Historically inconsistent productivity and respiration fluxes in the global terrestrial carbon cycle

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The terrestrial carbon cycle is a major source of uncertainty in climate projections. Its dominant fluxes, gross primary productivity (GPP), and respiration (in particular soil respiration, Rs), are typically estimated from independent satellite-driven models and upscaled in situ measurements, respectively. We combine carbon-cycle flux estimates and partitioning coefficients to show that historical estimates of global GPP and Rs are irreconcilable. When we estimate GPP based on Rs measurements and some assumptions about Rs:GPP ratios, we found the resulted global GPP values (bootstrap mean $149\pm29/23\text{ Pg C yr}^{-1}$) are significantly higher than most GPP estimates reported in the literature ($113\pm18/18\text{ Pg C yr}^{-1}$). Similarly, historical GPP estimates imply a soil respiration flux ($871\pm8\text{ Pg C yr}^{-1}$) statistically inconsistent with most published Rs values ($871\pm8\text{ Pg C yr}^{-1}$), although recent, higher, GPP estimates are narrowing this gap. Furthermore, global Rs:GPP ratios are inconsistent with spatial averages of this ratio calculated from individual sites as well as CMIP6 model results. This discrepancy has implications for our understanding of carbon turnover times and the terrestrial sensitivity to climate change. Future efforts should reconcile the discrepancies associated with calculations for GPP and Rs to improve estimates of the global carbon budget.
The terrestrial carbon sink removes about a quarter of anthropogenic CO₂ emissions but is highly variable in time and space depending on climate. The magnitude of gross primary productivity (GPP) is therefore one of the largest sources of uncertainty in predicting future trajectories of global temperature. For example, GPP is a first-order control on plant turnover times, a dominant uncertainty term in the terrestrial carbon sink. There has been substantial progress in quantifying and constraining GPP and other major global carbon fluxes, typically using models driven by satellite remote sensing and upscaled in situ ecosystem-scale flux measurements. Recent syntheses suggest that global GPP is 120–125 Pg C yr⁻¹, and such estimates from the literature (GPP₁₀) have been incorporated into synthesis efforts such as the Global Carbon Project as well as model benchmarking frameworks. The magnitude of terrestrial GPP thus has implications for the dynamics and resilience of the terrestrial C sink in the face of global environmental change.

Global GPP is roughly balanced by ecosystem-to-atmosphere respiratory fluxes. The difference between these two major fluxes, minus smaller fluxes such as fire and lateral (e.g., dissolved, particulate) organic carbon losses, comprises the terrestrial C balance. Terrestrial ecosystem respiration is dominated by the soil-to-atmosphere CO₂ flux (soil respiration or RS), the combined flux generated by microbial and plant root respiration. Respiration is rarely estimated, even indirectly, from satellite observations, and thus global Rₛ is generally derived by upscaling in situ measurements. Published Rₛ estimates from the literature (Rₛₐ) range from 68 to 109 Pg C yr⁻¹ (Supplementary Table 1), with a central range of 85–90 Pg C yr⁻¹. Because GPP and Rₛ are physiologically linked, the biophysical balance between GPP and Rₛ could be used as a constraint on the global carbon budget. To date, however, no attempt has been made to quantify how consistent these independent GPP and Rₛ estimates are at the global scale. This study compares these two large carbon fluxes and the results emphasize the importance of cross-comparing datasets and models to understand terrestrial carbon cycling as well as future climate change.

Results and discussion

Inconsistency between photosynthesis and soil respiration. We partitioned global Rₛₐ estimates into microbial and root respiration based on all available (published) partitioning values, and calculated distributions of the resulting implied GPP (GPPₐₐ) using literature estimates of net primary production (NPP) and root-to-shoot respiration ratios (Supplementary Figs. 1–7). Using a nonparametric bootstrap, we generated 10,000 such GPPₐₐ estimates based on random draws from Rₛₐ, NPP, the partitioning parameters (see Methods and Supplementary Figs. 5, 8–10 and Supplementary Tables 1, 2), and the corresponding uncertainties. The resulting GPPₐₐ distribution was 149 ± 25 Pg C yr⁻¹ (mean ± 95% confidence interval; Fig. 1), which contrasts with the GPPₐₐ average of 113 ± 18 Pg C yr⁻¹. The intersection of these two distributions is 127.6 Pg C yr⁻¹ (Fig. 1), a point at the 95.2% quantile of GPPₐₐ and the 9.8% quantile of GPPₐₐ. The null hypothesis (that these distributions are from the same underlying population) is highly unlikely: τₛₐ = -12.68; P < 0.001. What characterizes the small number of estimates consistent with both GPPₐₐ and GPPₐₐ? Bootstrap draws in the overlap region were characterized by low root contribution to Rₛ (averaging 34% below the intersection point, versus 42% above it) and high root contribution to autotrophic respiration (45 vs. 38%, respectively; Supplementary Fig. 11), resulting in low GPPₐₐ values.

We performed a comparative analysis of published data to derive Rₛ from GPP, partitioning GPPₐₐ into NPP and belowground autotrophic respiration components, while accounting for other carbon loss pathways (see Methods). The resulting implied Rₛₐ (i.e., the global Rₛ as implied by GPPₐₐ) 68 ± 10 Pg C yr⁻¹ (Fig. 1) is highly unlikely to be consistent with Rₛₐ values (87 ± 4 Pg C yr⁻¹; see Methods). Only 1.8% of the Rₛₐ distribution in Fig. 1 is below the intersection point of 78.2 Pg C yr⁻¹, and only 2.5% of the Rₛₐ distribution is above it. This is strong evidence against the null hypothesis that these curves are mutually consistent (i.e., that they represent the same underlying population, τₛₐ = -11.59; P < 0.001). The overlap between these distributions is characterized by high GPPₐₐ (averaging 125.6 Pg C yr⁻¹, versus 112.5 Pg C yr⁻¹ below the intersection point), high NPP, and a high contribution of roots to overall autotrophic respiration (46 and 39% for above and below the intersection point, respectively; Supplementary Fig. 12). The cumulative result of these values produced the small percentage of Rₛₐ that draws consistent with Rₛₐ.

We identified sources of variability in Fig. 1 using a variance decomposition procedure to explore which parameters were both uncertain and influential in the distribution of GPPₐₐ and Rₛₐ. Variability in GPPₐₐ was dominated (63% of total variance) by uncertainties in the ratio of root respiration to total autotrophic respiration, for which field measurements are limited. Other influential variables were variance in global Rₛₐ (12%) and the root contribution to total Rₛ of a desert, wetland, and savanna (other, 7%). For bootstrapped Rₛₐ, uncertainty in GPPₐₐ was the largest (35%) contributor to variability, with root contribution to total Rₛ of cropland, savanna, grassland, and wetland (other, 32%) and global NPP (28%) also large. No other factor contributed more than 2% for variability in GPPₐₐ.

We also employed a second, complementary approach, one independent of any assumptions about carbon partitioning. In this step, we compared site-level measurements of Rₛ and GPP from a global soil respiration database (SRDB) and FLUXNET. These were compared against the same global GPPₐₐ and Rₛₐ estimates shown in Fig. 1. The site-level Rₛₐ/GPP ratios (i.e., the values directly reported by investigators and compiled in SRDB) averaged 0.56 ± 0.26 (Fig. 2), very similar to the Rₛₐ/GPP ratios from combining SRDB and FLUXNET data (0.54 ± 0.85). These were both significantly (P < 0.001 based on a nonparametric Wilcoxon test) lower than the Rₛₐ/GPPₐₐ ratios of 0.72 ± 0.11.

We found no evidence that this difference was driven by a lack of spatial representativeness in the global distribution of SRDB data. For example, the arithmetic mean of the Rₛₐ/GPP ratio in the SRDB is 0.56, and 0.57 when weighted by vegetation areas globally. We highlight that this does not mean that the difference cannot be influenced by sampling errors related to the sparsity of the underlying measurements. Figure 2 also shows Rₛ/GPP and Rₛ/GPP from models in the Coupled Model Intercomparison Project phase 6 (CMIP6) at both local (grid cell site-level) and global scales. These models are global in extent, similar to satellite data products, but their explicit physiological processes mean that their Rₛ outputs are constrained by GPP. In the CMIP6 models examined, Rₛ/GPP values were 0.609 ± 0.11 at both the global scale (i.e., the ratio of the models’ global fluxes) and the scale of individual grid cell site-level, which were significantly lower (W = 375,206, P < 0.001) than global Rₛₐ/GPPₐₐ values shown in Fig. 2.

The Rₛ/GPP ratios from CMIP6 models do not significantly differ from the global Rₛ/GPP ratio from the literature (P = 0.93, Fig. 2d), indicating that the low Rₛ/GPP ratio of the CMIP6 models (Fig. 2b) is likely due to too-low Rₛ root values, either because the fluxes are incorrectly parameterized, or because the allocation of carbon across different pools is incorrectly represented. Carbon allocation is a notable weak link in current...
ESMs due to both a lack of empirical observations and uncertainty over the underlying physiological mechanisms, and the RS:GPP ratio could be a valuable model benchmark to constrain root allocation. An even stronger approach, in our view, is to use data assimilation in model benchmarking efforts to estimate multiple C and biogeochemical fluxes simultaneously, so that they are constrained by each other. These independent lines of the analysis demonstrate that GPPlit and Rslit, the historical global flux estimates reported in the published scientific literature, are almost certainly inconsistent with each other. One possible interpretation of this problem is that many published global GPP estimates are biased low. If the mean of the GPPRs distribution (149 Pg C yr\(^{-1}\)) in Fig. 1 is the actual global flux, for example, that would be close to that implied by atmospheric \(^{18}\)O:16O ratios of CO\(_2\), which suggest that a global GPP of 150–175 Pg C yr\(^{-1}\) is needed to explain rapid CO\(_2\) cycling times. A similar conclusion was reached in recent studies using novel methods such as O\(_2\):CO\(_2\) ratios associated with the land carbon exchange as well as GPP derived using solar-induced fluorescence (SIF) data assimilation.

In an effort to derive new and independent estimates of R\(_S\) and GPP, we used R\(_S\) data from a recently updated global daily R\(_S\) database (DGRsD) to parameterize Random Forest (RF) models for each month, and estimated global monthly R\(_S\) at a spatial resolution of 0.1° (Supplementary Figs. 13, 14). Such daily data can provide more robust estimates than do annual numbers used until now to estimate global-scale R\(_S\). The resulting global annual R\(_S\) was 93 Pg C yr\(^{-1}\), with a corresponding GPPRs of 157 Pg C yr\(^{-1}\) (Fig. 1), close to the mean Rslit (87\(\pm\)9 Pg C yr\(^{-1}\)) and GPPRs (149\(\pm\)29 Pg C yr\(^{-1}\)). This also suggests that higher GPP is a possible explanation for any discrepancy between GPPlit and Rslit, but it should be noted that DGRsD is not independent of SRDB, and therefore more evidence is needed to ensure there are no systematic biases in Rslit.

**Possibilities to close the gap.** A number of factors might produce too-low global GPPlit estimates (Table 2). We found that purely remote-sensing derived GPP values, in particular from MODIS, tended to be smaller than estimates from site-level upscaling or a mixture of remote sensing and site-based measurements (Supplementary Fig. 5), consistent with recent work on the uncertainties in GPP estimation. Note however that if GPPlit groups are weighted equally (i.e., aggregated into six different groups

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**Fig. 1 Distribution and comparison of annual global soil respiration (R\(_S\)) and gross primary productivity (GPP).**

a) Distributions of global gross primary productivity (GPPlit and GPPRs); b) Joint distribution of annual global soil respiration (R\(_S\)) and gross primary productivity (GPP); c) Distribution of global soil respiration (Rslit and RsGPP) estimates. Two distributions are shown: literature-reported GPP (GPPlit) versus GPP implied by those R\(_S\) estimates (GPPRs); or literature-reported R\(_S\) (Rslit) versus R\(_S\) implied by those GPP estimates (RsGPP); Distributions are based on 10,000 random draws of the underlying estimates from published literature (summarized in supplementary Fig. 8). The red arrow represents from GPPlit to calculate RsGPP, the light-blue arrow represents from Rslit to calculate GPPRs, and the blue dots and line represent R\(_S\) from the random forest model developed in this study and based on that to calculate the GPPRs. The arrows and direction corresponding to the arrows in supplementary Fig. 1.
before bootstrap resampling), the bootstrapped results (GPPlit, group) are higher and closer to the GPPRs (Supplementary Fig. 5). This suggests that older remote sensing approaches may underestimate GPP in the highly-uncertain tropics, as well as in managed and fertilized cropland, where there are substantial uncertainties and mismatches in the algorithms that partition towers' net ecosystem exchange into GPP and respiration (Supplementary Table 3), and also mismatches between these respiration estimates with direct measurements of Rs (Table 2 and Supplementary Table 3).

Conversely, it is possible that RsLit estimates are biased consistently high (Table 2). One important factor may be that Rs data are less diverse than those of GPP, with almost all RsLit ultimately deriving from a large but single global database of thousands of small-scale studies using generally similar methods. This database is based on published data of annual fluxes, most of which are extrapolated (to an annual flux) from sporadic daytime measurements made at widely varying intervals, which might introduce bias. Nevertheless, when additional published data were included in the database, the Rs models were predicted to be 93 Pg C yr⁻¹, very close to RsLit (Fig. 1). Finally, the local- and/or large-scale models used to upscale measured Rs temporally and spatially may not accurately represent soil moisture responses (e.g., due to hysteresis effects) because of its confounding effect with temperature.

A common potential problem affecting large-scale estimates of both GPP and Rs concerns spatial coverage and representativeness of the terrestrial land surface and climate space, GPP and Rs measurements have differing tradeoffs in this regard. The former is characterized by a spatially complete and large measurement domain (hundreds of m² to km², depending on the eddy covariance tower or pixel), but also nontrivial measurement uncertainties (e.g., methods used to calculate GPP from the measured net flux). By contrast, Rs is upscaled from spatially small (~1 m²) but locally accurate chamber measurements dispersed in time that are, however, with better global coverage. Sites in both FLUXNET and SRDB are biased towards higher estimates but still with high uncertainty. There is also a temporal disparity when comparing literature estimates: while GPPRs and RsLit cover a similar period overall (1980–2020), most GPPLit values are centered between 2000 and 2010, but a majority of RsLit occurs between 1985 and 1995. If GPPLit and RsLit are weighted equally by time (i.e., aggregated by the same breakpoints before bootstrap resampling, Supplementary Fig. 8), bootstrapped GPPLit,agg and RsLit,agg are closer to GPPRs and RsGPP (by ~10 Pg C yr⁻¹, Supplementary Fig. 8), although significant disparities remain. Furthermore, when considering the temporal coverage and changing methods for GPP, we found that the gaps between carbon-cycle flux collected from the literature (GPPLit and RsLit) and the results implied by the other fluxes (GPPRs and RsGPP) decreases, but still significantly differ from each other (P < 0.01, Supplementary Fig. 9).

**Perspective view.** How could we address these discrepancies and close the terrestrial C budget once and for all? The distribution of our GPPRs and RsGPP results is driven by a few key variables (Tables 1, 2), some of which are relatively rarely measured. These include the ratio of root respiration to total autotrophic respiration, the ratio of root respiration to total soil respiration, and the ratio of autotrophic respiration to GPP; those data came from sites covering a similar range compared with global GPP, but lack measurements for regions with low photosynthesis (Supplementary Fig. 7). Acquiring (via field measurements or other approaches) additional constraints on these ratios may be a particularly fruitful way to resolve the inconsistencies identified in this study. For example, increasing numbers of studies have separated Rs into its autotrophic and heterotrophic components in the last decade, enabling large-scale heterotrophic respiration synthesis efforts upsampling global estimates. Recent studies have shown that Rs are relatively less measured in low-productivity regions, arctic regions, and Tibetan Plateau, and that this uneven spatial distribution of data may create large uncertainties when scaling up and estimating global Rs. Inference GPP from RsLit and inferring Rs from GPPLit (Table 1) also show that RsGPP group results from the desert, wetland, cropland, and savanna are key variables to close the gap between productivity and respiration fluxes in the global terrestrial carbon cycle. In addition, arctic regions and the Tibetan Plateau store a large amount of organic matter and are experiencing fast climate change. In the future, increasing field measurements of RsGPP group.
and regrowth, especially in low-productivity regions, arctic regions, and Tibetan Plateau, is important to close the terrestrial carbon budget. Here, we show large discrepancies between published estimates of global GPP and Rs, producing uncertainties that hamper our capacity to close the global C budget. Despite substantial efforts to understand carbon-climate feedbacks in the last decades, changes to carbon uptake rates in response to climate change remain uncertain. Importantly, more recent GPP estimation methods—in particular, moving from MODIS-derived information to alternative measurements of plant photosynthetic activity (i.e., SIF)—seem to be closing the gap between our estimates of these two dominant terrestrial C fluxes, it will be impossible to correctly determine the land carbon sink and its variability. Resolving the inconsistency between global GPP and Rs is a necessary precondition for understanding the future of the global carbon cycle, and thus the possible future global climate change.

**Methods**

**Carbon cycle terms and consistency.** This study explored the consistency of global gross primary productivity (GPP) and soil respiration (Rs) estimates in the global carbon cycle. Terrestrial GPP is the photosynthetic gain of C by plants; soil respiration, the soil-to-atmosphere CO2 flux, the sum of root respiration and heterotrophic respiration as measured at the soil surface, and represents carbon fixed by plants at some point in the past. While GPP and Rs may diverge significantly at local scales and for short time periods, they should however be coupled to a degree consistent with our understanding of the C cycle. Plant autotrophic respiration (including leaf and stem respiration, Rshoot and root respiration, Rroot) consumes part of GPP, and the remainder is termed net primary productivity (NPP). Parts of NPP are consumed by heterotrophs (Rh) and herbivores (Cherb).

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**Figure 2** Observations, estimates, and model results of the ratio of soil respiration (Rs) or heterotrophic respiration (Rh) to gross primary productivity (GPP), at different spatial scales and from different sources. **a** Observations, estimates, and model results of the ratio of Rs to GPP at grid cell site-level; **b** Observations, estimates, and model results of the ratio of Rs to GPP at a global scale; **c** Observations, estimates, and model results of the ratio of Rh to GPP at grid cell site-level; **d** Observations, estimates, and model results of the ratio of Rh to GPP at a global scale. Observational site-level data are from the global Soil Respiration Database (SRDB) and FLUXNET data (see Methods). The ratio of global Rs and Rs to global GPP is shown in red (and emphasized by the horizontal dashed lines), while results from the Coupled Model Intercomparison Project Phase 6 (CMIP6) at both the local grid cell site-level (values were extracted at coordinates corresponding to specific SRBD and FLUXNET sites) and global scale are shown in blue. Note that the odd distribution of the former results from the diversity of model ensemble realization used. Each point grouping is arranged distributionally, with overlaid box-and-whisker plots summarizing the mean, 25 and 75% quantiles, and extreme values. There are 16 models from CMIP6 with Rh data; Rs from CMIP6 models was calculated based on Rh and Rroot:Rs ratio using a bootstrap approach.
**Table 2 Summary of uncertainties and possible biases: factors that might explain why gross primary production (GPP) would be biased low, and/or soil respiration (Rs) too high.**

| Possibilities for Rs are biased too high | Possibilities for GPP are biased too low |
|----------------------------------------|----------------------------------------|
| 1) Rs data are less diverse than those of GPP, with almost all Rsult ultimately deriving from a large but single global database. | 1) Satellite data algorithms and thus products have significant uncertainties (e.g., LAI and PAR conversion efficiency, ε)³⁵,³⁶. |
| 2) Tropical and subtropical forests are greatly under-sampled³². | 2) Remote sensing may not fully account for understory production²⁴ or belowground C allocation²⁵. |
| 3) Jian et al.³⁹ showed that uneven distribution of Rs sites may cause overestimation of global Rs by -6Pg C yr⁻¹. | 3) GPP is probably underestimated in the tropics⁹, ²⁷, as well as in managed and fertilized croplands²⁸. |
| 4) In situ Rs measurements may not be representative of Rs at ecosystem-scale⁵³, ⁵⁴. | 4) There are totally more than 900 flux tower sites worldwide (https://fluxnet.org/sites/site-summary/), but they are not evenly distributed, with some ecosystem types (e.g., tropic forests) less represented⁵³ (Supplementary Fig. 5). |
| 5) Rs cannot be measured directly at the ecosystem scale or using remote sensing, and we must upscale in situ measurements¹⁴, ⁵⁵, ⁵⁶, ⁵⁷. | 5) Lack of Rsupt-Rs data for low photosynthesis productivity region (Supplementary Fig. 7d). |
| 6) Models do not have a clear mechanistic representation of Rs (as compared with GPP)¹⁴, ¹⁵. | |

**Data sources.** Global Rs and GPP were collected from published literature. We collected 23 global Rs estimates (Supplementary Table 1) from published articles, the majority of which upscaled site Rs measurements based on a global database⁴¹. Approximately 100 scientific manuscripts estimated global GPP, and we used the following criteria to determine whether the GPP estimate should be included: (1) the GPP year (or middle year if GPP was averaged across a period, Supplementary Table 2) was after 1980; (2) GPP was estimated from satellite remote sensing products or upscaled from global flux data (as opposed to process-based modeling). With those criteria, 49 GPP estimates from published articles were used in this study (Supplementary Table 2).

Our primary source of global NPP estimates was a literature survey⁴² that compiled 251 global NPP estimates. We noticed that there are several extreme NPP values within the dataset, we thus detected outliers using Rs whatever an NPP estimate above 75% quantile +1.5 interquartile range or below 25% quantile—1.5 interquartile range were considered as outliers. After outliers were removed, total 237 global NPP estimates were used in this study (Supplementary Fig. 1), similar to GPP. Cfix, Csink, DOC, and BVOC emissions were also collected from published literature (Supplementary Table 4). Ratios of root respiration to autotrophic respiration (Rroot:Rs) can be calculated. GPP can be calculated (GPPRs, Supplementary Table 5) was after 1980; (2) GPP was estimated from satellite remote sensing products or upscaled from global flux data (as opposed to process-based modeling). With those criteria, 49 GPP estimates from published articles were used in this study (Supplementary Table 2).

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estimated (R_Root = NPP – C_{chern} – C_{tree} – C_{fire} – DOC – BVOC; Supplementary Fig. 1 and Supplementary Table 4).

The precise chain of reasoning and computation was as follows. The difference between GPP and NPP is R_P, meaning that an R_P:GPP ratio was required to estimate R_P based on GPP (Eq. 4). The R_P:GPP ratios used in this study were from two sources: (1) a literature search that produced 123 R_P:GPP ratio estimates across diverse conditions, primarily from forest and grassland; all the other vegetation types (cropland, wetland, and tundra) only had samples combined (Supplementary Fig. 4). R_P can also be calculated by subtracting NPP from GPP (Eq. 5), and calculated R_P was very similar when computed by the above two methods.

In turn, R_P consists of root respiration (R_root) and shoot respiration (R_shoot), and thus R_root:R_P and R_shoot:R_P are ratios calculated to R_root and R_shoot from R_P. The R_root:R_P ratios used in this study were from two sources: (1) 35 RRoot:R_P ratios estimated from 28 literature studies (Supplementary Table 5); and (2) an additional 94 estimates from SRDB-V5. The R_root:R_P values covered seven vegetation types (Supplementary Fig. 3), mainly from forests, all other vegetation types (cropland, savanna, grassland, and wetland) had only 18 samples.

Finally, starting with the GPP_P values and using NPP, R_P:GPP, R_P:R_P, and R_P:GPP, GPP can be separated into R_P:R_P and R_P:GPP and thus the implied global R_P calculated (R_P:GPP: lower panel in Supplementary Fig. 1 and Eqs. 4–9 below). We then compared this R_P:GPP with R_P:GPP to determine their consistency.

\[
R_P = R_GPP - R_P
\]

\[
R_A = GPP - NPP
\]

\[
R_H = NPP - C_{chern} - C_{tree} - C_{fire} - DOC - BVOC
\]

\[
R_{root} = R_P - R_{shoot}
\]

\[
R_{shoot} = R_P - R_{root}
\]

\[
R_{GPP} = R_{root} + R_{shoot}
\]

Bootstrap resampling. A critical factor is uncertainty that compounds at each step in this process. We used a bootstrap resampling approach to estimate GPP_P and R_P:GPP, as the sample size of each step is different, and many of the input data do not follow a normal distribution (Supplementary Figs. 1–5). For each bootstrap sample, we first generated a new estimate of GPP or R_P by sampling from the published data (Supplementary Tables 1, 2, and 4, 5). We evaluated four different resampling methods, differing in how they treated the presence and absence of errors associated with each flux estimate. Method 1 did not use error information (i.e., any error estimate associated with each published R_P or GPP value) when resampling. Methods 2–4 used errors but handled missing values differently. Method 2 replaced missing error with values calculated from the median coefficient of variability (CV) of non-missing values; method 3 replaced missing errors with values calculated from the maximum CV across the dataset; and method 4 set missing errors to zero. We used method 3 in the main analysis, which is the most conservative (produces the widest distribution for both R_P and GPP; cf. Supplementary Fig. 10).

In addition, a random value for each partitioning coefficient (e.g., above- to belowground autotrophic respiration ratio or herbivory fraction) was used in each bootstrap sample; note that errors are seldom reported for these data, and so were not considered here. We then the global R_P calculated (R_P:GPP: lower panel in Supplementary Fig. 1 and Eqs. 4–9 below). Starting from the randomly-drawn R_P or GPP value, and randomly-drawn partitioning coefficients, the resulting R_P or GPP was then calculated following Eqs. 1–9 described above.

Variable importance analysis. As noted above, many variables related to C partitioning were used to derive GPP from R_P (Eqs. 1–3) or to derive R_P from GPP (Eqs. 4–9). To determine the relative importance of each variable to the overall distributional uncertainty, as well as the sensitivity of the estimate to that variable, we fixed each variable (e.g., NPP) in turn to the median of all its observations. All other variables were randomly drawn, as normal, in the bootstrap process, and the output variable (GPP_P or R_P:GPP) mean and distribution were calculated. We then compared the output variance with the result when no variables were fixed, i.e., that shown in Fig. 1, to determine the importance of each variable: larger decreases in output variance when a particular parameter was fixed to be constant, imply greater importance for this parameter.

Representativeness analysis. We connect the R_Root:R_P, R_P:R_P, and R_P:GPP sites with external global GPP data from FLUXCOM ([https://www.fluxcom.org/]; last accessed on 2021/06/22) through latitude and longitude to obtain mean GPP between 2001 and 2015. We then compared the GPP of sites used in this study with the global GPP (spatial resolution of 0.5°) to test the representation of the sites (Supplementary Fig. 7).

Overlap calculation. We calculated the overlap between the GPP_P distribution and the distribution of GPP_P to quantify the agreement between GPP_P and GPP_P. If a sample was not significantly different from a normal distribution (based on a Shapiro–Wilk test in R), we used a normal distribution with sample mean and variance to approximate the distribution; if a sample was significantly different from a normal distribution, we used a numerical approximation based on linear interpolation (approxfunc in R) to approximate the distribution’s probability density function. We then calculated the intersection point of these probability density functions, as well as the proportion of each curve that overlapped with the other using a trapezoidal rule numerical integration. Finally, we sampled each approximated distribution for the original number of GPP or R_P values. With these samples, a two-sample Welch’s t-test (t.test with var.equal = FALSE in R) was performed to determine if the means of the two distributions differed significantly.

Global soil respiration modeling. Following a similar approach as Jian et al. (2018), measurements from a global daily soil respiration database (DGRSd) and nine environmental factors (i.e., nitrogen deposition, monthly precipitation, monthly air temperature, soil bulk density, soil organic carbon, soil clay percentage, aboveground biomass, belowground biomass, and Enhanced Vegetation Index, details please see supplementary Table 6) were used to build Random Forest (RF) models for each month. Only R_P measurements with no field manipulation were used, totally 27,214 samples were separated into two datasets, 80% of samples were used to train the models, and the rest 20% were used to test the model performance. The results showed that the RF models can explain ~66% R_P variability, and the performance is consistent with both training and validation datasets. R_P for each month with a spatial resolution of 0.1° were predicted by the RF models, estimated monthly R_P were then summarized to estimate global annual R_P. Permanent ice sheets and bare soils were removed according to the MODIS landcover map.

Other statistical analyses. All analyses were conducted using R 3.6.1. Bootstrap means were compared using a two-sided Student’s t-test. A one-sided, non-parametric Wilcoxon rank-sum test with continuity correction was used to compare R_P to GPP ratios calculated from global estimates, the SRDB, and CMIP6 outputs.

Data availability

The data to support all the analysis in this study have been deposited in the GitHub repository [https://github.com/PNNL-TES/GlobalC] and zenodo [https://doi.org/10.5281/zenodo.5900964]51.

Code availability

The code to reproduce all the results in this study have been deposited in the GitHub repository [https://github.com/PNNL-TES/GlobalC] and zenodo [https://doi.org/10.5281/zenodo.5900964]51.

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numerical calculations. D.H. processed the Enhanced Vegetation Index data, was involved in the random forest modeling to predict global monthly soil respiration, and generated NetCDF data for the global soil respiration as well as generated the global soil respiration map. V.B., A.G.K., M.S., M.T., D.H., and R.V. provided feedback and insights in all phases. J.J. and B.B.-L. wrote the manuscript in close collaboration with all authors.

**Competing interests**
The authors declare no competing interests.

**Additional information**

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