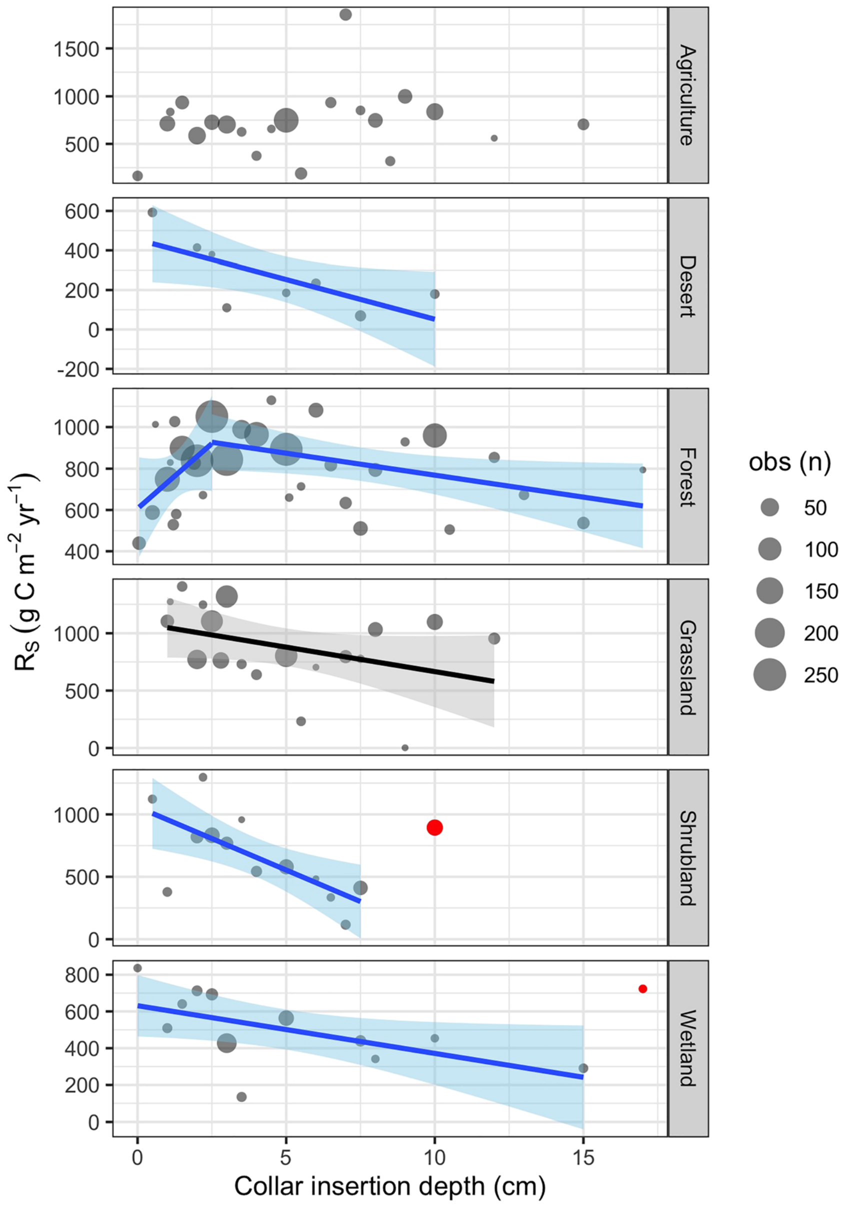

Figure 4. Relationship between annual soil respiration (R_S) and collar insertion depth in different vegetation types (agriculture, desert, forest, grassland, shrubland, and wetland). The dot size represents the number of observations under different collar insertion depth. The linear regression (with 95% confidence interval in light blue, which were determined by *geom_smooth* function with method = "lm" under R) is shown in blue with significant level of $p < 0.05$ and shown in black (with 95% confidence interval in gray) with significant level of $p < 0.1$ (grassland). Influential points or outliers (Cook's distance >0.5, marked in red) were identified and excluded from the linear regression.

found an ~6.5% decrease ($5.9 \times 10 \div 893$, Table 1) in annual R_S. For every 100-cm^2 increase in collar coverage area, we found an ~1% decrease ($0.1 \times 100 \div 891.9$, Table 1) in annual R_S. Data from SRDB-V5 showed that collar heights ranged from 1 to 100 cm but were most commonly centered from 5 to 15 cm (Figure 3a). Collar coverage areas ranged from 1 to 11,000 cm^2 but most commonly (78% of observations) ranged from 50 to 500 cm^2 (Figure 3b).

Collar insertion depth was negatively correlated with annual R_S, but the relationships varied when vegetation types were analyzed separately (Figure 4). We found a significant negative regression between R_S and collar insertion depth in desert, grassland, shrubland, and wetland vegetation types ($p < 0.05$). In forests,

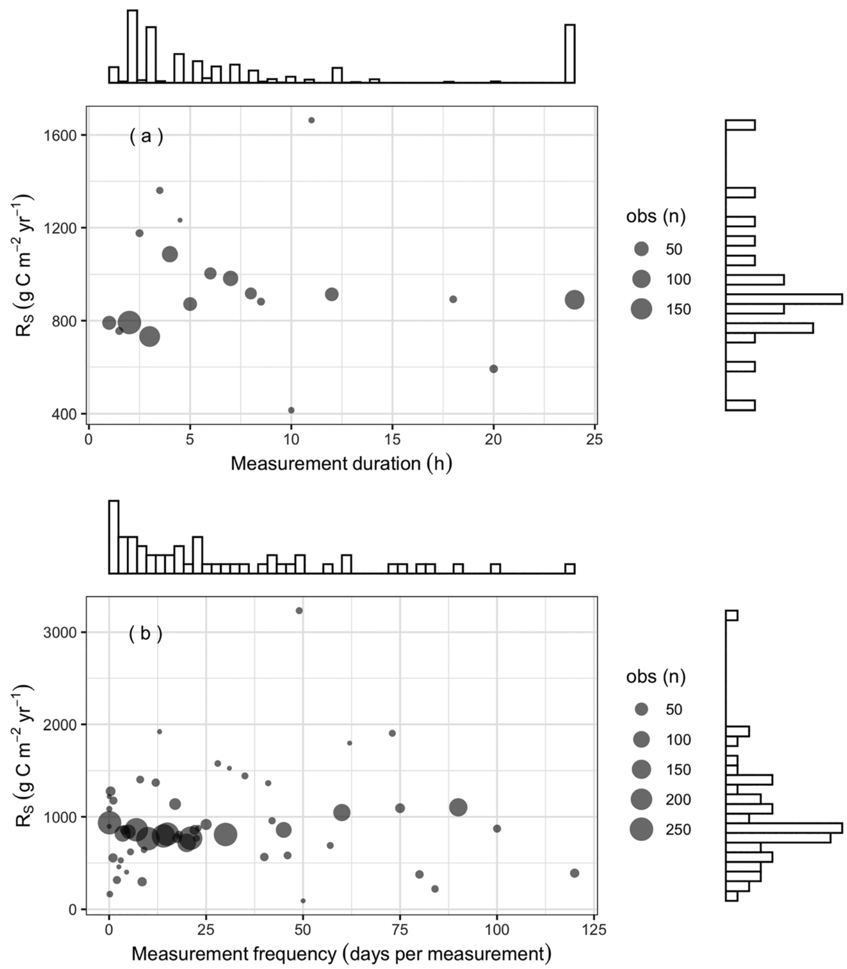

Figure 5. (panel a) Scatter plot between annual soil respiration (R_S) and measurement duration (how many hours the measurement lasts, e.g., if the R_S survey was from 8:00 to 12:00, then measurement duration was 4). (panel b) Scatter plot between annual soil respiration (R_S) and measurement frequency (how often the R_S survey was taken, e.g., 30 days represent once per month). The dot size represents the number of observations under different measurement duration and frequencies. The top and right panels are marginal distributions of the underlying data. We found no significant relationship between measurement duration/or measurement frequency and annual R_S, and therefore, the regression lines are not shown in the figure.

a breakpoint at 2.5-cm collar insertion was detected; collar insertion was positively correlated with annual R_S when insertion depth <2.5 cm but negatively correlated with annual R_S when insertion depth >2.5 cm. However, no significant trend was detected for agriculture sites. The scatter diagram between the model residuals and MAT (Figure S1, top panel), MAP (Figure S1, middle panel), and R_{root}:R_S ratio (Figure S1, bottom panel) showed no trend, indicating that it is unlikely the MAT, MAP, or R_{root}:R_S ratio masked relationships between annual R_S and collar insertion depth. We analyzed the statistical interaction between MAT and MAP and collar insertion depth, and found no relationship (results not shown), further supporting this conclusion.

R_S measurement duration and frequency showed no relationship with annual R_S (Figure 5 and Table 1). A nonparametric Wilcoxon test showed no significant difference between annual R_S when measured using continuous, 24-hr monitoring versus no full-day monitoring ($p > 0.5$, Figure S2). We simulated relationships between measurement duration, measurement frequency, and annual R_S by different biome and found no significant differences between biomes (Figure S3), indicating that it is unlikely that biome variability masks the relationship between measurement duration, measurement frequency and annual R_S.

4. Discussion

Collar height and collar coverage area were negatively related with annual R_S, probably because it is harder to achieve uniform air mixing in larger chambers (Brændholt et al., 2017; Hooper et al., 2002; Pumpanen et al., 2004). According to the data from SRDB-V5, the average collar height from 4,508 samples is ~14 cm. The slope of regression between annual R_S and collar height is −5.85 (Table 1 and Figure 3); therefore, the bias is ~82 g C m^{-2} yr^{-1} (5.85 × 14), which is approximately 10% of the mean (855 g C m^{-2} yr^{-1}). Based on 7,542 samples from SRDB-V5, the average collar coverage area is ~507 cm^2; given that the slope of the regression between annual R_S and collar coverage area is −0.10 (Table 1 and Figure 3), the estimated bias is ~51 g C cm^{-2} yr^{-1} (0.1 × 507), which is approximately 6% of the mean. Importantly, smaller chambers are more vulnerable to edge effects (Davidson et al., 2002; Pongracic et al., 1997; Rochette et al., 1997) and are also less representative of the sites due to the small soil surface coverage. Therefore, it is difficult to determine whether the collar height and collar coverage area related bias cause underestimation or overestimation annual R_S. While these potential sources of measurement error and sampling bias must be carefully considered, it should be noted that the effects of collar height and area on annual R_S are modest, indicating that properly designed and deployed chambers can provide a reliable means of accurately measuring R_S in terrestrial ecosystems.

Annual R_S and collar insertion depth showed a significant negative trend in desert, grassland, shrubland, and wetland vegetation types, but no relationship was found in agriculture (Figure 4). Importantly, when all data were used to simulate a single model, no relationship between collar insertion depth and annual R_S was found across the data set (Table 1), indicating that the relationship between collar insertion and annual R_S varies among vegetation types and thus should be analyzed separately. More than 97% of annual R_S values in SRDB-V5 used collar based methods and the average collar insertion depth was 4.0 cm (5.0, 5.4, 3.6, 4.2, 5.2, and 4.1 cm for agriculture, desert, forest, grassland, shrubland, and wetland, respectively). Therefore, the bias is ~12 g C m^{-2} yr^{-1} (calculated based on the regression between annual R_S and collar insertion shown in Table 1, −3.11 × 4.0), which is approximately 2% of the mean, suggesting that collar insertion minimally alters R_{root} and subsequent annual R_S estimates. These findings are in line with previous studies that determined shallow soil depth collars may not cause a large bias to annual R_S measurements (Wang et al., 2005) but smaller than other research that has found 5-cm collar insertions to reduce R_S by 15–50% (Batubara et al., 2019; Heinemeyer et al., 2011; Jovani-Sancho et al., 2017). However, when ecosystem-specific relationships were analyzed, we found desert, grassland, shrubland, and wetland annual R_S estimates to be inversely correlated with collar insertion (Figure 4). Desert, grassland, shrubland, and wetland plants usually have well-developed root systems (Iversen et al., 2018) and therefore may be more sensitive to collar installation. In addition, water-limited desert and shrubland systems may also recover more slowly from root damage. We hypothesized that if a large bias related to collar insertion exists, then annual R_S measured using methods involving collar insertion (AA, GC, and IRGA) should be significantly smaller than that measured by methods with no collar insertion (EC, Equation, and Gradient). Following the same logic, the R_{root}:R_S ratio measured by AA, GC, and IRGA (with collar insertion) should be smaller than the ratio measured by EC, Equation, and Gradient (without collar insertion). We found R_{root}:R_S ratio estimated by the methods without collar insertion is higher than that estimated by the method with collar insertion (Figure 2d), somewhat supporting our expectation that collar insertion cause measurement bias. Thus, we suggest that future experiments in those vegetation types attempt to avoid severing roots whenever possible.

However, we found no relationship between collar insertion and annual R_S in agriculture. In forest, a breakpoint at 2.5 cm was found; collar insertion was positively correlated with annual R_S when collar insertion depth <2.5 cm. This is a surprising finding; a possible explanation is that collar insertion to a shallow depth changes the soil surface environment in a way that stimulates decomposition, making the soil surface wetter and enhancing root and mycorrhizal activity. Previous studies found that severed roots are a labile source of soil carbon, stimulating CO_2 emissions through accelerated decomposition and thereby offsetting reductions in R_S due to root excision (Díaz-Pinés et al., 2010; Luo & Zhou, 2010; Savage et al., 2018). We carefully investigated whether the lack of a relationship between annual R_S and collar insertion depth was due to a Type II error (false negative). Annual R_S is closely correlated with the MAT and MAP (Hashimoto et al., 2015; Raich & Potter, 1995; Raich & Schlesinger, 1992); therefore, if annual R_S samples were not evenly distributed along MAT and MAP gradients, the relationship between annual R_S and collar insertion could be masked. To address this issue, we plotted MAT and MAP versus the residuals from the "annual R_S ~ collar insertion depth regression model," and found no clear pattern in the scatter plot (Figure S1). Thus, it is unlikely that this trend was masked by climatic variables. In addition, we hypothesized that if collar insertion depth has a significant effect on annual R_S, then sites with more root biomass should have larger effect sizes. However, the scatter plot between the R_{root}:R_S ratio and standard residual does not show a consistent trend (Figure S1).

The intention of this study was to investigate whether collar properties, measurement duration, and measurement frequency exert bias on annual R_S from SRDB were used for synthesis and modeling. Therefore, this study focuses on detecting systematic errors at annual time scales and across multi-site (global) spatial scales. Our results showed that annual R_S measurements from SRDB could be directly used without any standardization or correction. However, at the site scale, the collar properties and measurement duration and frequency related bias should be carefully considered in any particular experiment. To understand the dissimilar responses of global-scale annual R_S and site-scale R_S to collar insertion, we must disentangle several ecological factors. First, in some studies, it is possible that the majority of root biomass occurred below 5 cm—the average collar insertion depth. For instance, Sinuraya (2010) found that Indonesian oil palm plantation roots were most abundant 30–45 cm below the soil surface, well below the average collar installation depth. Second, root density exhibits extensive spatial variation which can be difficult to accurately capture when using static chamber experimental design that does not consider environmental heterogeneity. For example, Jauhiainen et al. (2012) and Dariah et al. (2014) found that root respiration in *Acacia* plantations became negligible when measurements were collected roughly 1.3–3 m from tree stems, necessitating a spatially informed chamber deployment to quantify ecosystem R_S. Third, many studies do not describe whether the litter layer and organic layer were included in the insertion depth (Heinemeyer et al., 2011; Kutsch et al., 2001), which can result in an overestimation of the collar insertion depth recorded in SRDB-V5 since the litter layer does not include the rooting zone. Finally, when the collar insertion is not very deep, it is possible that roots regrow within the collar-covered area (Wang et al., 2005).

R_S measurement duration and measurement frequency showed no significant relationship with annual R_S when integrating sites' measurements across the globe (Figure 5). Some site-scale experiments have found similar results; for example, based on 20-min frequency continuous R_S measurements at a riparian and an upland site, Riveros-Iregui et al. (2008) found that cumulative CO_2 showed no difference if measurement frequency decreased from 20 min to 2 or 7 day. There are many possibilities to explain this: First, the magnitude of bias related to measurement duration may be relatively small. This is supported by the conclusion from a global analysis by Jian et al. (2018b) using daytime sampled R_S to represent diurnal averages contributes less than 6% bias. Second, researchers are good at what they do, that is, choosing their measurement frequencies carefully based on their knowledge of the ecosystem. Samples from SRDB-V5 had an average R_S measurement frequency of 22 days ($n = 7{,}545$), corresponding to ~17 sampling events per year. Jian et al. (2018b) determined that this annual sampling frequency resulted in annual R_S values that were within $\pm 30\%$ of the true R_S mean 80% of the time. A similar conclusion was found in three temperate forests (Bond-Lamberty et al., 2019). This study thus demonstrated that while large uncertainty may exist with a 21-day measurement frequency, it may still reasonably capture the average annual mean of R_S. Third, it is possible that we failed to detect the effect of measurement duration and frequency due to a Type II error. For example, there could be a scenario in which annual R_S are systematically overestimated by measuring during the time at which R_S is higher than the daily/or annual mean R_S; however, those observations are mostly from the sites with lower R_S rates, and therefore, the effect of measurement duration and frequency could be masked.

To accurately test the bias associated with measurement duration, two instruments of the same method, each at similar time window but with different sampling duration, should be compared in the future studies. To test the effect of measurement frequency, a comparison of two methods at different sampling frequencies or resampling from continuous measurements can be used to test the effect of measurement frequency. Evaluating the effect of measurement duration and frequency in depth is outside the scope of this paper, but a new community database for continuous soil respiration (COSORE, Bond-Lamberty et al., 2020) provides an opportunity to test it in the future.

The results from this study have significant implications for future R_S synthesis, modeling, and site-scale experiment design. First, compiling site-scale R_S measurements into a standardized database is an important practice to support future synthesis efforts, statistical modeling, and process model benchmarking (Shao et al., 2013). For instance, since the first version of SRDB was published (Bond-Lamberty & Thomson, 2010a), it has been widely used to support meta-analyses (Hursh et al., 2017; Jian et al., 2020), global R_S modeling (Bond-Lamberty & Thomson, 2010a; Hashimoto et al., 2015; Jian et al., 2018; Jian et al., 2018a), and global climate change related analyses (Bond-Lamberty & Thomson, 2010b) Our findings lead us to conclude that annual R_S values derived using disparate methods can be used in subsequent analyses with little standardization or correction, resolving and removing an important potential barrier to the scientific user community. Second, we found no significant difference among annual R_S measured using different methods (Figures 2a and 2b), agreeing with the conclusions of many site-scale comparison (Baldocchi et al., 2006; Riveros-Iregui et al., 2008; Tang et al., 2003). Many types of R_S measurement methods (e.g., AA, EC, GC, Gradient, and IRGA) have been used to investigate spatial and temporal variations in R_S across the globe, and each method has its advantages and disadvantages. Our results suggest that scientists could choose a R_S measurement method according to the scientific question, environmental condition, and cost. Third, collar height, collar coverage area, and collar insertion depth are important factors affecting R_S measurement and should be carefully considered in the future site-scale experiments. Finally, our results suggest that R_S point measurements during the day may be sufficient for estimating diurnal mean R_S, which is much more efficient and economical compared to 24-hr continuous measurements to measure spatial variability of R_S in multiple sites. From SRDB-V5 we showed that approximately 85% of R_S measurements do not measure 24 hr continuously, and likely many more of R_S estimated from non-continuous measurement will be reported in the future due to its low cost and portability. We thus suggest that linking SRDB-V5 (strength at spatial coverage, Jian & Bond-Lamberty, 2020) with COSORE (strength at temporal resolution, Bond-Lamberty et al., 2020) in the future could provide an opportunity for better understanding global R_S spatiotemporal variability.

5. Conclusions

Many site-scale experiments have shown that collar properties and R_S measurement duration may bias R_S measurements. Site-scale annual R_S measurements from different climate and vegetation types have been integrated into global R_S databases for synthesis analysis and global annual R_S estimation. Therefore, a comprehensive analysis of collar properties and sampling time related bias is necessary. In this study, based on an updated global soil respiration database, we tested the influence of collar height, collar insertion depth, collar coverage area, measurement duration, and measurement frequency on annual R_S. We found that annual R_S was negatively correlated with collar height, collar coverage area, and collar insertion depth. Measurement duration and frequency, however, showed no relationship with annual R_S. Together, our results indicate that collar properties and measurement duration contribute minimal bias overall on annual soil respiration measurements, but the bias is nonnegligible at ecosystem and site level. To summarize, the results in this study provide strong support of integrating site-scale annual R_S measurements for global synthesis analysis and R_S modeling based on the global soil respiration database.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

Code and data to reproduce all results are available at Jian and Bond-Lamberty (2020; jinshijian/ESSD: SRDB-V5 release for time and collar analysis [Version v1.0.1]; Zenodo, http://doi.org/10.5281/zenodo.3970952).

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