

JGR Biogeosciences

RESEARCH ARTICLE

10.1029/2019JG005265

Key Points:

- Variability of soil respiration (R_S) had different characteristics at subhourly to seasonal time scales in a coastal deciduous forest
- Successive hourly and daily measurements were rarely correlated beyond more than one or two time lags
- Soil temperature and moisture consistently explained most of the R_S variability across all time scales

Supporting Information:

- Supporting Information S1

Correspondence to:

B. Bond-Lamberty,
bondlamberty@pnnl.gov

Citation:

Bond-Lamberty, B., Pennington, S. C., Jian, J., Megonigal, J. P., Sengupta, A., & Ward, N. (2019). Soil respiration variability and correlation across a wide range of temporal scales. *Journal of Geophysical Research: Biogeosciences*, 124, 3672–3685. <https://doi.org/10.1029/2019JG005265>

Received 22 MAY 2019

Accepted 5 NOV 2019

Accepted article online 11 NOV 2019

Published online 29 NOV 2019

Author Contributions:

Conceptualization: Ben Bond-Lamberty

Formal analysis: Ben Bond-Lamberty, Nicholas Ward

Funding acquisition: Ben Bond-Lamberty

Investigation: Ben Bond-Lamberty, Stephanie C. Pennington, Jinshi Jian, Aditi Sengupta

Project administration: Ben Bond-Lamberty, J. Patrick Megonigal

Resources: J. Patrick Megonigal

Software: Ben Bond-Lamberty,

Stephanie C. Pennington

Supervision: Ben Bond-Lamberty

Visualization: Ben Bond-Lamberty

Writing - original draft: Ben Bond-Lamberty

Writing - review & editing: Ben Bond-Lamberty, Stephanie C.

Pennington, Jinshi Jian, J. Patrick (continued)

Soil Respiration Variability and Correlation Across a Wide Range of Temporal Scales

Ben Bond-Lamberty¹ , Stephanie C. Pennington¹ , Jinshi Jian¹ , J. Patrick Megonigal² , Aditi Sengupta³ , and Nicholas Ward^{4,5} 

¹Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, MD, USA, ²Smithsonian Environmental Research Center, Edgewater, MD, USA, ³Biological Sciences Division, Pacific Northwest National Laboratory, Richland, WA, USA, ⁴Marine Sciences Laboratory, Pacific Northwest National Laboratory, Sequim, WA, USA, ⁵School of Oceanography, University of Washington, Seattle, WA, USA

Abstract The high temporal variability of the soil-to-atmosphere CO_2 flux (soil respiration, R_S) has been studied at hourly to multiannual time scales but remains less well understood than R_S spatial variability. How R_S fluxes vary and are autocorrelated at various time lags has practical implications for sampling and more fundamentally for our understanding of its abiotic and biotic underlying mechanisms. We examined the variability, correlation, and sampling requirements of R_S over a wide range of temporal scales in a temperate deciduous forest in eastern Maryland, USA, using both automated (temporally continuous, $N = 30,036$ over 10 months) and survey (spatially diverse, temporally sparse, $N = 1,912$ over 17 months) data. Data from a global R_S database were also used to examine interannual variability in comparable forests. The coefficient of variability of successive measurements generally varied from the minute (median coefficient of variation 16%) to hourly and daily (11–12%) time scales. Successive R_S values measured at a given collar exhibited a strong hour-to-hour correlation ($r = 0.931$) and a moderate correlation at a 2-hr lag (0.289); day-to-day (i.e., 24 hr lag) hourly observations were uncorrelated. Daily R_S means were well correlated at a 1-day lag ($r = 0.856$) but not at any further time lag. In a linear mixed-effects model predicting R_S , soil temperature and moisture exerted consistently strong effects regardless of time scale, and model coefficient of variability was generally high (>80%). These results provide new opportunities to explore the drivers and variability of R_S fluxes, quantify sampling requirements, and improve error propagation.

Plain Language Summary Soils give off carbon dioxide, generated by microbes and plant roots, to the atmosphere. How this “soil respiration” (R_S) varies in time, as one measures at minute, hourly, daily, or longer time scales, is related to the processes driving it and has implications for how we estimate this flow of carbon across space and time. We measured R_S in a coastal deciduous forest in Maryland, USA, and found that the variability of R_S —how much it changed between successive measurements—varied at the different time scales. R_S values quickly became increasingly random (i.e., uncorrelated with each other) as one measured repeatedly over time. These results help us understand the factors driving this large flow of carbon to the atmosphere and improve our ability to estimate R_S at times and places not directly measured.

1. Introduction

Soil respiration (R_S), the soil-to-atmosphere flux of CO_2 primarily generated by root and microbial respiration, is a significant part of ecosystem- to global-scale carbon (C) cycles (Le Quéré et al., 2018; C. L. Phillips et al., 2017; M. Xu & Shang, 2016). Understanding its sources (Subke et al., 2006), magnitude, variability, and drivers such as soil temperature and moisture (Hurst et al., 2017) provides opportunities to explore its climate feedback potential (Bond-Lamberty et al., 2018; Hashimoto et al., 2015) and biogeochemical constraints (Hurst et al., 2017). R_S can also be used to probe other parts of the C cycle (Bond-Lamberty et al., 2018; C. L. Phillips et al., 2017), for example, as a constraint on eddy covariance-derived estimates of net ecosystem exchange (Barba et al., 2018; Wang et al., 2017).

The high temporal variability of field-measured R_S has been recognized for decades (Rochette et al., 1991; Tang & Baldocchi, 2005) at time scales ranging from minutes to hours (La Scala et al., 2000; Leon et al.,

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2014) to years (Raich et al., 2002; Savage & Davidson, 2001). In general, the temporal variability of R_S is less well studied than its spatial variability, particularly in the context of variability in other parts of the C cycle (e.g., D. Baldocchi et al., 2018); the degree to which successive R_S observations are correlated in time is rarely reported, and there are no central databases for continuous R_S observations equivalent to FLUXNET (D. D. Baldocchi et al., 2001).

One particular aspect of temporal variability that has been frequently addressed is the “best” (most representative) time of day to measure R_S , as this has immediate implications depending on the ultimate goal of the sampling (Savage et al., 2008). For example, Davidson et al. (2002) found that diel variation was ~25% of the daily mean, and that midmorning was the best time to measure a representative daily flux. This time-of-day question was shown to have a large effect in shrubland (Cueva et al., 2017) and agricultural (Parkin & Kaspar, 2004) ecosystems. In general it will be more important in systems with larger diel flux variability (Jian et al., 2018), driven by strong day-to-night contrasts; conversely, it might be expected to be weaker in the long summer daylight at high latitudes, for example. At a longer time scale, Perez-Quezada et al. (2016) used hourly measurements in a temperate rainforest over 1 year to determine what sampling frequency was required to accurately estimate daily and annual R_S fluxes. In addition, effective gap filling is strongly dependent on understanding temporal dynamics (Gomez-Casanovas et al., 2013) and the degree to which successive measurements in time are correlated with each other (Ramsey, 1974).

The temporal variability and correlation (how closely related fluxes are to each other across varying time lags) of R_S have implications beyond sampling, as the structure of temporal correlation reflects the degree to which R_S is driven by microbial versus plant root growth and respiration (Vargas et al., 2011; Vargas et al., 2011), as well as short-term air and/or water pressure effects. R_S temporal patterns shift with the presence of roots, canopy characteristics, and tree physiology (Han et al., 2007; Savage et al., 2013; Tang et al., 2005; Tang & Baldocchi, 2005), and thus variability and correlation are critical to understand how R_S temperature and moisture sensitivities vary in time and space (Hursh et al., 2017; Liu et al., 2016; Zhou et al., 2009). For this reason extreme events can only be understood in the context of a “normal” background of temporal variability (Borken et al., 2006; Reichstein et al., 2013; Vargas, 2012).

A final aspect of temporal variability revolves around “hot spots” and “hot moments” in space and time (Leon et al., 2014). These localized and/or short bursts of CO_2 and other greenhouse gases (Kim et al., 2012) affect sampling priorities (Bond-Lamberty et al., 2016) but also provide insight into the degree to which these fluxes are driven by soil microbes or via plant roots (Jarvis et al., 2007; Smith et al., 2017; Vargas et al., 2018). Such dynamics have implications for how microbial processes might be appropriately represented in microbially explicit soil biogeochemical models (Bradford et al., 2019), as microbial activity depends on both the “hospitality” of the environment and the microbial community composition (Wieder et al., 2015).

This study examined the variability, correlation, and sampling requirements of R_S in a temperate deciduous forest in eastern Maryland, USA, aiming to explore how the controls on, and characteristics of, R_S change over a wide range of temporal scales (~1 min to ~1 year). We combined (i) continuous hourly measurements made using an eight-chamber infrared gas analyzer (IRGA) over 10 months with (ii) survey measurements made every 10–14 days over 17 months at the same site. We also used (iii) data on annual fluxes from a global soil respiration database (SRDB) as a point of reference, with the goal of characterizing the general temporal dynamics of similar temperate deciduous forests in the database.

2. Methods

2.1. Study Sites

This study was conducted in three mid-Atlantic, temperate, deciduous forest sites at the Smithsonian Environmental Research Center (SERC) in Edgewater, MD, USA. The upland and lowland forests sampled here are ~60 years old with a mean annual precipitation of 1,001 mm and mean annual temperature of 12.9 °C (Pitz & Megonigal, 2017). Dominant tree species included deciduous broadleaf hardwoods *Liriodendron tulipifera*, *Fagus grandifolia*, and *Quercus* spp. (Parker et al., 1989), which are typically dormant November–March, during a winter dominated by rain and occasional snow. Soil types varied between Collington, Wist, and Annapolis soils (fine-loamy, active, mesic Typic Hapludults) (Yesilonis et al., 2016).

Lowland forests occur immediately adjacent to Muddy Creek, a third-order stream draining into the Chesapeake Bay, and are hydrologically connected with the creek's tidal swings (Jordan et al., 1991), while the upland stands are ~50 m away from the creek and ~5 m higher in elevation. The sample sites were located by the creek mouth (38.875°N, 76.552°W) as well as roughly 1 km (38.884°N, 76.557°W) and 2 km (38.887°N, 76.562°W) upstream; all sites had plots both close to the creek and farther uphill. Further site and measurement details are described by Pennington et al. (2019).

2.2. Soil Respiration Measurements

Three sources of data were used in this study. The first was 10 months of continuous R_S measurements (totaling 31,559 raw hourly observations) made using an eight-chamber automated LI-8100A connected to a LI-8150 multiplexer (LI-COR Biosciences, 2015) from October 2018 to July 2019. These were made in the creek mouth forest stand (see above) immediately adjacent to the Global Change Research Wetland forest site (Pennington et al., 2019); this was also the furthest downstream site used for the survey measurements described below. All IRGAs used were set to local standard time; that is, no daylight savings adjustment was performed.

The second data set was composed of survey measurements (raw $N = 1,939$) of R_S taken every ~14 days across three sites at SERC over 17 months using an IRGA (LI-8100A, LI-COR Inc., Lincoln, NE) with a 20-cm diameter soil chamber attached. We randomly installed twelve 20-cm diameter PVC collars at each site, separated from each other by 2–15 m, ~1 week prior to initial sampling, and measured them every 10–14 days from April 2018 to July 2019. After installation, collars were not moved throughout the entire study. The IRGA measures CO_2 concentrations every second and calculates the resulting soil-to-atmosphere flux from one or more successive 1-min periods. For all continuous and survey measurements, all vegetation was removed from inside collars, new vegetation was reclipped as necessary, and soil moisture and temperature were recorded at 5-cm soil depth concurrently using handheld probes wired directly to the IRGA.

The third data source was a global soil respiration database (SRDB, Bond-Lamberty & Thomson, 2010b), used to examine R_S interannual variability for contextual and comparison purposes. This SRDB includes 6,711 records on seasonal to annual R_S fluxes measured worldwide over the last five decades. The data (commit c84b377, downloaded 1 April 2019 from <https://github.com/bpbond/srdb>) were filtered for “deciduous forests” with no experimental manipulation and ≥ 2 years of data (so that an interannual coefficient of variation [CV] value could be calculated). For comparability with our observations, we used only IRGA-measured data. The resulting data set had 245 observations of internannual CV from temperate deciduous forests worldwide.

2.3. Statistical Analysis

A two-step process was used to identify extreme outliers in the SERC R_S observations. First, we excluded any values with an IRGA-calculated $R^2 < 0.75$, judging that this indicated a chamber closure problem or other mechanical issue (LI-COR Biosciences, 2015); second, the mean absolute deviation (MAD, using R's stats::mad() function), a measure of deviation robust against outliers, was computed for each individual week of observations. We excluded values more than four MADs from the week's median, a level that we deemed sufficient to remove extreme outliers while leaving most of the natural variability. These two steps removed 4.8% of the continuous data, resulting in a final data set of 30,036 observations, and 1.7% of the survey data, for 1912 final observations.

Much of this analysis focuses on the variability between successive R_S measurements. For this we use the CV, the ratio of the standard deviation to the mean, as it provides a standardized measure of dispersion and has a long history in ecological studies (Hendricks & Robey, 1936). In general we computed the CV between successive measures in a variety of time series, that is, for $x = \{x_1, x_2, \dots\}$ focused on the CV of $\{x_1, x_2\}$, $\{x_2, x_3\}$, etc.

A complementary and more specific technique is the partial autocorrelation function (PACF), which gives the partial correlation of a stationary time series with its own lagged values, after controlling for the values of the time series at all shorter lags (Box et al., 2015; Cowpertwait & Metcalfe, 2009; Ramsey, 1974). This provides a summary, computed using the *pacf* function in base R, of the relationship between an observation and observations at prior time steps, and was computed for both the hourly data and their daily means.

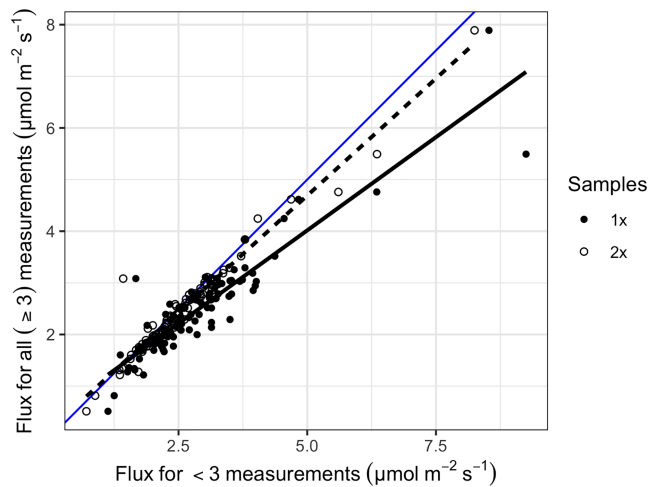


Figure 1. Comparison between repeatedly sampling soil respiration at the same collar from 1–4 sequential minutes. The mean of the longer-term (3- and 4-min) samples is on the y axis; less-frequent sampling is on the x axis, and points indicate whether one (filled circle, solid line) or two (hollow circle, dashed line) 1-min measurements were made. Lines are regression fits, and the solid blue line is 1:1.

We imposed a limit of ± 2 on the PACF values, removing four outliers with very high values out of 120 total observations.

The continuous ($N = 8$ collars) R_S data were also used to estimate the number of samples required for a robust estimate of the “population mean” over a month, that is, how many randomly timed observations would be required for a temporally representative mean for a month in winter 2018–2019. We used a Student’s t test to calculate this based on the standard deviation of hourly R_S , the desired power of the test, and the allowable delta (difference from the true mean value), following Davidson et al. (2002).

Respiration, in general, scales nonlinearly with temperature (Davidson & Janssens, 2006), and the CV of normally distributed data will typically be nonnormal (Hendricks & Robey, 1936). We thus used a nonparametric test, the Fligner-Killeen (median) statistic, to compare variances across sample groups (i.e., between CVs computed at different time scales); this simple linear rank test is highly robust against departures from normality (Conover et al., 1981).

A subset of the survey observations was performed three to four times consecutively at the same collar, allowing us to test whether the initial one or two observations were sufficient to represent the mean of three to four measurements over the span of a few minutes. This was done using

Tukey’s honest significant difference test in base R (Tukey HSD) with a default confidence level of 0.95. These were successive measurements with a dead band of 0, that is, were performed without opening the chamber between measurements, allowing for high-frequency but not truly independent sampling.

Finally, we used a linear mixed-effects model to examine the effects of soil temperature and moisture on R_S . This treated temperature at 5 cm (T_5), soil moisture, and their interactions as fixed effects, and collar as a random effect (to account for the repeated measures nature of the observations); the natural logarithm of R_S was the dependent variable. For each time scale, the model was estimated using restricted maximum likelihood estimation using the *lme4* package version 1.1.21 (Bates et al., 2015) in R. All models were examined for influential outliers and deviations from normality assumptions.

All statistical analyses were performed in the statistical computing language R version 3.6.1 (R Development Core Team, 2019). Code and data to reproduce all results are available at <https://github.com/PNNL-PREMIS/PREMIS-ghg> and permanently archived at [<https://doi.org/10.5281/zenodo.3549586>].

3. Results

3.1. Minutes to Hours to Days

The median CV between successive measurements at the same collar and taken ~ 1 min apart (from a subset of the survey data, $N = 798$, fluxes between 0.46 and $15.77 \mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$) was 16% (minimum 0%, maximum 84%). We found that a single 60-s measurement differed considerably from taking the mean of two to four successive measurements (Tukey HSD $P = 0.032$, Figure 1). Conversely, there was no significant difference between two measurements versus three or four ($P = 0.859$). We conclude that, at this site, two successive 60-s measurements are the minimum needed for accuracy at this time scale, but there was no benefit to further measurements beyond two.

The median CV between successive measurements at the same collar and taken ~ 1 hr apart (from the continuous data, $N = 29,335$; fluxes between -0.78 and $48.56 \mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$) was 11% (minimum $-11,172\%$, maximum $1,669\%$, with these very high extreme values due to rare but extremely high excursions; the first and third quartiles were 5% and 23%, respectively). Successive R_S values (i.e., those measured at a 1-hr lag) exhibited a strong correlation ($r = 0.931$), and remained moderately correlated (0.289) at a 2-hr lag. Day-to-day (24-hr lag) observations at a given collar were essentially uncorrelated (Figure 2). This pattern was consistent throughout the study period (supporting information Figure S1).

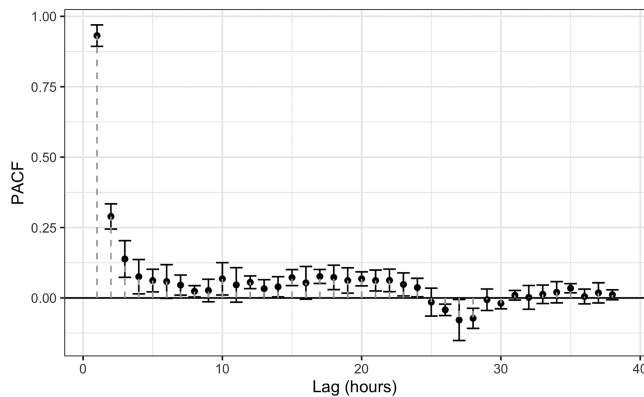


Figure 2. Partial autocorrelation function (PACF, the correlation of a stationary time series with its own lagged values, after accounting for the correlation at all shorter lags) between hourly soil respiration measurements. Values are mean \pm s.d. based on $N = 8$ individual collars from the 10-month continuous measurement data set. Dashed gray vertical lines provide a visual reference for the x axis intercept of each point.

The variability of the hourly data meant that if one wants to estimate the mean monthly flux from sporadic measurements with high confidence, the sampling requirements can become large; being 90% certain of being within 10% of the true mean requires over twice-daily sampling (69 ± 24 observations; plot mean \pm plot-to-plot standard deviation) at this site (Table 1). Conversely, measuring once per week means that there is only 65% likelihood (power) of being within 25% of the true monthly mean, or 95% certain of being within 50%. There was considerable small-scale spatial variability, which meant that the sample sizes required differed considerably between measurement collars; for example, to be 95% certain of being within 50% of the true mean (4 ± 2 samples, Table 1) required anywhere from three to seven samples.

3.3. Annual

The median interannual CV between site years in the deciduous forest SRDB data was 9% (min = 0%, max = 39%, $N = 245$). Measurement interval had no effect on the distribution of interannual CV (Fligner-Killeen med $\chi^2 = 3.372$, $df = 3$, $P = 0.338$), but only a small number of studies had measurement intervals longer than 30 days (Figure 5). Annual fluxes based on studies with an annual observation coverage of $<90\%$ of the year, however, had significantly smaller interannual CV than did fluxes based on $\geq 90\%$ of the year ($\chi^2 = 11.107$, $df = 1$, $P < 0.001$), suggesting that year-round measurement coverage is necessary to accurately estimate the annual R_S flux.

The distribution of successive measurement CV values across all time scales is summarized in Figure 6. The median CV of minute-to-minute R_S was higher (16.3%) than hour-to-hour and day-to-day R_S (both 11–12%); the strong seasonal signal at this site meant that the month-to-month CV was much higher. Year-to-year CV was the lowest at 9%, although we emphasize the different data source of these data, and the lack of multiyear data from the SERC site measured here. The distribution of CVs was long-tailed, extending out to $>75\%$ except for annual fluxes, which overall had the lowest successive-measurement variability of any time scale. These CV distributions and their median values were significantly different overall ($\chi^2 = 515.63$, $df = 4$, $P < 0.001$). A post hoc pairwise comparison showed that the minute, hour, and daily CV distributions were not significantly different from each other, while month-to-month and interannual distributions differed from everything else (Bonferroni-corrected $P < 0.001$ for both), consistent with different biotic and abiotic controls operating at these longer time scales.

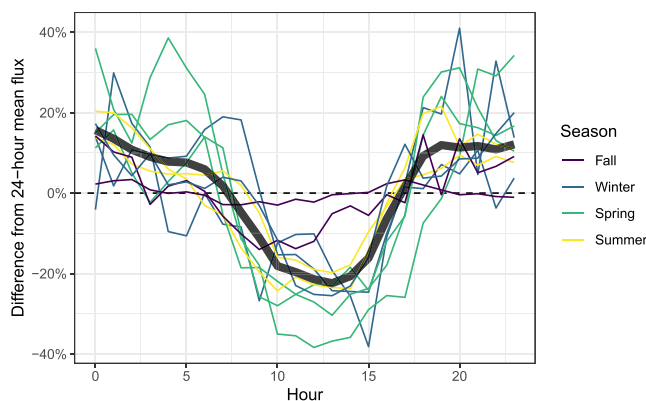


Figure 3. Most representative times of day to sample soil respiration, based on 10 months of continuous (hourly, $N = 8$ separate collars) soil respiration measurements. Each line is the mean of a month of data; lines are colored by 3-month seasons of the year, where “Fall” is September–October–November, “Winter” is December–January–February, etc. The heavy dark line shows the mean value, that is, based on all data pooled together.

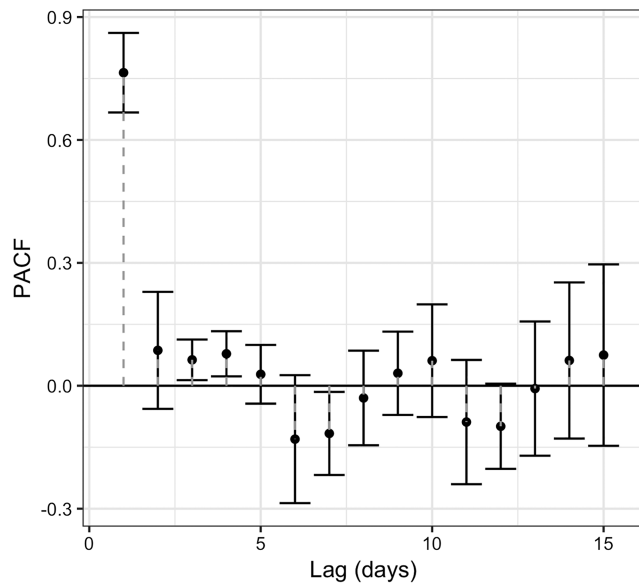


Figure 4. Partial autocorrelation function (PACF, cf. Figure 2) between daily means of hourly soil respiration measurements. Values are mean \pm s.d. based on $N = 8$ individual measurement collars.

3.4. Abiotic Factors

The correlations between soil temperature and moisture on R_S stayed largely consistent as continuous data were aggregated to longer temporal scales (Table 2). Soil moisture and soil temperature were always highly significant as fixed-effect predictors ($P < 0.01$ in all cases). Although direct comparisons of the models in Table 2 should not be made because of the varying sizes of the underlying data, it is interesting that the coefficient of variability (R^2) was roughly constant across time scales. The survey data, that is, taken sporadically throughout the year at a larger set of plots, was most similar to the weekly model of continuous data—that is, roughly the time scale at which the survey data were collected, although the former covered only 10 months, while the latter more than a full year.

4. Discussion

We found that the R_S characteristics—specifically, the variability and correlation between successive observations in time—varied at different temporal scales. In general the CV values (12–17%, except month-to-month variability which was 28%) were somewhat smaller than the spatial variability observed at this site (Pennington et al., 2019) and in other forests (e.g., 26–62% in Kosugi et al., 2007). The year-to-year data were from a broad spectrum of temperate deciduous for-

ests, not this SERC site specifically, but in general their mean interannual CV (9%) was consistent with the site-specific values observed here (Braswell et al., 1997; Jung et al., 2017).

At the minute-to-minute time scale, the relatively high R_S variability (CV of 17%) observed here is likely driven primarily by measurement error, for example, chamber pressure excursions due to the Venturi effect (Davidson et al., 2002; L. Xu, 2006) or CO_2 saturation effects (Pumpanen et al., 2010). Rapid changes in light-driven photosynthesis feeding root respiration (Bader et al., 2016) could potentially contribute as well. Another factor potentially influencing short-term R_S variability is the rapid response of microbes to varying conditions. For example, increases in water availability can drive a rapid release of microbial biomass into soils, resulting in respiration pulses in temperate soils (Cleveland et al., 2007; Fierer & Schimel, 2003; Kieft et al., 1987). Large pulses in microbial respiration can be related to freeze/thaw cycles (Kim et al., 2012; Schimel & Klein, 1996), but in this study temperatures rarely ($<0.1\%$ of the data) dropped below 0° . C. Nonmicrobe mediated greenhouse gas production processes such as photodegradation may also contribute to short-term R_S variability (Rey, 2015).

R_S hour-to-hour and day-to-day variability was lower than minute-to-minute variability in this study, and is often associated with soil temperature, and more generally, diurnal fluctuations in environmental conditions such as temperature, moisture, wind speed, and light. Any factor that affects plant and microbial metabolism can affect R_S as measured at the soil surface (Bader et al., 2016). Rainfall events can result in abrupt changes in R_S at these time scales, likely due to some combination of the fast response of soil microbial activity to moisture changes that trigger decomposition of active carbon compounds (Fierer & Schimel, 2003; Kim et al., 2012; Lee et al., 2004). Soil moisture also affects R_S , particularly at longer time scales; for example, Jia et al. (2006) found that the diurnal R_S pattern was closely related to temperature, but seasonal R_S variation could be explained by soil moisture change.

The interannual variability of C fluxes generally can be large, for example, $\sim 81\%$ for net ecosystem exchange (D. Baldocchi et al.,

Table 1

Sample Sizes Required to Estimate Wintertime Monthly Mean Soil Respiration in the Temperate Deciduous Forest Studied Here, by t Test Power (i.e., β) and Allowable Delta (Deviation From the Mean Flux)

Power	Allowable delta (percentage of mean flux)			
	5%	10%	25%	50%
0.50	47 \pm 16	12 \pm 4	2 \pm 1	1 \pm 1
0.60	72 \pm 25	18 \pm 7	3 \pm 1	1 \pm 1
0.70	110 \pm 37	28 \pm 10	5 \pm 2	2 \pm 1
0.75	135 \pm 46	34 \pm 12	6 \pm 2	2 \pm 1
0.80	167 \pm 56	42 \pm 14	7 \pm 3	2 \pm 1
0.85	211 \pm 72	53 \pm 18	9 \pm 3	3 \pm 1
0.90	276 \pm 93	69 \pm 24	12 \pm 4	3 \pm 1
0.95	392 \pm 132	98 \pm 33	16 \pm 6	4 \pm 2

Note. Values are the overall mean \pm s.d. based on $N = 8$ soil collars; that is, here the standard deviation reflects small-scale spatial variability. The underlying data set (the “true” population mean) is based on 1 month of continuous hourly measurements made in February–March 2019.

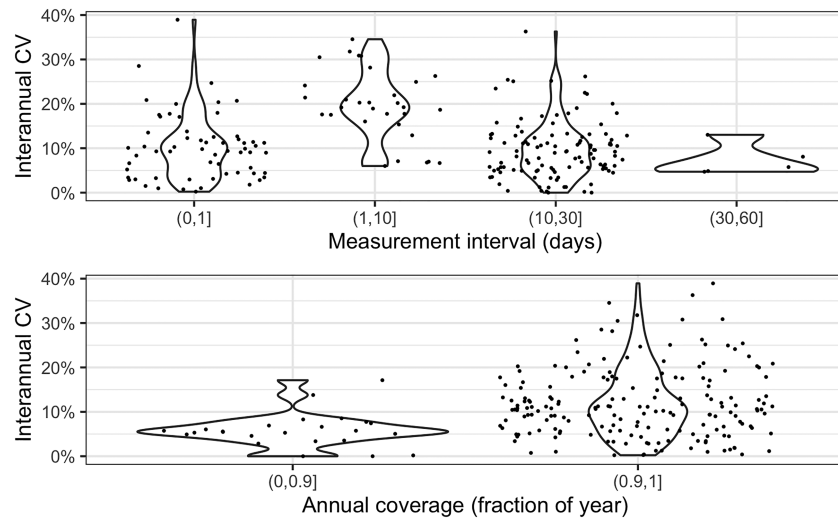


Figure 5. Effect of measurement interval (time between measurements) and annual coverage (fraction of the year measured) on the interannual coefficient of variability (CV) between successive site years in the global soil respiration database (SRDB; Bond-Lamberty & Thomson, 2010b) for unmanipulated, temperate deciduous forests. Measurement interval (top panel) is the mean number of days between measurements, and annual coverage (bottom panel) reflects the fraction of the year measured when computing the annual flux (e.g., if an annual flux is inferred from only April–September measurements, the fraction is 0.5). The width of the violin plots (enclosed areas behind points) correspond to distribution of CV values; their horizontal lines show the 90% and 95% values in each distribution, and dots the median CV. The x axis follows standard mathematical notation: A parenthesis is used when the point or value is not included in the interval, and a square bracket indicates that the value is included.

2018). While soil respiration interannual variability can be larger in absolute terms than net ecosystem exchange (NEE, Savage & Davidson, 2001), we found relatively small CVs in annual R_s (Figure 6); there was a “long tail” in the distribution, with values as large as 39%, but these were much smaller than the larger CVs at shorter time scales. This is consistent with soil acting as a buffer against larger swings in plant growth (Raich et al., 2002), with the effect changing at different spatial scales (Kicklighter et al.,

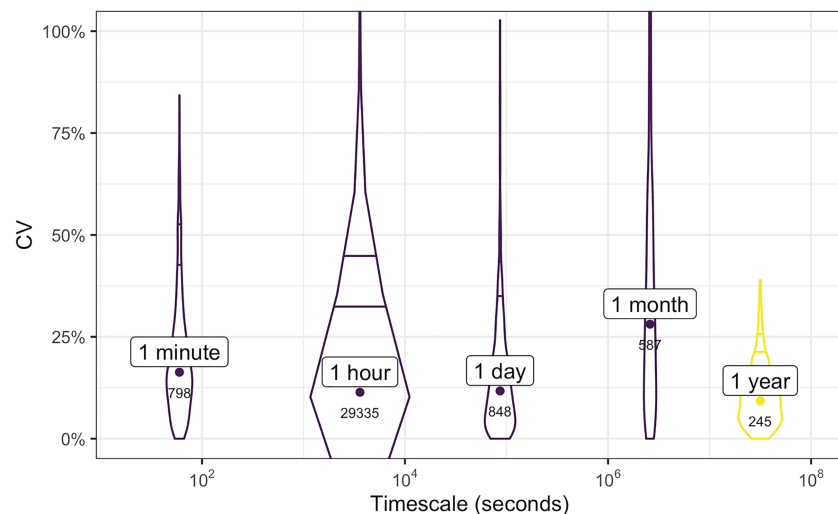


Figure 6. Coefficient of variability (CV) between successive measurements made at minute, hourly, daily, monthly, and annual time scales. The width of the violin plots (enclosed areas behind points) correspond to distribution of CV values; their horizontal lines show the 90% and 95% values in each distribution; and dots the median CV. The small number below the median reports N for each distribution. The right-hand annual (“1 year”) distribution plot is shown in a different color to emphasize its different data source (245 interannual observations from a global soil respiration database covering many different deciduous forest stands); its comparability with the other distributions should be treated with caution.

Table 2
Summary of Linear Mixed-Effects Models Characterizing the Relationship Between Soil Respiration With Soil Temperature and Moisture at Various Time Scales

Metric	Hourly	Daily	Weekly	Monthly	Survey
<i>N</i>	29,448	950	244	72	1,912
AIC	26,640.5	213.0	87.7	−1.83	1,078.5
R^2	0.828	0.876	0.873	0.920	0.600
Terms:					
T_5	<0.001	<0.001	<0.001	<0.001	<0.001
SM	<0.001	<0.001	<0.001	0.093	0.727
SM ²	<0.001	<0.001	0.009	0.185	0.032
$T_5 \times \text{SM}$	<0.001	<0.001	<0.001	0.005	0.949

Note. Table entries include number of observations in the model (*N*), Akaike information criterion (AIC), and conditional R^2 (the fraction of variance explained by both fixed and random effects). Individual terms in each model include soil temperature at 5 cm (T_5 , °C), volumetric soil moisture (SM, cm³/cm³) and its square to account for nonlinear moisture effects, and the $T_5 \times \text{SM}$ interaction. The dependent variable was the natural logarithm of soil respiration (μmol·m^{−2}·s^{−1}). Hourly data over 10 months were aggregated as necessary to each time scale, except for the right-hand column, which uses data from the discontinuous (every 10–14 days) survey data over 17 months. Note that the high variability in sample size (*N*) means that model metrics such as AIC and R^2 should not be compared between columns.

1994). Interestingly, annual fluxes from the SRDB based on annual coverage of observations <90% had significantly smaller interannual CV than did fluxes based on measurements covering ≥90% of the year (Figure 5). We suspect that the common decision not to measure during the dormant season and to instead extrapolate nonwinter measurements to an annual flux) results in significant “missed” variability. Significant numbers of studies estimate annual R_S from growing-season only fluxes (Jian et al., 2018), and the errors on these estimates are almost certainly larger than ones based on full-year sampling.

The broad consistency in R_S models in terms of significant predictors and overall explained variability (Table 2) is somewhat surprising as many of these factors are thought to change at different temporal scales. For example, interactions among soil temperature, soil moisture, microbial community size and composition, root biomass, and plant production may control temporal and spatial R_S variation during the growing season (e.g., Han et al., 2007), but change radically in the dormant season, when soils may be wetter or drier depending on climate and respiration of roots is minimal and relatively insensitive (Leon et al., 2014). Rubio and Detto (2017) found soil moisture was responsible for seasonal cycles and rain-induced pulses following dry spells, and increased variability at shorter time scales.

4.1. Time of R_S Sampling and Sampling Requirements

An interesting question is how many successive measurements are required to robustly estimate the current flux at a given measurement point (e.g., Figure 1 in Davidson et al., 2002). At these sites, we found that two successive 60-s measurements were the minimum needed for accuracy at this time scale, consistent with the manufacturer's recommendations (LI-COR Biosciences, 2015), but there was no benefit to further measurements. We do not know how broadly this conclusion applies to other sites or ecosystem types, however, given the wide diversity in soil structure, hydrology, biota, and microbial communities seen in terrestrial ecosystems, and the resulting diversity in R_S dynamics across spatial scales (Reichstein et al., 2003).

We found that midmorning and late afternoon were the most representative times of day to sample across the 10 months of measurements (Figure 3). Similar times of day are commonly reported in the literature, but in a broad synthesis Jian, Steele, Thomas, Day, and Hodges (2018) found that in general 9–10 a.m. and 7–8 p.m. local time was when diurnal soil temperature tended to be closest to its daily mean, and thus when R_S measurements will most closely approximate the daily mean flux. However, the exact time will likely vary because soil heat flux varies with many other factors such as time of year, and the soil depth of peak respiration driving R_S also varies.

The overall shape of the lines in Figure 3 is driven by a consistent midday depression in R_S we observed in many days and months of the year. This is quite different from the diurnal pattern observed in many ecosystems (see, e.g., Figure 3 in Jian, Steele, Day, Quinn Thomas, & Hodges, 2018) and deserves further investigation in the future. Similar dynamics have been observed in other forest ecosystems when root respiration is diminished, with some time lag, following a limitation in tree transpiration (Adachi et al., 2009; Bekku et al., 2011). Ecosystems with such (possibly transient) water limitations may have quite different dynamics; for example, at a dry shrub site Cueva et al. (2017) found the optimal measurement time to be at night, with potential biases ranging from −29% to +40%.

We found the month-to-month R_S CV distribution to be relatively higher (median of 26%, Figure 6) than the CV at shorter time scales. This is expected as months are disconnected from the predictable cyclic daily and annual temperature and moisture cycles that drive R_S (Raich, 2017); but it has significant sampling implications given the popularity of monthly sampling. Our sampling requirement numbers (Table 1) are largely consistent with the results of Jian, Steele, Thomas, Day, and Hodges (2018), who found (for deciduous forests, Table 1 in that study) that 183 measurements were required to be 95% certain of being within 10%

of the true mean, and 9 measurements to be 80% certain of being within 30%. In an agricultural field, Parkin and Kaspar (2004) concluded that sampling every 3 days was required to be within 20% of the true flux, while sampling every 20 days would result in errors from -40% to $+60\%$. Conversely, tropical forests studied by Perez-Quezada et al. (2016) tended to require relatively low measurement frequency (Jian, Steele, Day, Quinn Thomas, & Hodges, 2018), probably due to their low monthly climatic variability. In a comprehensive analysis of temporal variations in R_S globally, Jian, Steele, Thomas, Day, and Hodges (2018) concluded that R_S should be measured at least once per day to achieve $\pm 10\%$ of the true mean with 95% confidence; once per month resulted in 80% confidence of being within $\pm 30\%$ of the mean. This is broadly consistent with our findings.

4.2. Error Propagation

Temporally high-resolution data provide new opportunities to explore the drivers and variability of R_S fluxes (Wayson et al., 2006); for example, using high temporal resolution methane flux data, Subke et al. (2018) showed that low-frequency sampling results in a systematic bias of upscaled flux estimates. Such data also provide an opportunity for the science community to better quantify the errors associated with sporadic “survey” measurements and improve gap-filling (Gomez-Casanovas et al., 2013) and error propagation practices more generally. This is similar to the advances made possible by the advent of continuous eddy covariance (Moncrieff et al., 1996). Measurement errors can be propagated to longer time spans (e.g., monthly to annual R_S) using Monte Carlo techniques (Larocque et al., 2008), parametric uncertainty of driving models (Curiel Yuste et al., 2005), or theoretical derivation of the uncertainty arising from mixing models (D. L. Phillips & Gregg, 2001); perhaps most commonly in our experience, however, they are simply ignored. To take a simple example, it is not uncommon in the literature to see an annual R_S estimate $X \pm Y$ calculated from the mean of 12 monthly measurements (X), with a collar-to-collar spatial variability estimate (Y); probabilities such as those presented in Table 1 are only rarely reflected in annual estimates or their errors.

The increasing availability of high-temporal-resolution data sets has potential applications to a number of areas such as fast-acting plant-soil ecohydrological dynamics (Volkman et al., 2016), phenological coupling to soil respiration (Järveoja et al., 2018), constraining and comparison with eddy covariance (C. L. Phillips et al., 2017), and novel inversion approaches (Latimer & Risk, 2016). We also suggest that it enables better standards for reporting R_S , specifically with respect to errors associated with temporally sparse data sets (Jian, Steele, Day, Quinn Thomas, & Hodges, 2018). This should allow us to better distinguish natural variability from measurement error, provide benchmarks for confidently ascribing observed changes in R_S to climatic drivers (Bond-Lamberty & Thomson, 2010a), and enable more accurate estimation of spatially and temporally upscaled fluxes (Jian, Steele, Day, & Thomas, 2018). For example, studies with limited data might apply some standard amount of uncertainty based on the CV distributions shown in Figure 6 (although rigorously defining and applying data reporting standards for such an approach would require a consensus among the soil research community). Two necessary steps to improve community practices in this regard are (i) a systematic assessment of measurement error and sampling requirements across a wide range of ecosystem types and (ii) a robust error propagation analysis of R_S data, following the examples of Moncrieff et al. (1996) and Larocque et al. (2008). In turn, both of these will depend on widespread availability of continuous R_S data, ideally in a community database following many other examples in soil respiration (Bond-Lamberty & Thomson, 2010b; Jian, Steele, Day, & Thomas, 2018) and carbon and energy exchange more generally (D. D. Baldocchi et al., 2001).

Author Contributions

This analysis was designed by B. B. -L., with all authors providing feedback on the study design, analysis, and interpretation of results. S. C. P. performed fieldwork, with site access and logistical support from J. P. M., and wrote the quality-control data processing scripts. Data analysis and writing of the manuscript was led by B. B. -L. in close collaboration with all authors.

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Acknowledgments

This research is part of the PREMIS Initiative at Pacific Northwest National Laboratory (PNNL). It was conducted under the Laboratory Directed Research and Development Program at PNNL, a multiprogram national laboratory operated by Battelle for the U.S. Department of Energy under Contract DE-AC05-76RL01830. This research was supported by the Smithsonian Environmental Research Center, and would not have been possible without the unflappable expertise of Nana Mills. The code and data to reproduce all results are available at <https://github.com/PNNL-PREMIS/PREMIS-ghg> and permanently archived online (at <https://doi.org/10.5281/zenodo.3549586>).

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