

References and Notes

1. E.-D. Schulze, *Flora* **159**, 177 (1970).
2. H. Poorter, C. Remkes, H. Lambers, *Plant Physiol.* **94**, 621 (1990).
3. E. H. DeLucia, J. E. Drake, R. B. Thomas, M. Gonzalez-Meler, *Glob. Change Biol.* **13**, 1157 (2007).
4. S. Luyssaert *et al.*, *Glob. Change Biol.* **13**, 2509 (2007).
5. C. M. Litton, J. W. Raich, M. G. Ryan, *Glob. Change Biol.* **13**, 2089 (2007).
6. I. C. Prentice *et al.*, *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, J. Houghton, *et al.*, Eds. (Cambridge University Press, Cambridge, 2001), pp. 183–237.
7. B. Saugier, J. Roy, H. A. Mooney, *Terrestrial Global Productivity*, J. Roy, B. Saugier, H. A. Mooney, Eds. (Academic Press, San Diego, CA, 2001).
8. G. D. Farquhar *et al.*, *Nature* **363**, 439 (1993).
9. P. Ciais *et al.*, *J. Geophys. Res.* **102** (D5), 5857 (1997).
10. L. Wingate *et al.*, *Proc. Natl. Acad. Sci. U.S.A.* **106**, 22411 (2009).
11. L. Sandoval-Soto *et al.*, *Biogeosciences* **2**, 125 (2005).
12. J. E. Campbell *et al.*, *Science* **322**, 1085 (2008).
13. P. Suntharalingam, A. J. Kettle, S. M. Montzka, D. J. Jacob, *Geophys. Res. Lett.* **35**, L19801 (2008).
14. P. Friedlingstein *et al.*, *J. Clim.* **19**, 3337 (2006).
15. D. Baldocchi, *Aust. J. Bot.* **56**, 1 (2008).
16. Materials and methods are available as supporting material on Science Online.
17. M. Jung, M. Reichstein, A. Bondeau, *Biogeosciences* **6**, 2001 (2009).
18. D. Papale, R. Valentini, *Glob. Change Biol.* **9**, 525 (2003).
19. C. Beer, M. Reichstein, P. Ciais, G. D. Farquhar, D. Papale, *Geophys. Res. Lett.* **34**, L05401 (2007).
20. C. Beer *et al.*, *Glob. Biogeochem. Cycles* **23**, GB2018 (2009).
21. J. Monteith, *J. Appl. Ecol.* **9**, 747 (1972).
22. S. W. Running, P. Thornton, R. Nemani, J. Glassy, *Methods in Ecosystem Science*, O. Sala, R. Jackson, H. Mooney, R. Howarth, Eds. (Springer-Verlag, New York, 2000), pp. 44–57.
23. H. Lieth, *Primary Productivity of the Biosphere*, H. Lieth, R. H. Whittaker, Eds. (Springer-Verlag, Berlin, 1975), pp. 237–263.
24. R. Myneni *et al.*, *Remote Sens. Environ.* **83**, 214 (2002).
25. N. Gobron *et al.*, *J. Geophys. Res.-Atmos.* **111** (D13), D13110 (2006).
26. F. Baret *et al.*, *Remote Sens. Environ.* **110**, 275 (2007).
27. M. New, D. Lister, M. Hulme, I. Makin, *Clim. Res.* **21**, 1 (2002).
28. T. D. Mitchell, P. D. Jones, *Int. J. Climatol.* **25**, 693 (2005).
29. A. Simmons, S. Uppala, D. Dee, S. Kobayashi, *ECMWF Newsletter No. 110* (European Centre for Medium-Range Weather Forecasts, Shinfield Park, Reading, UK, 2007).
30. Median absolute deviation times 1.48.
31. B. Fekete, C. Vorosmarty, J. Roads, C. Willmott, *J. Clim.* **17**, 294 (2004).
32. M. Zhao, S. W. Running, R. R. Nemani, *J. Geophys. Res.-Biogeosci.* **111** (G1), G01002 (2006).
33. C. Rödenbeck, S. Houweling, M. Gloor, M. Heimann, *Atmos. Chem. Phys.* **3**, 1919 (2003).
34. A. Bondeau *et al.*, *Glob. Change Biol.* **13**, 679 (2007).
35. L. M. Mercado *et al.*, *Nature* **458**, 1014 (2009).
36. R. H. Whittaker, G. E. Likens, *Primary Productivity of the Biosphere*, H. Lieth, R. H. Whittaker, Eds. (Springer-Verlag, Berlin, 1975), pp. 305–328.
37. R. R. Nemani *et al.*, *Science* **300**, 1560 (2003).
38. D. Gerten *et al.*, *Geophys. Res. Lett.* **32**, L21408 (2005).
39. G. Mehl *et al.*, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, S. Solomon *et al.*, Eds. (Cambridge University Press, Cambridge and New York, 2007), pp. 747–845.
40. This work used eddy covariance data acquired by the FLUXNET community and in particular by the following networks: AmeriFlux [U.S. Department of Energy, Biological and Environmental Research, Terrestrial Carbon Program (DE-FG02-04ER63917 and DE-FG02-04ER63911)], AfriFlux, AsiaFlux, CarboAfrica, CarboEuropeIP, CarboItaly, CarboMont, ChinaFlux, Fluxnet-Canada (supported by CFCAS, NSERC, BIOCAP, Environment Canada, and NRCAN), GreenGrass, KoFlux, LBA, NECC, OzFlux, TCOS-Siberia, and USCCC. We acknowledge the support to the eddy covariance data harmonization provided by CarboEuropeIP, FAO-GTOS-TCO, Integrated Land Ecosystem-Atmosphere Processes Study, Max Planck Institute for Biogeochemistry, National Science Foundation, University of Tuscia, Université Laval and Environment Canada and U.S. Department of Energy and the database development and technical support from Berkeley Water Center, Lawrence Berkeley National Laboratory, Microsoft Research eScience, Oak Ridge National Laboratory, University of California–Berkeley, and University of Virginia. Remotely sensed land cover, fAPAR, and LAI were available through the Joint Research Centre of the European Commission, the National Aeronautics and Space Administration, and the projects GLC2000 and CYCLOPES. Climate data came from the European Centre for Medium-Range Weather Forecasts, the Climate Research Unit of the University of East Anglia, and the GEWEX project GPCP. We thank Mahendra K. Karki at GMAO/NASA for extracting the MOD17 required surface meteorological variables from the GMAO reanalysis dataset and Maosheng Zhao at NTSF of University of Montana for calculating the respective daytime VPD. We further acknowledge support by the European Commission FP7 projects COMBINE and CARBO-Extreme and a grant from the Max-Planck Society establishing the MPRG Biogeochemical Model-Data Integration. C.B., D.P., M.R., P.C., D.B., and S.L. conceived the study. C.B., C.R., D.P., E.T., M.J., M.R., and N.C. contributed diagnostic modeling results. C.B., A.B., G.B.B., M.L., F.I.W., and N.V. contributed process model results. C.B., E.T., and M.R. performed the analysis. C.B. and M.R. wrote the manuscript. All other coauthors contributed with data or substantial input to the manuscript.

Supporting Online Material

www.sciencemag.org/cgi/content/full/science.1184984/DC1

Materials and Methods

SOM Text

Figs. S1 to S34

Tables S1 to S9

References

20 November 2009; accepted 8 June 2010

Published online 5 July 2010;

10.1126/science.1184984

Include this information when citing this paper.

Global Convergence in the Temperature Sensitivity of Respiration at Ecosystem Level

Miguel D. Mahecha,^{1,2*} Markus Reichstein,¹ Nuno Carvalhais,^{1,3} Gitta Lasslop,¹ Holger Lange,⁴ Sonia I. Seneviratne,² Rodrigo Vargas,⁵ Christof Ammann,⁶ M. Altaf Arain,⁷ Alessandro Cescatti,⁸ Ivan A. Janssens,⁹ Mirco Migliavacca,¹⁰ Leonardo Montagnani,^{11,12} Andrew D. Richardson¹³

The respiratory release of carbon dioxide (CO₂) from the land surface is a major flux in the global carbon cycle, **antipodal** to photosynthetic CO₂ uptake. Understanding the sensitivity of respiratory processes to temperature is central for quantifying the climate–carbon cycle feedback. We approximated the sensitivity of terrestrial ecosystem respiration to air temperature (Q_{10}) across 60 FLUXNET sites with the use of a methodology that **circumvents confounding effects**. **Contrary to previous findings, our results suggest that Q_{10} is independent of mean annual temperature, does not differ among biomes, and is confined to values around 1.4 ± 0.1 .** The strong relation between photosynthesis and respiration, by contrast, is highly variable among sites. The results may partly explain a less pronounced climate–carbon cycle feedback than suggested by current carbon cycle climate models.

Quantifying the intensity of feedback **mechanisms** between terrestrial ecosystems and climate is a central challenge for understanding the global carbon cycle and a prerequisite for reliable future climate scenarios (1, 2). One crucial determinant of the climate–carbon cycle feedback is the temperature sensitivity of respiratory processes in terrestrial ecosystems (3, 4), which has been subject to

much debate (5–10). On the one hand, empirical studies have found high sensitivities of soil respiration to temperature, with values of Q_{10} (here an indicator of the sensitivity of terrestrial ecosystem respiration to air temperature) well above 2 (11, 12). Dependencies of Q_{10} values on mean temperatures (12, 13) have been attributed to the acclimatization of soil respiration (5), among other factors (13). On the other hand, global-scale

models often make use of globally constant Q_{10} values of 2 or below to generate carbon dynamics consistent with global atmospheric CO₂ growth rates (3, 14, 15). Nonetheless, several models have directly included empirical dependencies of the parameterization of respiratory processes to environmental dynamics (16–18). This inclusion is questionable, given that single-site studies have indicated that factors seasonally covarying with temperature can confound the experimental **retrieval**

¹Max Planck Institute for Biogeochemistry, 07745 Jena, Germany.

²Institute for Atmospheric and Climate Science, ETH Zürich,

Universitätsstrasse 16, 8092 Zürich, Switzerland. ³Faculdade de

Ciências e Tecnologia, FCT, Universidade Nova de Lisboa, 2829-516

Caparica, Portugal. ⁴Norsk Institutt for Skog og Landskap, N-1431

Ås, Norway. ⁵Department of Environmental Science, Policy and

Management, University of California, Berkeley, CA 94720, USA.

⁶Agroscope ART, Federal Research Station, Reckenholzstr. 191,

CH-8046 Zürich, Switzerland. ⁷McMaster Centre for Climate Change,

McMaster University, Hamilton, Ontario L8S 4L8, Canada. ⁸Euro-

pean Commission, Joint Research Center, Institute for Environment

and Sustainability, I-21027 Ispra, Italy. ⁹Department of Biology,

University of Antwerpen, Universiteitsplein 1, 2610 Wilrijk, Belgium.

¹⁰Remote Sensing of Environmental Dynamics Laboratory, DISAT,

University of Milano-Bicocca, 20126 Milano, Italy. ¹¹Servizi Forestali,

Agenzia per l'Ambiente, Provincia Autonoma di Bolzano, 39100

Bolzano, Italy. ¹²Faculty of Sciences and Technologies, Free Uni-

versity of Bozen-Bolzano, Piazza Università 1, 39100 Bolzano,

Italy. ¹³Harvard University Department of Organismic and

Evolutionary Biology, Harvard University Herbaria, 22 Divinity

Avenue, Cambridge, MA 02138, USA.

*To whom correspondence should be addressed. E-mail:

mmahecha@bgc-jena.mpg.de

of the intrinsic temperature dependence of respiration (8, 9, 19). Davidson and Janssens (20) therefore proposed to distinguish intrinsic temperature sensitivities by quantifying the inherent kinetic properties of substrate decomposition from apparent temperature responses. Moreover, it has been recognized that the direct inference of process sensitivities from emergent ecosystem behavior is not possible (19, 21).

Our aim here was to retrieve the unconfounded (intrinsic) temperature sensitivities of ecosystem respiration across different climates and ecosystems, to resolve the question of whether we have to account for a globally varying and environmentally controlled Q_{10} in global carbon cycle modeling. The study is based on a global collection of eddy covariance CO_2 flux observations—the FLUXNET (22, 23) LaThuile Database—which allows us to investigate greenhouse gas fluxes in response to meteorological variables across ecosystems. To minimize the influence of confounding effects, we apply a model-data fusion approach, scale-dependent parameter estimation (SCAPE) (24), that investigates processes on different time scales. The SCAPE concept exploits the idea that measured time series $Y(i)$, $i = 1, \dots, N$, result from superimposed modes of characteristic variability X_f , where the index f indicates the attributable frequency class per subsignal (fig. S1). In SCAPE we can distinguish rapid and slow system responses (here, direct responses to temperature versus long-term organic matter dynamics described by the base respiration R_b). SCAPE differentiates the parameter estimation process according to identified time scales. We can therefore report temperature sensitivities ($Q_{10,sc}$) derived from specific (high-frequency) subsignals X_f such that confounding factors that operate on other (generally low-frequency) scales are excluded. Moreover, a nonparametric estimate of the low-frequency R_b time series is directly provided (24). In an experiment with artificial data (24) (fig. S2), we show that with this methodology the unconfounded $Q_{10,sc}$ of respiration is retrieved within ± 0.1 units, even under unfavorable conditions of noise (fig. S3) (25).

The examination of the ecosystem respiration data shows that the unconfounded $Q_{10,sc}$ values are generally lower than temperature sensitivities reported by conventional estimates (Fig. 1) with very few exceptions (table S1). Conventional estimates would suggest an average sensitivity to air temperature of $\langle Q_{10} \rangle \approx 2.3$ across sites. The corresponding 95% confidence range is $2.0 \leq Q_{10} \leq 2.6$, estimated via a block bootstrapping across sites (24). This large range of possible Q_{10} values is very likely caused by confounding factors. However, once we derive the sensitivities using SCAPE, the weighted arithmetic mean is $\langle Q_{10,sc} \rangle \approx 1.4$; the 95% confidence range collapses to the narrow interval of $1.3 \leq Q_{10,sc} \leq 1.5$. The observed systematic difference between apparent and short-term temperature sensitivities corresponds exactly to what was expected by theoretical considerations reported previously (9).

The reported range of $Q_{10,sc}$ values is low, given that soil organic matter incubation experiments, which should not be hampered by seasonally confounding effects, typically find sensitivities of $Q_{10} > 2$ (7, 26, 27). We argue that this discrepancy is due to the controlled laboratory conditions, which partially exclude a number of factors relevant to ecosystem respiration. Measurements at ecosystem level always include multiple processes, such as the mobilization, transport, and transfer (e.g., via depolymerization) of carbon compounds, such that they are metabolizable in the mitochondria. At the end, the rate-limiting step will determine the overall temperature response of a chemical reaction chain, and the overall Q_{10} is lower than for the individual processes (28). For instance, it has been shown that the mycorrhizal respiration is largely limited by the carbon supply from the roots but is virtually insensitive to temperature variations (29, 30). Moreover, growth respiration of plants is largely independent of temperature (31). Because ecosystem respiration is a mixed response of temperature-sensitive and -insensitive subprocesses, we assume that the comparable low $Q_{10,sc}$ values reported here are plausible estimates.

Despite a narrow range of identified $Q_{10,sc}$ values, the site-to-site variability in the $Q_{10,sc}$ estimates does not fully disappear. These differences may be partially caused by a propagation of noise in the nighttime eddy covariance data into parameter estimates. Also, slightly delayed system responses (32) can affect our estimates at ecosystem level. Minor confounding factors operating at comparable time scales, as the effective system responses may also play a role. The latter are not

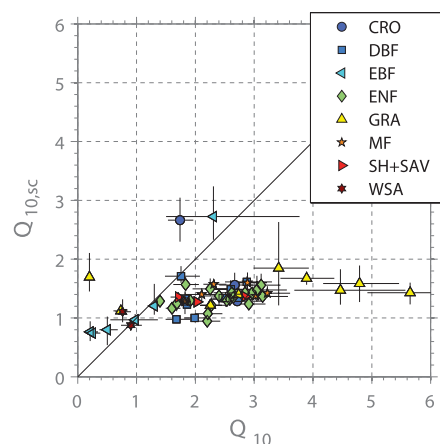


Fig. 1. Estimation of apparent Q_{10} values versus the approximated intrinsic $Q_{10,sc}$ values (SCAPE methodology) across 60 FLUXNET sites using nighttime observations of ecosystem-atmosphere CO_2 fluxes. Error bars show the 95% range of the parameter distributions. These uncertainties are identified via a bootstrapping approach (Q_{10}) or propagated from the SCAPE uncertainties of the time series decomposition [for $Q_{10,sc}$ (24)]. The color code indicates the plant functional type at each site: CRO, cropland; SH, shrubs; SAV, savanna; DBF, deciduous broadleaf forest; EBF, evergreen broadleaf forest; ENF, evergreen needleleaf forest; GRA, grassland; MF, mixed forest; WSA, woody savanna.

easily distinguishable, given that we are confronted with a signal comprising both soil and plant respiration at ecosystem level. Hence, it is very likely that the intrinsic temperature sensitivities of the involved subprocesses are confined to an even narrower range compared to our approximation at ecosystem level. This is remarkable because it implies a convergence of relative proportions of temperature-sensitive and -insensitive respiration fluxes among ecosystems.

To clarify whether a general environmental control might explain the site-to-site variability in the temperature sensitivities of ecosystem respiration, we investigated the relationship of mean annual temperature to the approximated intrinsic $Q_{10,sc}$ and apparent Q_{10} (Fig. 2). The $Q_{10,sc}$ estimates do not confirm the previously found or hypothesized patterns (Fig. 2B). Our results show a global convergence in the temperature sensitivity of terrestrial ecosystem respiration: An almost universal $Q_{10,sc}$ value across climate zones and ecosystem types (see also Fig. 1) is identified. Using the conventional estimates of Q_{10} instead,

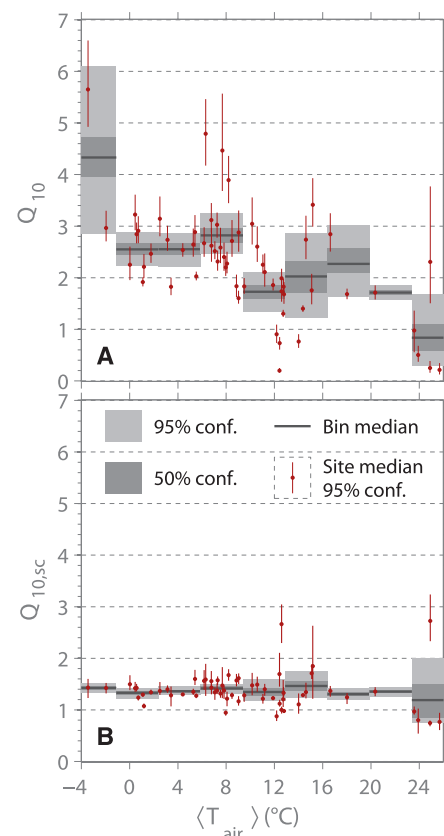


Fig. 2. Apparent Q_{10} and approximated intrinsic $Q_{10,sc}$ values binned over mean annual temperature (bin with 3.5°). Bin medians and their 50% and 95% uncertainty ranges are estimated via block bootstrapping (24). Original site-level parameter medians (and 95% confidence ranges) are shown in red. (A) The conventionally determined ecosystem-level Q_{10} values suggest an apparent temperature dependence. (B) The SCAPE $Q_{10,sc}$ estimates do not show any relationship with the mean annual temperature at the investigated FLUXNET sites.

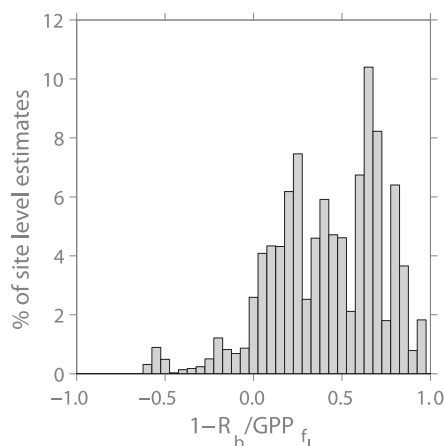


Fig. 3. Distribution of the ratio of base respiration to GPP_f , $1 - (R_b/GPP_f)$. Base respiration is a low-frequency signal (periods >3 months) and is compared here to GPP fluctuations in the same frequency range (f_f) for all sites. The ratio is recomputed 1024 times per site from a randomly chosen combination of subsignal estimates (of GPP_f and R_b), such that the methodological uncertainty is considered (24).

we reproduce the effects of an apparent temperature control on the sensitivity (Fig. 2A). This underscores the problem that some unconsidered process, such as substrate supply, can be erratically interpreted as an oversensitivity of ecosystem metabolic processes to temperature.

Our analysis further emphasizes that despite having comparable short-term temperature sensitivities, ecosystems strongly differ in their carbon metabolism on longer time scales (Fig. 3): Low-frequency ecosystem responses are reflected in the temporal dynamics of the base respiration R_b (fig. S5). These time series show a tight relationship with corresponding low-frequency modes in independently estimated time series of gross primary productivity GPP_f (33) (fig. S6). If we allow R_b to respond to GPP_f with a time delay of a few days, which is a plausible assumption (32), all relationships are close to linear (fig. S7), confirming recent findings (34). The ratio $1 - (R_b/GPP_f)$ hints at how the low-frequency dynamics of carbon uptake is propagated to the metabolism potential of labile soil organic carbon by autotrophic and heterotrophic respiration (19). Contrary to the global convergence in the temperature sensitivity, Fig. 3 shows that the low-frequency dynamics within the ecosystem spreads over a wide range. Consequently, future analyses of the climate-carbon cycle feedback have to emphasize the role of long-term dynamics in the terrestrial carbon cycle, rather than focusing on the short-term sensitivities. In particular, the role of intricate nonbiological stabilization processes versus carbon supply rates needs to be further investigated when trying to predict climate change effects on soil carbon dynamics.

The estimated average value for $Q_{10,sc}$ at ecosystem level likely also underlies recent observations of moderate global temperature responses of respiration in the long term (35). Also, modeling

studies reporting that the global carbon cycle can be well modeled only if it is based on ecosystem-level Q_{10} values below 2 (36) are empirically confirmed by our findings. Consequently, carbon process model results will need to be investigated for their capacity to predict similar short-term $Q_{10,sc}$ and the variation of R_b at ecosystem level. However, given the nontrivial ecophysiological interpretation of a multitude of processes summing up to the observed ecosystem respiration, our results do not justify the prescription of $Q_{10} = 1.4$ for all rate constants in soil carbon models. Rather, a deeper understanding of the different factors and processes limiting soil carbon metabolism is needed for overcoming the “dead-soil box modeling paradigm” (37). Moreover, continuous time series of soil respiration, measured with automatic chambers, should be analyzed with the presented methodology, using soil temperature as a driving variable. Such studies could allow exclusive insights to the soil system, whereas our analysis at ecosystem level included aboveground respiration. Furthermore, we suggest exploring the SCAPE methodology in other fields of research, where confounding factors at different scales obscure the intrinsic relation between two variables of interest.

Our findings offer substantial evidence for the existence of universal intrinsic temperature sensitivities of terrestrial ecosystem respiration. The empirically inferred results suggest a $Q_{10,sc} \approx 1.4$ at ecosystem level. These results reconcile the empirical evidence with findings that the global carbon cycle can be well modeled only with an ecosystem level sensitivity of $Q_{10} < 2$. Moreover, our results may partly explain recent findings indicating a less pronounced climate-carbon cycle sensitivity (38) than assumed by current climate-carbon cycle model parameterizations. Contrary to the global convergence in temperature sensitivities, we find complex patterns in the low-frequency influence of photosynthetic carbon uptake and available assimilates on ecosystem respiration dynamics. Future research should strive for an in-depth understanding of carbon pathways through slow pools in terrestrial ecosystems.

References and Notes

- C. D. Jones, P. Cox, C. Huntingford, *Tellus B* **55**, 642 (2003).
- M. Heimann, M. Reichstein, *Nature* **451**, 289 (2008).
- P. Friedlingstein et al., *J. Clim.* **19**, 3337 (2006).
- M. U. Kirschbaum, *Glob. Change Biol.* **16**, 2117 (2010).
- Y. Luo, S. Wan, D. Hui, L. L. Wallace, *Nature* **413**, 622 (2001).
- W. Knorr, I. C. Prentice, J. I. House, E. A. Holland, *Nature* **433**, 298 (2005).
- C. Fang, P. Smith, J. B. Moncrieff, J. U. Smith, *Nature* **433**, 57 (2005).
- M. Reichstein et al., *Glob. Change Biol.* **11**, 1424 (2005).
- E. A. Davidson, A. Janssens, I. Y. Luo, *Glob. Change Biol.* **12**, 154 (2006).
- L. Gu, P. J. Hanson, W. Mac Post, Q. Liu, *Global Biogeochem. Cycles* **22**, GB4009 (2008).
- J. Lloyd, J. A. Taylor, *Funct. Ecol.* **8**, 315 (1994).
- M. F. U. Kirschbaum, *Soil Biol. Biochem.* **27**, 753 (1995).
- S. Peng, S. Piao, T. Wang, J. Sun, Z. Shen, *Soil Biol. Biochem.* **41**, 1008 (2009).
- W. Knorr, M. Heimann, *Tellus B Chem. Phys. Meteorol.* **47**, 471 (1995).
- M. L. Lenton, C. Huntingford, *Glob. Change Biol.* **9**, 1333 (2003).
- P. E. Thornton et al., *Agric. For. Meteorol.* **113**, 185 (2002).
- S. Sitch et al., *Glob. Change Biol.* **9**, 161 (2003).
- G. Kinner et al., *Glob. Biogeochem. Cycles* **19**, GB1015 (2005).
- D. A. Sampson, I. A. Janssens, J. Curiel Yuste, R. Ceulemans, *Glob. Change Biol.* **13**, 2008 (2007).
- E. A. Davidson, I. A. Janssens, *Nature* **440**, 165 (2006).
- M. Reichstein, C. Beer, *J. Plant Nutr. Soil Sci.* **171**, 344 (2008).
- D. Baldocchi, *Aust. J. Bot.* **56**, 1 (2008).
- FLUXNET Synthesis data set (www.fluxdata.org).
- See supporting material on Science Online.
- The whole methodology and results are also reproducible with the Arrhenius model, because this is linearizable in an analog way. However, for the sake of a more intuitive parameter interpretation we chose the Q_{10} model here.
- T. Kätterer, M. Reichstein, O. Andren, A. Lomander, *Biol. Fert. Soils* **27**, 258 (1998).
- M. Reichstein, J.-A. Subke, A. C. Angeli, J. D. Tenhunen, *Glob. Change Biol.* **11**, 1754 (2005).
- G. I. Ågren, J. A. M. Wetterstedt, *Soil Biol. Biochem.* **39**, 1794 (2007).
- A. Heinemeyer, P. Ineson, N. Ostle, A. H. Fitter, *New Phytol.* **171**, 159 (2006).
- F. Moyano, W. L. Kutsch, C. Rebmann, *Agric. For. Meteorol.* **148**, 135 (2008).
- J. S. Amthor, *Ann. Bot.* **86**, 1 (2000).
- Z. Kuzyakov, O. Gavrichovka, *Glob. Change Biol.* **10.1111/j.1365-2486.2010.02179.x** (2010).
- G. Lasslop et al., *Glob. Change Biol.* **16**, 187 (2010).
- M. Migliavacca et al., *Glob. Change Biol.* **10.1111/j.1365-2486.2010.02243.x** (2010).
- B. Bond-Lamberty, A. Thomson, *Nature* **464**, 579 (2010).
- J. T. Randerson et al., *Glob. Change Biol.* **15**, 2462 (2009).
- M. Bahn, I. A. Janssens, M. Reichstein, P. Smith, S. E. Trumbore, *New Phytol.* **186**, 292 (2010).
- D. C. Frank et al., *Nature* **463**, 527 (2010).
- This work is the outcome of the La Thuile FLUXNET workshop 2007, which would not have been possible without the support provided by CarboEuropeIP, FAO-GTOS-TCO, the Integrated Land Ecosystem-Atmosphere Processes Study (iLEAPS, a core project of IGBP), Max Planck Institute for Biogeochemistry, NSF, University of Tuscia, and U.S. Department of Energy. Moreover, we acknowledge databasing and technical support from the Berkeley Water Center, Lawrence Berkeley National Laboratory, Microsoft Research eScience, Oak Ridge National Laboratory, University of California-Berkeley, and University of Virginia. The following networks provided flux data: AmeriFlux, AsiaFlux, CarboEuropeIP, ChinaFlux, Fluxnet-Canada, Canadian Carbon Program, LBA, NECC, OzFlux, TCOS-Siberia, and USCCC. AmeriFlux is supported by U.S. Department of Energy, Biological and Environmental Research, Terrestrial Carbon Program grant DE-FG02-04ER63917. This work was also supported by the European Research Council via the ERC-Staring Grant QUASOM, the European Commission project CARBO-Extreme (FP7-ENV-2008-1-226701), and a grant by the Max Planck Society establishing the MPRG Biogeochemical Model-Data Integration. We appreciate the collaboration of the FLUXNET synthesis team as documented at (23), and we thank M. Bahn, D. Baldocchi, H.-R. Künisch, D. Papale, P. Rayner, M. Rodeghiero, and S. Zaehle for very valuable comments. M.D.M., M.R., N.C., and G.L. conceived the study and developed the methodology with substantial input from H.L. M.D.M. performed the analysis and co-wrote the paper with M.R. All other authors gave substantial scientific input during the analysis and/or writing phase.

Supporting Online Material

www.sciencemag.org/cgi/content/full/science.1189587/DC1
Materials and Methods
SOM Text
Figs. S1 to S7
Table S1
References

15 March 2010; accepted 15 June 2010
Published online 5 July 2010;
10.1126/science.1189587
Include this information when citing this paper.

Global Convergence in the Temperature Sensitivity of Respiration at Ecosystem Level

Miguel D. Mahecha, Markus Reichstein, Nuno Carvalhais, Gitta Lasslop, Holger Lange, Sonia I. Seneviratne, Rodrigo Vargas, Christof Ammann, M. Altaf Arain, Alessandro Cescatti, Ivan A. Janssens, Mirco Migliavacca, Leonardo Montagnani, and Andrew D. Richardson

Science, 329 (5993), • DOI: 10.1126/science.1189587

Carbon Cycle and Climate Change

As climate change accelerates, it is important to know the likely impact of climate change on the carbon cycle (see the Perspective by Reich). Gross primary production (GPP) is a measure of the amount of CO₂ removed from the atmosphere every year to fuel photosynthesis. Beer *et al.* (p. 834, published online 5 July) used a combination of observation and calculation to estimate that the total GPP by terrestrial plants is around 122 billion tons per year; in comparison, burning fossil fuels emits about 7 billion tons annually. Thirty-two percent of this uptake occurs in tropical forests, and precipitation controls carbon uptake in more than 40% of vegetated land. The temperature sensitivity (Q₁₀) of ecosystem respiratory processes is a key determinant of the interaction between climate and the carbon cycle. Mahecha *et al.* (p. 838, published online 5 July) now show that the Q₁₀ of ecosystem respiration is invariant with respect to mean annual temperature, independent of the analyzed ecosystem type, with a global mean value for Q₁₀ of 1.6. This level of temperature sensitivity suggests a less-pronounced climate sensitivity of the carbon cycle than assumed by recent climate models.

View the article online

<https://www.science.org/doi/10.1126/science.1189587>

Permissions

<https://www.science.org/help/reprints-and-permissions>

Use of this article is subject to the [Terms of service](#)