

## Divergent data-driven estimates of global soil respiration

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The release of carbon dioxide from the soil to the atmosphere, known as soil respiration, is the second largest terrestrial carbon flux after photosynthesis, but the convergence of the data-driven estimates is unclear. Here we collate all historical data-driven estimates of global soil respiration to analyze convergence and uncertainty in the estimates. Despite the development of a dataset and advanced scaling techniques in the last two decades, we find that inter-model variability has increased. Reducing inter-model variability of global soil respiration is not an easy task, but when the puzzle pieces of the carbon cycle fit together perfectly, climate change prediction will be more reliable.

The increase in atmospheric carbon dioxide (CO<sub>2</sub>) concentration caused by human activity since the Industrial Revolution has resulted in climate change, making the global terrestrial carbon cycle a major concern<sup>1</sup>. Land absorbs and emits about 10 times more carbon than anthropogenic emissions<sup>2</sup>. Terrestrial vegetation takes in atmospheric CO<sub>2</sub> through photosynthesis, while respiration by vegetation and soil releases almost the same amount of CO<sub>2</sub> back into the atmosphere. The size of land uptake and emission fluxes is estimated to be ~130 Pg C yr<sup>-1</sup><sup>2</sup>. The difference between uptake and emissions represents the net carbon uptake by land, and maintaining and even enhancing this uptake is critical for mitigating climate change. The net carbon uptake by plants, which is the difference of photosynthetic carbon assimilation and autotrophic respiration by plants, is referred to as net primary productivity. The mean ± standard deviation and median of the estimates are 56.2 ± 14.3 and 56.4 Pg C yr<sup>-1</sup>, respectively, based on an intensive review<sup>3</sup>.

The primary flux from the land to the atmosphere is the soil-to-atmosphere CO<sub>2</sub> flux, also known as soil respiration<sup>2,4</sup>. Soil respiration comprises two sources: heterotrophic respiration, which is the decomposition of soil organic matter by microbes, and belowground autotrophic respiration, which is plant root respiration<sup>5–7</sup>. The total soil CO<sub>2</sub> production is the sum of these two sources, and it can be measured as soil-to-atmospheric CO<sub>2</sub> flux on the soil surface. Since the 1980s, this flux has been intensively observed<sup>8</sup>. Soil respiration is a key flux of the global carbon cycle because it is large and potentially increases with climate change due to the accelerated decomposition of stored soil organic carbon caused by warming, as well as potential disturbances caused by changes in precipitation. Therefore, soil respiration flux is as important as the uptake flux by vegetation<sup>9–11</sup>.

Accurately quantifying global carbon fluxes is essential to understanding the global carbon cycle and predicting future climate more accurately. In 2011, an intensive literature review found 251 estimates of total terrestrial net primary productivity using various methodologies (i.e., inventory aggregation, modeling, remote sensing, etc.), demonstrating that uptake by vegetation has been well-studied<sup>3</sup>. However, despite its importance, global soil respiration estimates have been limited; for instance, the number of data-driven estimates is less than half of the net primary productivity.

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The development of the global Soil Respiration Database (SRDB) was a key milestone for soil respiration studies<sup>8</sup>. Soil respiration is generally measured using the chamber method, which monitors changes in CO<sub>2</sub> concentration in a chamber placed on the soil surface. Due to the large spatio-temporal variability of soil respiration across sites, landscapes, biomes, climates, and globally, a substantial amount of data is essential to comprehensively understand this phenomenon and to obtain accurate scaled-up global estimates. In general, observed data at various biomes, climate, and soil are used to develop a data-driven model and the model is applied on a global scale to obtain a global estimate of soil respiration. The SRDB collated observed soil respiration values published in the literature, providing easy access to a global dataset essential for upscaling field scale soil respiration data to a global scale. Dozens of global estimates have been reported<sup>12–14</sup>, but it is still unclear whether the total sum of global soil respiration is consistent among various estimates, and how much uncertainty remains in its spatio-temporal distributions. To constrain the global carbon budget, an accurate estimate of global soil respiration is crucial.

This Perspective aims to present the spatio-temporal uncertainty of global soil respiration, discuss the potential causes of this uncertainty and future research directions. First, we summarize the methodologies and historical estimates. Next, we compile and quantitatively analyze available data-driven spatio-temporal estimates of global soil respiration. We compared the spatial distributions of

soil respiration in these estimates and identified areas with notable inter-model variability, and quantified the inter-model variability in temporal trends. Finally, we reflect on the achievement of historical estimates and address the remaining challenges.

### Reviewing historical data-driven estimates of global soil respiration estimates

We collected all global estimates of total soil respiration from various sources, including literature surveys, data-repositories, and direct contact with authors (Supplementary Table 1). We identified 23 studies of global estimates of total soil respiration, spanning from the first estimate by Schlesinger in 1977 to a recent estimate by Jian in 2022. Out of these, map data were available for 14 studies. We recalculated global estimates using the available map data, and selected datasets with appropriate grid areas for analysis (see the Method section). After screening, we obtained 11 spatial estimates of global soil respiration. In addition to data-driven soil respiration data, we analyzed heterotrophic respiration data from the Coupled Model Intercomparison Project Phase 6 (CMIP6)<sup>15</sup>, specifically rh (soil heterotrophic respiration of CMIP6 variables). More details of the methods are described in Supplementary information.

### Methodology of upscaling—data, techniques, resolutions.

Table 1 provides an overview of the upscaling methodology. The compilation showed that since the release of the first SRDB in

**Table 1 Summary of the methodologies used in historical global soil respiration estimates (data, method, spatio-temporal resolutions).**

ID	Study	Data <sup>a</sup>	Method	Spatial resolution <sup>b</sup>	Temporal resolution
1	1970's Schlesinger <sup>19</sup>	Compilation	Carbon balance	NE	Annual
2	1990's Raich and Schlesinger <sup>64</sup>	Compilation	Area × Mean	NE	Annual
3	Raich and Potter <sup>25,65</sup>	Compilation	Semi-empirical model	0.5° (~50 km)	Monthly
4	2000's Peng and Apps <sup>24</sup>	Compilation	Semi-empirical model	0.5° (~50 km)	Annual
5	Raich et al. <sup>66,67</sup>	Compilation	Semi-empirical model	0.5° (~50 km)	Monthly
6	2010's Bond-Lamberty and Thomson <sup>68</sup>	SRDB	Linear model	0.5° (~50 km)	Annual
7	Hashimoto <sup>69</sup>	Compilation	Semi-empirical model	0.5° (~50 km)	Monthly
8	Chen et al. <sup>70</sup>	Compilation	Semi-empirical model	0.5° (~50 km)	Annual
9	Hashimoto et al. <sup>12,71</sup>	SRDB	Semi-empirical model	0.5° (~50 km)	Monthly
10	Oertel et al. <sup>72</sup>	Compilation	Area × Mean	NE	Annual
11	Xu and Shang <sup>73</sup>	SRDB + C + E	Area × Mean	NE	Annual
12	Adachi et al. <sup>74</sup>	Compilation	Semi-empirical model	2 min (~4 km)	Daily
13	Zhao et al. <sup>75</sup>	SRDB + C + E + S	Machine learning	5 min (~10 km)	Annual
14	Hursh et al. <sup>76</sup>	SRDB	Statistical model & Semi-empirical model	0.5° (~50 km)	Annual
15	Jian et al. <sup>77</sup>	SRDB + compilation	Machine learning & Semi-empirical model	0.5° (~50 km)	Annual & Monthly & Daily
16	Jian et al. <sup>78</sup>	MGRsD + C	Semi-empirical model	0.5° (~50 km)	Monthly
17	Warner et al. <sup>79,80</sup>	SRDB	Machine learning	30 s (~1 km)	Annual
18	2020's Tang et al. <sup>37,38,81,82</sup>	SRDB + compilation	Machine learning	0.5° (~50 km)	Annual
19	Huang et al. <sup>83,84</sup>	SRDB + C + E	Machine learning & Semi-empirical model	30 s (~1 km)	Annual
20	Lei et al. <sup>85</sup>	SRDB	Linear model	0.5° (~50 km)	Annual
21	Lu et al. <sup>22,86</sup>	SRDB	Machine learning	0.5° (~50 km)	Annual
22	Stell et al. <sup>14,87</sup>	SRDB	Machine learning	30 s (~1 km)	Annual
23	Jian et al. <sup>57c</sup>	Global GPP (DGRsD)	Carbon balance & (Machine learning)	NE (0.1° (~10 km))	Annual (Monthly)

<sup>a</sup>Compilation: data compilation by the author; SRDB: Global Soil Respiration Database; MGRsD: Monthly Global Soil Respiration Database; C: Chen et al.<sup>70</sup>; E: Epule<sup>88</sup>; S: Song et al.<sup>89</sup>; DGRsD: Global Daily Soil Respiration Database.

<sup>b</sup>NE: spatial distribution was not estimated.

<sup>c</sup>Machine learning was used with DGRsD at monthly time resolution and 0.1° spatial resolution to provide a supporting estimate in the study.

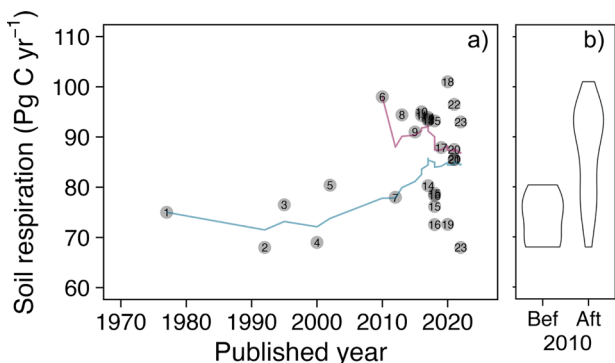
2010, most estimates were based on the SRDB, including solely the SRDB or extended SRDB. The SRDB has been updated, and the latest version is version 5, which includes 10,366 observations. From the late 2010s, machine learning approaches replaced other methods. Before that, semi-empirical modeling was the primary approach. Regarding resolution, the most commonly used resolution was 0.5°, and the very fine spatial resolution of 30 seconds (~1 km) was also adopted from the late 2010s. Both 0.5° and 30 s have been the most common resolutions in the past two decades. In contrast to spatial resolution, the adopted temporal resolution has been annual in the past decade, while older estimates with semi-empirical models often used monthly time steps.

**Is the total sum converging?** Over the last 50 years, a total of 23 studies have reported global estimates of soil respiration (Fig. 1 and Table 1). Global soil respiration ranged from less than 70 Pg C yr<sup>-1</sup>

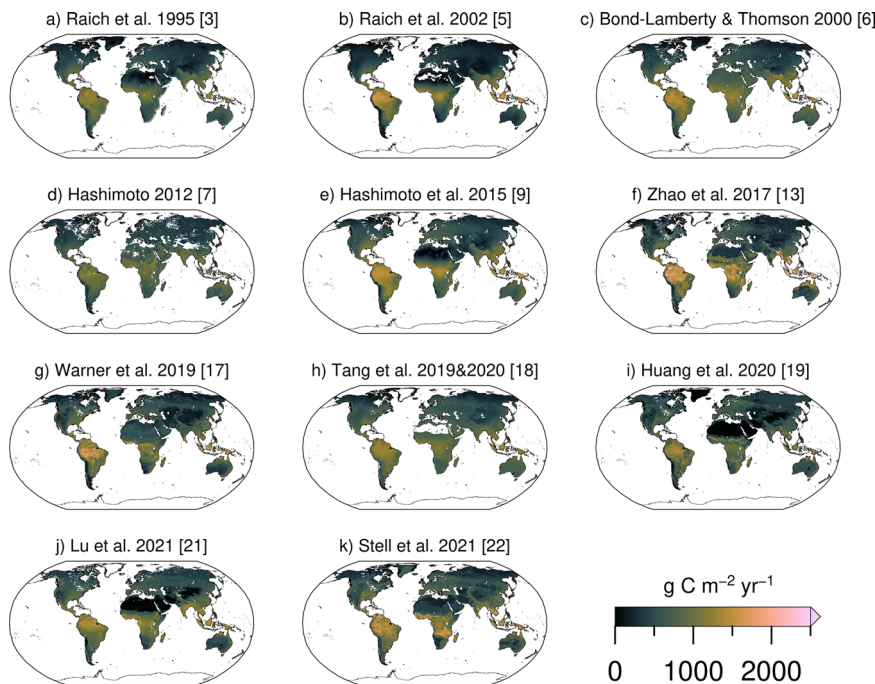
to more than 100 Pg C yr<sup>-1</sup> (range: 68–101 Pg C yr<sup>-1</sup>, excluding screened estimates, see the Methods section). Before 2010, the majority of estimates were below 80 Pg C yr<sup>-1</sup> (mean value 74 Pg C yr<sup>-1</sup>, range: 68–80 Pg C yr<sup>-1</sup>), and after 2010, much higher estimates were often reported. The mean estimate published after 2010 is 89 Pg C yr<sup>-1</sup> (range: 68–101 Pg C yr<sup>-1</sup>). The higher values reported after 2010 do not mean that the global estimates converged, but rather that the variability increased (standard deviation before/after 2010: 5.2, 9.0 Pg C yr<sup>-1</sup>, respectively). The global estimates after 2010 contain both higher and lower values (i.e., below 80 Pg C yr<sup>-1</sup>). While machine learning approaches using the SRDB are more common (Table 1), the difference between semi-empirical (including linear model; mean value 90 Pg C yr<sup>-1</sup>, range: 80–98 Pg C yr<sup>-1</sup>) and machine-learning estimates (mean value: 89 Pg C yr<sup>-1</sup>, range: 73–101 Pg C yr<sup>-1</sup>) was not significant (Supplementary Fig. 1).

**Which regions have higher inter-model variability?** Figure 2 illustrates the spatial distributions of soil respiration estimated in 11 studies. While soil respiration is generally high in warm, humid regions and low in dry and/or cold regions, the maps demonstrate varying magnitudes and spatial patterns of soil respiration. We divided the land into 14 regions based on the continents, latitudes, and primary biomes to identify areas with high inter-model variability, evaluated the regional inter-model variability using the coefficient of variation (CV) (Fig. 3 and Supplementary Fig. 2). The analysis showed that most regions had CV values below 25%, but regions B2, C2, and C5 had higher values (>25%) (Fig. 3). These regions include the north African dry area (e.g., the Sahara Desert, B2), deserted areas in the central Eurasian continent (e.g., Gobi and Taklamakan Deserts, C2), and the islands in Southeast Asia, such as the Malay Peninsula, Sumatra, Java, Borneo, and New Guinea (C5). Notably, the number of data points in each region did not always correlate with CV (Supplementary Fig. 3). While regions B2, C2, and C5 had fewer data points, CVs were smaller for many regions with similar data points.

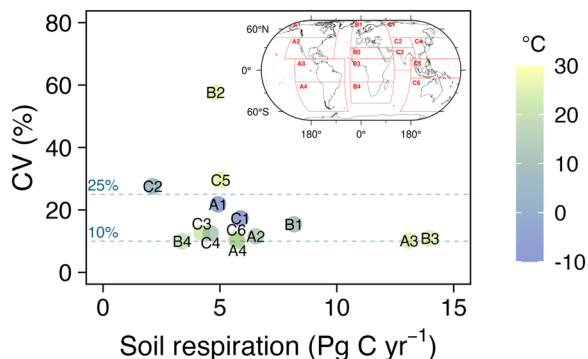
**How the global soil respiration is changing with time?** Time series estimates demonstrated clear interannual variability (Fig. 4).



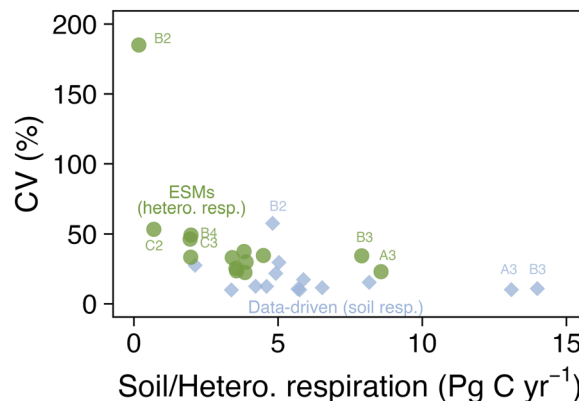
**Fig. 1 Historical estimates of global soil respiration.** Temporal change (a) and violine plots for before 2010 and after 2010 (b). Each number label represents a different study (see Table 1 for details). The blue line shows the cumulative mean for all data, while the purple line shows the cumulative mean for data published since 2010. Note that some studies reported multiple estimates using different methodologies, and the estimates are plotted according to the year of publication, as some studies did not specify the exact year for the estimates.



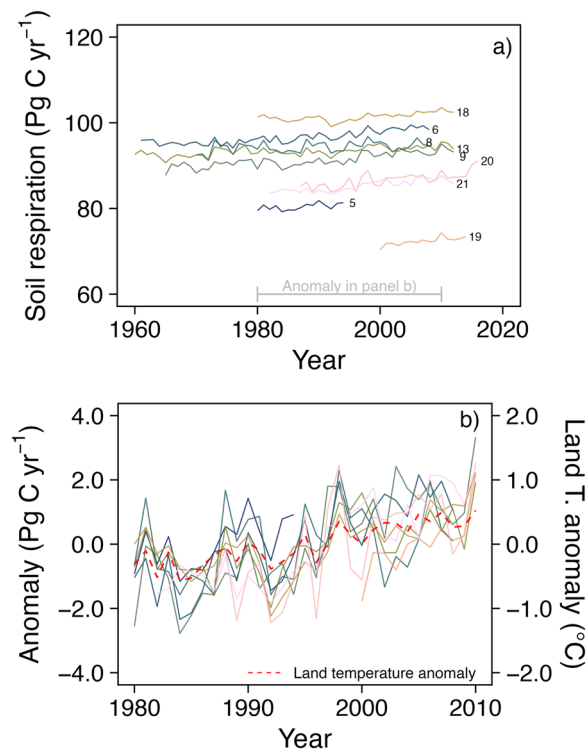
**Fig. 2 Estimates of the spatial distribution of soil respiration.** The number indicated in brackets is the study ID (see Table 1).



**Fig. 3 Relationships between the amount of soil respiration per region and the coefficient of variation (CV).** Refer to the map panel for the region label. Color indicates the mean annual temperature of the region.



**Fig. 5 Coefficient of variation values for the outputs of CMIP6.** Comparison between the inter-model coefficient of variation (CV) values for data-driven soil respiration estimates and those for heterotrophic respiration of the outputs of the Coupled Model Intercomparison Project Phase 6 (CMIP6). The x-axis shows the amount of soil/heterotrophic respiration per region. Refer to the map panel in Fig. 3 for the region label.



**Fig. 4 Temporal variations in global soil respiration among studies (N = 9).** The number label indicates the study ID in panel (a). Refer to Table 1 for the study ID. The red dashed line in panel (b) is the global mean temperature.

The anomaly suggests that the interannual variability of soil respiration varies from  $-5 \text{ Pg C yr}^{-1}$  to  $+5 \text{ Pg C yr}^{-1}$ , and the magnitude of anomaly differs among estimates (Fig. 4). While all estimates synchronized in some years, such as low in around 1984–1985 and 1992 and high in 1998 and 2010, which are correlated with El Nino-Southern Oscillation and global temperature (1991 eruption of Mount Pinatubo for 1992 in part), the anomaly varied in other years.

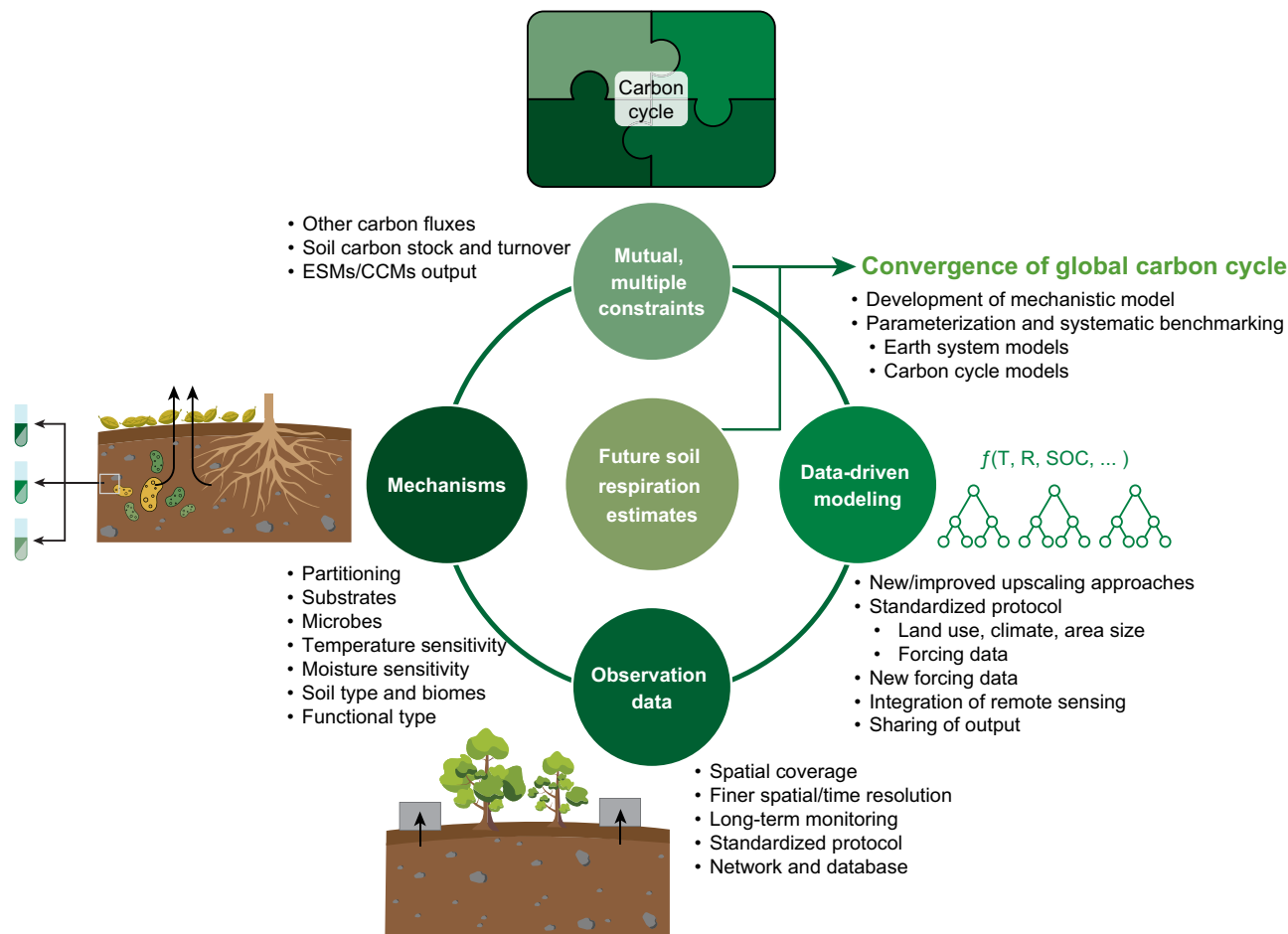
All but one estimate showed an increasing trend over time, but the slope of the linear trend differed between estimates. Examining the time period from 1980 to 2010, during which multiple estimates were available, the trends ranged from  $0.038 \text{ Pg C yr}^{-1}$  ( $p = 0.13, R^2 = 0.05$ ) to  $0.23 \text{ Pg C yr}^{-1}$  ( $p = 0.003, R^2 = 0.61$ ) with a mean of  $0.11 \text{ Pg C yr}^{-1}$ . Although no negative trend was found, the trends for some estimates were considerably smaller than for others.

The global scale temperature sensitivity of soil respiration against the anomaly of the global land mean annual temperature ranged from  $1.9 \text{ Pg C yr}^{-1}\text{ }^\circ\text{C}^{-1}$  ( $p = 0.005, R^2 = 0.23$ ) to  $5.0 \text{ Pg C yr}^{-1}\text{ }^\circ\text{C}^{-1}$  ( $p = 0.004, R^2 = 0.58$ ), with a mean of  $3.5 \text{ Pg C yr}^{-1}\text{ }^\circ\text{C}^{-1}$  (Supplementary Fig. 4).

Monthly seasonality was evaluated to a lesser extent (Supplementary Fig. 5). Only four estimates were found, and they demonstrated that global soil respiration was highest in July and August or northern summer ( $8\text{--}9 \text{ Pg C mo}^{-1}$ ) and lowest in February ( $4\text{--}6 \text{ Pg C mo}^{-1}$ ). Soil respiration in July was slightly higher than that in August, but the values were almost comparable within each study. The amplitude of the monthly seasonal soil respiration ranged from 2 to  $4 \text{ Pg C mo}^{-1}$ .

**Comparing the data-driven estimates with the output of Earth System Models (CMIP6).** We compared the spatial inter-model uncertainty of the data-driven global soil respiration estimates with the heterotrophic respiration from Earth system models of the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Fig. 5). The comparison showed that the inter-model variability for the ESMs was, on the whole, twice as high as that for the data-driven soil respiration estimates. This is mainly because ESMs calculate heterotrophic respirations using process-based carbon cycle models with varying parameter settings while data-driven estimates are directly generated from observed soil respiration. Moreover, the CVs for the B2 and C2 regions were also higher for CMIP6, while that for C5 was of the same magnitude as that of the data-driven estimates.

**History of global soil respiration estimates.** The earliest studies of soil respiration date back to the late 19th and early 20th centuries<sup>16–18</sup>, with the first attempt to estimate global soil respiration made by Schlesinger in 1977<sup>19</sup>, more than a century after the first attempt to estimate global net primary productivity by von Liebig<sup>3,20</sup>. While the history of global soil respiration estimates is shorter and fewer in number than estimates of net primary productivity, progress has been rapid in recent decades due to the development of databases and machine learning techniques. In the last decade, there has been a notable increase in the number of studies as a result of the urgent need to understand the global carbon cycle. However, surprisingly, the efforts to estimate global soil respiration have not yet led to a convergence of estimates. Instead, the divergence appears to be increasing. Our



**Fig. 6 Conceptual diagram of the future direction to better constrain global soil respiration estimates.** These directions are categorized into four fundamental pillars: data-driven modeling, observation data, mechanisms, and mutual, multiple constraints.

comprehensive review uncovered several key findings: (1) There is an increase in inter-model variability in the total sum despite the development of a global dataset and advanced scaling techniques. (2) The inter-model variability varies across different regions, with some regions having CV values exceeding 25%. (3) There is substantial inter-model variability in the temporal changes, as well as in their sensitivity to temperature, which is the primary driver of these changes. To converge estimates, what do we need (Fig. 6)?

**To converge estimates.** The creation of the global SRDB has been the most outstanding factor in boosting the study of global soil respiration estimates<sup>8</sup>. While tower flux data (FLUXNET)<sup>21</sup> have a standardized data network, there was previously no such dataset for soil respiration data. All recent global estimates of soil respiration are now based on the SRDB, which has tripled the amount of observed soil respiration data in the last 20 years, allowing for more data-driven global estimates. However, the uneven spatial coverage of data remains an issue, and has been identified as a critical problem in estimating global soil respiration<sup>14,22,23</sup>. The data are biased toward temperate regions and sparse in dry areas, northern areas, the African continent, and South America<sup>14,23</sup>. This problem was noted as early as the 1990s<sup>24,25</sup>, suggesting that despite early cautions and the rapid increase in data over the last two decades, the problem has not been resolved. The finer spatio-temporal resolution of data is also crucial. The SRDB has data with an annual time step, which affects estimates. Ongoing efforts to develop high-resolution temporal resolution data (COSORE (Continuous SOIL

REspiration))<sup>26</sup> and advances in high-precision Global Navigation Satellite System technology<sup>27</sup> could help to log more precise location of observations at lower cost, making it easier to match observational data with high-resolution forcing data<sup>28–31</sup>. Advances in remote sensing of the terrestrial carbon cycle are also promising<sup>32</sup>. However, scaling up from the field scale to the global scale continues to be a source of uncertainty due to the higher spatial heterogeneity of soil respiration at the field scale in nature<sup>33</sup>, and variability caused by different observation methods<sup>34,35</sup>.

In the past two decades, the use of machine learning has been implemented to upscale global soil respiration estimates<sup>36</sup>. This approach has shown higher performance in reproducing observed data and extracting important explaining variables. However, even with the same dataset and similar techniques, there has been an increase in spatio-temporal inter-model variability. This variability is partly due to different protocols and variations of forcing data, such as land use, climate, and area size, indicating the need for an international Model Intercomparison Project with a standardized protocol (i.e., CMIP6)<sup>15</sup> to evaluate uncertainty rooted in the scale-up methodology. Analyzing the causes of this variability of data-driven estimates is challenging when relying solely on outputs like this study. Therefore, such intercomparisons will also be instrumental in identifying the key factors influencing global soil respiration.

Heterotrophic and autotrophic respiration are based on different processes, but measuring each separately has been challenging. This has hindered our understanding and ability to constrain soil respiration in the past<sup>7</sup>. However, in the past two decades, many

studies have disentangled the complexity of soil respiration through experiments, observations, modeling, and synthesis. The SRDB contains both heterotrophic and autotrophic respiration, and has contributed to global estimates of each respiration<sup>37,38</sup>, although additional observational data for each respiration are necessary. Some new processes are already incorporated in process-based carbon cycle models (CCMs) (e.g., microbes)<sup>39</sup>, and newly developed datasets on soil carbon<sup>28</sup>, minerals<sup>3</sup>, microbes<sup>40</sup>, and fungi<sup>41,42</sup> can improve the performance of machine learning approaches. Although their effectiveness is unknown, some soil-based functional types (e.g., soil functional type, decomposition functional type, etc.) have been proposed<sup>43,44</sup>, which may contribute to a better understanding and constraint of global soil respiration. Isotopic studies (<sup>14</sup>C and <sup>13</sup>C) are also essential to separate autotrophic and heterotrophic respiration and disentangle soil carbon processes<sup>45–48</sup> through field observation and model evaluation.

Temperature sensitivity and its impact on soil respiration have been studied extensively, but they remain one of the most important yet unsettled issues<sup>9,49</sup>. Recent studies have shed new light on this topic, and ongoing discussions among researchers<sup>50–52</sup> are expected to lead to further insights. Changes in precipitation patterns also play a crucial role in the sensitivity of soil respiration to climate<sup>14</sup>. More refined temporal observations and modeling would incorporate short-term responses of soil respiration to climate events such as droughts, freeze/thaw cycles, precipitation events, and priming<sup>53</sup> into global estimates. The development of a new soil moisture dataset may replace the use of precipitation as a proxy for moisture conditions in the future<sup>54</sup>. These spatio-temporal changes in forcing data (e.g., climate) and sensitivity contribute to inter-model variability in temporal trends of global soil respiration. In particular, deserted areas in the B2 and C2 regions show different responses to precipitation and variability of precipitation, which may have caused the higher CV, while the reason for C5 is unclear. The mix of heterotrophic and autotrophic respiration processes makes the climate responses of soil respiration even more complex. Recent studies suggest that each component may contribute differently to total soil respiration based on observational data synthesis<sup>13,55,56</sup>. Therefore, it is important to evaluate each type of respiration as well as the total soil respiration.

In an effort to constrain global estimates based on the bottom-up approach, another important way of constraint is mutual, multiple constraints using other fluxes and stocks in global carbon cycle. Global carbon fluxes and stocks on land are interconnected and are often spatio-temporally estimated based on independent observed data (e.g., gross primary productivity, net primary productivity, soil carbon stock, net ecosystem exchange). These mutual multiple constraints would not decisively constrain all carbon fluxes and stocks, but would work to lessen the uncertainty and find inconsistencies<sup>57</sup>. Like fitting puzzle pieces together, constraining global soil respiration estimates with multiple other fluxes and stocks are an essential process.

**Benchmarking of carbon cycle models and ESMs.** The primary purpose of global data-driven estimates of soil respiration is to allow for benchmarking of carbon cycle models and ESMs. To predict future climate, process-based carbon cycle models are necessary, and it is essential to constrain them properly. Soil respiration consists of heterotrophic and autotrophic respiration, so constraining models with each respiration component is ideal. However, for data-driven global estimates, total soil respiration is the most intensively studied, while most ESMs only output

heterotrophic respiration. To improve the constraint on soil processes in ESMs, more data-driven global estimates of both total soil respiration and its individual components are needed. ESMs should output separate estimates for heterotrophic and belowground autotrophic respiration and use both the total soil respiration and its individual components for constraining model simulations<sup>58,59</sup>.

Comparing the total and heterotrophic respirations, our analysis suggested that the inter-model variability from CMIP6 can potentially be reduced through processes, parameterization, and constraints. Recent studies also suggest the importance of selecting model predictions with comparable model performance with data (emergent constraint)<sup>60–62</sup>, which can further reduce inter-model variability in future predictions.

**Outlook.** We have traced back historical estimates of global soil respiration in the last half-century to demonstrate the progress made and remaining uncertainty. Future efforts to better constrain global soil respiration estimates can be categorized into four fundamental pillars: data-driven modeling, observation data, mechanisms, and mutual, multiple constraints. Reducing inter-model variability is not an easy task, but when the puzzle pieces of the carbon cycle fit together perfectly, climate change prediction will be more reliable. Refining estimates of critical components like soil respiration is a step towards ensuring all pieces of the global carbon cycle fit together.

#### Data availability

The datasets used in this study are available from each repository or supplementary information of each study or direct request to the authors of the original paper (see Supplementary Table 1). The map data converted to NetCDF format is also available in the ZENODO repository <https://doi.org/10.5281/ZENODO.840474763>.

#### Code availability

The scripts used are available from the corresponding author on reasonable request.

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#### References

- Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A. & Totterdell, I. J. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature* **408**, 184–187 (2000).
- Friedlingstein, P. et al. Global carbon budget 2022. *Earth Syst. Sci. Data* **14**, 4811–4900 (2022).
- Ito, A. A historical meta-analysis of global terrestrial net primary productivity: are estimates converging? *Glob. Change Biol.* **17**, 3161–3175 (2011).
- Schlesinger, W. H. & Andrews, J. A. Soil respiration and the global carbon cycle. *Biogeochemistry* **48**, 7–20 (2000).
- Bond-Lamberty, B., Wang, C. & Gower, S. T. A global relationship between the heterotrophic and autotrophic components of soil respiration? *Glob. Change Biol.* **10**, 1756–1766 (2004).
- Ryan, M. G. & Law, B. E. Interpreting, measuring, and modeling soil respiration. *Biogeochemistry* **73**, 3–27 (2005).
- Subke, J.-A. & Bahn, M. On the ‘temperature sensitivity’ of soil respiration: Can we use the immeasurable to predict the unknown? *Soil Biol. Biochem.* **42**, 1653–1656 (2010).
- Bond-Lamberty, B. & Thomson, A. A global database of soil respiration data. *Biogeosciences* **7**, 1915–1926 (2010).
- Jenkinson, D. S. The turnover of organic carbon and nitrogen in soil. *Phil. Trans. R. Soc. Lond. B* **329**, 361–368 (1990).
- Crowther, T. W. et al. Quantifying global soil carbon losses in response to warming. *Nature* **540**, 104–108 (2016).
- van Gestel, N. et al. Predicting soil carbon loss with warming. *Nature* **554**, E4–E5 (2018).

12. Hashimoto, S. et al. Global spatiotemporal distribution of soil respiration modeled using a global database. *Biogeosciences* **12**, 4121–4132 (2015).
13. Bond-Lamberty, B., Bailey, V. L., Chen, M., Gough, C. M. & Vargas, R. Globally rising soil heterotrophic respiration over recent decades. *Nature* **560**, 80–83 (2018).
14. Stell, E., Warner, D., Jian, J., Bond-Lamberty, B. & Vargas, R. Spatial biases of information influence global estimates of soil respiration: How can we improve global predictions? *Glob. Change Biol.* **27**, 3923–3938 (2021).
15. Eyring, V. et al. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* **9**, 1937–1958 (2016).
16. Deherain, P. P. & Demoussy, E. Sur l'oxydation de la matiere organique du sol. *Ann. Agron.* **22**, 305–337 (1886).
17. Gainey, P. L. Parallel formation of carbon dioxide, ammonia and nitrate in soil. *Soil Sci* **7**, 293–312 (1919).
18. Lundegardh, H. Carbon dioxide evolution of soil and crop growth. *Soil Sci* **23**, 417–453 (1927).
19. Schlesinger, W. H. Carbon balance in terrestrial detritus. *Annu. Rev. Ecol. Syst.* **8**, 51–81 (1977).
20. von Liebig, J. Der chemische Process der Ernahrung der Vegetabilien. (Friedrich Vieweg und Sohn, 1862).
21. Baldocchi, D. et al. FLUXNET: a new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bull. Amer. Meteorol. Soc.* **82**, 2415–2434 (2001).
22. Lu, H. et al. Comparing machine learning-derived global estimates of soil respiration and its components with those from terrestrial ecosystem models. *Environ. Res. Lett.* **16**, 054048 (2021).
23. Jian, J. et al. A restructured and updated global soil respiration database (SRDB-V5). *Earth Syst. Sci. Data* **13**, 255–267 (2021).
24. Peng, C. & Apps, M. J. Simulating global soil-CO<sub>2</sub> flux and its response to climate change. *J. Environ. Sci.* **12**, 257–265 (2000).
25. Raich, J. W. & Potter, C. S. Global patterns of carbon dioxide emissions from soils. *Global Biogeochem. Cy.* **9**, 23–36 (1995).
26. Bond-Lamberty, B. et al. COSORE: A community database for continuous soil respiration and other soil-atmosphere greenhouse gas flux data. *Glob. Change Biol.* **26**, 7268–7283 (2020).
27. Krofcheck, D. J., Litvak, M. E. & Hurteau, M. D. Allometric relationships for *Quercus gambelii* and *Robinia neomexicana* for biomass estimation following disturbance. *Ecosphere* **10**, e02905 (2019).
28. Hengl, T. et al. SoilGrids250m: Global gridded soil information based on machine learning. *PLoS ONE* **12**, e0169748 (2017).
29. Yamazaki, D. et al. A high-accuracy map of global terrain elevations: Accurate Global Terrain Elevation map. *Geophys. Res. Lett.* **44**, 5844–5853 (2017).
30. Zhou, T. et al. Prediction of soil organic carbon and the C:N ratio on a national scale using machine learning and satellite data: a comparison between Sentinel-2, Sentinel-3 and Landsat-8 images. *Sci. Total Environ.* **755**, 142661 (2021).
31. Rossiter, D. G. Past, present & future of information technology in pedometrics. *Geoderma* **324**, 131–137 (2018).
32. Xiao, J. et al. Remote sensing of the terrestrial carbon cycle: A review of advances over 50 years. *Remote Sens. Environ.* **233**, 111383 (2019).
33. Ohashi, M., Kume, T., Yamane, S. & Suzuki, M. Hot spots of soil respiration in an Asian tropical rainforest. *Geophys. Res. Lett.* **34**, L08705 (2007).
34. Pumpanen, J. et al. Comparison of different chamber techniques for measuring soil CO<sub>2</sub> efflux. *Agri. For. Meteorol.* **123**, 159–176 (2004).
35. Davidson, E. A., Savage, K., Verchot, L. V. & Navarro, R. Minimizing artifacts and biases in chamber-based measurements of soil respiration. *Agri. For. Meteorol.* **113**, 21–37 (2002).
36. Reichstein, M. et al. Deep learning and process understanding for data-driven Earth system science. *Nature* **566**, 195–204 (2019).
37. Tang, X. et al. Global variability in belowground autotrophic respiration in terrestrial ecosystems. *Earth Syst. Sci. Data* **11**, 1839–1852 (2019).
38. Tang, X. et al. Spatial and temporal patterns of global soil heterotrophic respiration in terrestrial ecosystems. *Earth Syst. Sci. Data* **12**, 1037–1051 (2020).
39. Wieder, W. R., Bonan, G. B. & Allison, S. D. Global soil carbon projections are improved by modelling microbial processes. *Nat. Clim. Change* **3**, 909–912 (2013).
40. Crowther, T. W. et al. The global soil community and its influence on biogeochemistry. *Science* **365**, eaav0550 (2019).
41. Tedersoo, L. et al. Global diversity and geography of soil fungi. *Science* **346**, 1256688 (2014).
42. Yu, K. et al. The biogeography of relative abundance of soil fungi versus bacteria in surface topsoil. *Earth Syst. Sci. Data* **14**, 4339–4350 (2022).
43. Petrakis, S., Barba, J., Bond-Lamberty, B. & Vargas, R. Using greenhouse gas fluxes to define soil functional types. *Plant Soil* **423**, 285–294 (2018).
44. Bond-Lamberty, B. et al. Estimating heterotrophic respiration at large scales: challenges, approaches, and next steps. *Ecosphere* **7**, e01380 (2016).
45. Hahn, V., Högberg, P. & Buchmann, N. <sup>14</sup>C - a tool for separation of autotrophic and heterotrophic soil respiration. *Glob. Change Biol.* **12**, 972–982 (2006).
46. Camino-Serrano, M. et al. Including stable carbon isotopes to evaluate the dynamics of soil carbon in the land-surface model ORCHIDEE. *J. Adv. Model Earth Syst.* **11**, 3650–3669 (2019).
47. Koarashi, J. et al. Quantitative aspects of heterogeneity in soil organic matter dynamics in a cool-temperate Japanese beech forest: a radiocarbon-based approach. *Glob. Change Biol.* **15**, 631–642 (2009).
48. Hanson, P. J., Edwards, N. T., Garten, C. T. & Andrews, J. A. Separating root and soil microbial contributions to soil respiration: a review of methods and observations. *Biogeochemistry* **48**, 115–146 (2000).
49. Boone, R. D., Nadelhoffer, K. J., Canary, J. D. & Kaye, J. P. Roots exert a strong influence on the temperature sensitivity of soil respiration. *Nature* **396**, 570–572 (1998).
50. Nottingham, A. T., Meir, P., Velasquez, E. & Turner, B. L. Soil carbon loss by experimental warming in a tropical forest. *Nature* **584**, 234–237 (2020).
51. Carey, J. C. et al. Temperature response of soil respiration largely unaltered with experimental warming. *Proc. Natl Acad. Sci. USA* **113**, 13797–13802 (2016).
52. Frey, S. D., Lee, J., Melillo, J. M. & Six, J. The temperature response of soil microbial efficiency and its feedback to climate. *Nat. Clim. Change* **3**, 395–398 (2013).
53. Guenet, B. et al. Impact of priming on global soil carbon stocks. *Glob. Change Biol.* **24**, 1873–1883 (2018).
54. Bogena, H. R. et al. COSMOS-Europe: a European network of cosmic-ray neutron soil moisture sensors. *Earth Syst. Sci. Data* **14**, 1125–1151 (2022).
55. Tang, X. et al. A decreasing carbon allocation to belowground autotrophic respiration in global forest ecosystems. *Sci. Total Environ.* **798**, 149273 (2021).
56. Jian, J. et al. The global contribution of roots to total soil respiration. *Glob. Ecol. Biogeogr.* **31**, 685–699 (2022).
57. Jian, J. et al. Historically inconsistent productivity and respiration fluxes in the global terrestrial carbon cycle. *Nat. Commun.* **13**, 1733 (2022).
58. Kim, D., Lee, M.-I. & Seo, E. Improvement of soil respiration parameterization in a dynamic global vegetation model and its impact on the simulation of terrestrial carbon fluxes. *J. Clim.* **32**, 127–143 (2019).
59. Guenet, B. et al. Spatial biases reduce the ability of earth system models to simulate soil heterotrophic respiration fluxes. *EGUsphere* <https://doi.org/10.5194/egusphere-2023-922> (2023).
60. Shioyama, H., Watanabe, M., Kim, H. & Hirota, N. Emergent constraints on future precipitation changes. *Nature* **602**, 612–616 (2022).
61. Varney, R. M. et al. A spatial emergent constraint on the sensitivity of soil carbon turnover to global warming. *Nat. Commun.* **11**, 5544 (2020).
62. Todd-Brown, K. E. O. et al. Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations. *Biogeosciences* **10**, 1717–1736 (2013).
63. Hashimoto, S., Ito, A. & Nishina, K. Map data of historical global estimates of soil respiration. <https://doi.org/10.5281/ZENODO.8404747> (2023).
64. Raich, J. W. & Schlesinger, W. H. The global carbon dioxide flux in soil respiration and its relationship to vegetation and climate. *Tellus B* **44**, 81–99 (1992).
65. Raich, J. & Potter, C. Global patterns of carbon dioxide emissions from soils on a 0.5 degree grid cell basis. <https://doi.org/10.3334/CDIAC/LUE.DB1015> (1996).
66. Raich, J. W., Potter, C. S. & Bhagawati, D. Interannual variability in global soil respiration, 1980–94. *Glob. Change Biol.* **8**, 800–812 (2002).
67. Raich, J., Potter, C. & Bhagawat, D. Interannual variability in global soil respiration on a 0.5 degree grid cell basis (1980–1994). <https://doi.org/10.3334/CDIAC/LUE.NDP081> (2003).
68. Bond-Lamberty, B. & Thomson, A. Temperature-associated increases in the global soil respiration record. *Nature* **464**, 579–582 (2010).
69. Hashimoto, S. A new estimation of global soil greenhouse gas fluxes using a simple data-oriented model. *PLoS ONE* **7**, e41962 (2012).
70. Chen, S. et al. A new estimate of global soil respiration from 1970 to 2008. *Chin. Sci. Bull.* **58**, 4153–4160 (2013).
71. Hashimoto, S. Global gridded soil respiration, heterotrophic respiration, autotrophic respiration, and Q<sub>10</sub> value (Hashimoto et al. 2015, Biogeosciences). <https://doi.org/10.5281/ZENODO.4708444> (2021).
72. Oertel, C., Matschullat, J., Zurba, K., Zimmermann, F. & Erasmí, S. Greenhouse gas emissions from soils—A review. *Geochemistry* **76**, 327–352 (2016).
73. Xu, M. & Shang, H. Contribution of soil respiration to the global carbon equation. *J. Plant Physiol.* **203**, 16–28 (2016).
74. Adachi, M., Ito, A., Yonemura, S. & Takeuchi, W. Estimation of global soil respiration by accounting for land-use changes derived from remote sensing data. *J. Environ. Manage.* **200**, 97–104 (2017).
75. Zhao, Z. et al. Model prediction of biome-specific global soil respiration from 1960 to 2012. *Earth's Future* **5**, 715–729 (2017).
76. Hursh, A. et al. The sensitivity of soil respiration to soil temperature, moisture, and carbon supply at the global scale. *Glob. Change Biol.* **23**, 2090–2103 (2017).
77. Jian, J., Steele, M. K., Thomas, R. Q., Day, S. D. & Hodges, S. C. Constraining estimates of global soil respiration by quantifying sources of variability. *Glob. Change Biol.* **24**, 4143–4159 (2018).

78. Jian, J., Steele, M. K., Day, S. D. & Thomas, R. Q. Future global soil respiration rates will swell despite regional decreases in temperature sensitivity caused by rising temperature. *Earth's Future* **6**, 1539–1554 (2018).
79. Warner, D. L., Bond-Lamberty, B., Jian, J., Stell, E. & Vargas, R. Spatial predictions and associated uncertainty of annual soil respiration at the global scale. *Glob. Biogeochem. Cy.* **33**, 1733–1745 (2019).
80. Warner, D. L., Bond-Lamberty, B. P., Jian, J., Stell, E. & Vargas, R. Global gridded 1-km annual soil respiration and uncertainty derived from SRDB V3. <https://doi.org/10.3334/ORNLDAAC/1736> (2019).
81. Tang, X. et al. A globally gridded heterotrophic respiration dataset based on field observations. <https://doi.org/10.6084/M9.FIGSHARE.8882567> (2019).
82. Tang, X. et al. A gridded dataset of belowground autotrophic respiration from 1980 to 2012 in global terrestrial ecosystems upscaling of observations. <https://doi.org/10.6084/M9.FIGSHARE.7636193> (2019).
83. Huang, N. et al. Spatial and temporal variations in global soil respiration and their relationships with climate and land cover. *Sci. Adv.* **6**, eabb8508 (2020).
84. Huang, N. & Wang, L. Global annual soil respiration from 2000 to 2014. <https://doi.org/10.5061/DRYAD.W3R2280NQ> (2020).
85. Lei, J. et al. Temporal changes in global soil respiration since 1987. *Nat. Commun.* **12**, 403 (2021).
86. Lu, H. Global soil respiration and its components dataset derived from the Random Forest method. <https://doi.org/10.5281/ZENODO.4686669> (2021).
87. Stell, E., Warner, D. L., Jian, J., Bond-Lamberty, B. P. & Vargas, R. Global gridded 1-km soil and soil heterotrophic respiration derived from SRDB v5. <https://doi.org/10.3334/ORNLDAAC/1928> (2021).
88. Epule, T. A new compendium of soil respiration data for Africa. *Challenges* **6**, 88–97 (2015).
89. Song, X. et al. Quantification of soil respiration in forest ecosystems across China. *Atmos. Environ.* **94**, 546–551 (2014).

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## Author contributions

S.H.: Conceptualization, methodology, software, data curation, writing, visualization A.I.: Methodology, supervision, writing, funding acquisition K.N.: Methodology, writing.

## Competing interests

The authors declare no competing interests.

## Additional information

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