Title: Soil moisture–atmosphere feedback dominates land carbon uptake variability

Authors: Vincent Humphrey*[1], Alexis Berg[2], Philippe Ciais[3], Pierre Gentine[4], Martin Jung[5], Markus Reichstein[5], Sonia I. Seneviratne[6], Christian Frankenberg[1,7]

Affiliations:
[1] Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, United States
[2] Department of Earth and Planetary Sciences, Harvard University, Cambridge, MA, United States
[3] Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, 91191 Gif-sur-Yvette, France
[4] Department of Earth and Environmental Engineering, Columbia University, New York, NY, United States
[5] Department of Biogeochemical Integration, Max Planck Institute for Biogeochemistry, 07745 Jena, Germany
[6] Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland
[7] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, United States

*vincent.humphrey@caltech.edu

Year-to-year changes in carbon uptake by terrestrial ecosystems play an essential role in determining atmospheric carbon dioxide concentrations[1]. It remains uncertain to what extent temperature and water availability can explain these variations at the global scale[2-5]. Here we use factorial climate model simulations[6] and show that variability in soil moisture drives 90% of the inter-annual variability in global land carbon uptake, mainly through its impact on photosynthesis. We find that most of this ecosystem response occurs indirectly as soil moisture–atmosphere feedbacks amplify temperature and humidity anomalies, and enhance the direct effects of soil water stress. The strength of this feedback mechanism explains why coupled climate models indicate a dominant role of soil moisture[4] which is not readily apparent in land surface model simulations and observational analyses[2,5]. These findings highlight the need to account for feedbacks between soil and atmospheric dryness when estimating the carbon cycle's response to climatic change globally[5,7], as well as when conducting field-scale investigations of the ecosystem response to droughts[8,9]. Our results show that most of the global variability in modelled land carbon uptake is driven by temperature and vapour pressure deficit effects which are controlled by soil moisture.

Improving the ability of Earth system models to correctly reproduce the observed variability in land carbon fluxes is essential for building confidence in projections of the long-term response of the carbon cycle to a warming and changing climate[10]. This research agenda has been evolving rapidly in the past decade thanks to coordinated model comparison experiments[11,12], theoretical advances[13], model developments[14,15], as well as new observations from ground-based networks[16,17] and satellite platforms[18]. Yet, the spread among Earth system models (ESMs) remains substantial[19,20] and highlights the need to better constrain the sensitivity of increasingly complex biogeochemical models to changes in atmospheric and hydrological drivers such as radiation[21], temperature[7], soil water availability[3], and vapour pressure deficit (VPD, a measure of atmospheric dryness which depends on air temperature and humidity). In particular, it remains unclear whether temperature or soil moisture is the dominant driver of the inter-annual variability (IAV) in land carbon uptake at the global scale[2-5]. Here, we investigate the extent to which temperature, VPD, and soil moisture effects co-vary as a result of soil moisture-atmosphere feedbacks and reconcile conflicting assessments of the sensitivity of global carbon fluxes to these variables.

Soil moisture drought is one of the key prerequisites for the development of extreme high temperatures[22-24], while atmospheric dynamics control the onset of such extremes[25]. During droughts, low soil moisture content limits evapotranspiration, which is the most efficient surface cooling flux[26]. This modification of the surface energy balance increases the air temperature, lowers the relative humidity and thus raises VPD. The importance of such soil moisture–atmosphere feedbacks, hereafter referred to as land-atmosphere coupling (LAC), is confirmed by both models and observations[27-29]. In current carbon cycle models, the impacts of soil moisture, temperature, and VPD on ecosystem productivity and respiration are usually parameterized using stress functions. Typically, simulated photosynthesis rates are limited by low soil moisture content and extreme temperatures via a scaling of V_{cmax}[30] (the maximum rate of Rubisco carboxylase activity), or through a downregulation of stomatal conductance (g_s) in response to VPD, relative humidity, or a soil water stress function[31,32]. Ecosystem respiration and fire occurrences are also controlled by soil moisture content, temperature, or atmospheric dryness[33,34]. Because of this situation, the overall influence of soil moisture can potentially occur as 1) a *direct* impact on photosynthesis and respiration processes through the soil water stress regulation or 2) as an *indirect* response to extreme temperature and VPD anomalies resulting from LAC.

Here, we investigate the magnitude of these two different causal pathways (i.e. direct and indirect) using coupled climate model simulations from the Global Land-Atmosphere Coupling Experiment, Coupled Model Intercomparison Project 5 (GLACE-CMIP5)[6] (Methods). To identify the overall influence of soil moisture variability on carbon fluxes and atmospheric conditions, we use an experiment (ExpA) where the (non-seasonal) variability in soil moisture is artificially removed. This is achieved by forcing the soil moisture in ExpA to follow the mean seasonal soil moisture cycle calculated from a reference control simulation (CTL) (Extended Data Fig. 1-2). Experiment ExpA thus simulates the temperature, VPD, and carbon fluxes that would occur under climatologically normal soil moisture conditions. We note that sea surface temperatures (SST) are identical in ExpA and CTL. This ensures that the main differences between ExpA and CTL are due to the different soil moisture conditions, and are not caused by differences in SST patterns (Methods). Using this framework, previous studies have shown that suppressing the non-seasonal soil moisture variability in ExpA strongly reduces the magnitude of temperature and VPD extremes compared to the control simulation[6,27,35] (Extended Data Fig. 3). Here, by comparing the carbon flux anomalies of ExpA with those of the control simulation, we are able to estimate the overall magnitude of soil moisture effects (i.e. direct and indirect effects) on the IAV of net biome production (NBP, which represents the net land carbon uptake). As we focus on IAV, all presented figures are based on anomalies (i.e. de-seasoned and de-trended data) from the period 1960-2005, unless otherwise noted.

Our results show that suppressing non-seasonal variability in soil moisture (SM) leads to a 91% (SD±2.3%) decrease in the variance of global mean NBP, consistently across all of the 4 participating climate models (Figure 1a, Supplementary Table 1). In other words, without SM variability, the IAV of net land carbon uptake is almost eliminated. This primarily occurs because of a reduction in the IAV of gross primary production (GPP) (Figure 1b-c, Supplementary Table 1), and to a lesser extent because of a reduction in the IAV of ecosystem respiration and disturbance fluxes (ReD, the sum of autotrophic and heterotrophic respiration, fires, and any other modelled disturbance). As explained above, both direct soil moisture effects and indirect temperature and VPD effects related to land-atmosphere coupling (LAC) can be responsible for the widespread reduction of NBP variability occurring in ExpA (Figure 2a).

Using a sensitivity analysis (Eq. 1-2, Supplementary Fig. 1-3) of the local model response to anomalies in SM, temperature (T), VPD, and shortwave solar radiation (R) in CTL versus ExpA, we isolate the contributions of direct soil moisture effects (Figure 2b) versus indirect effects (Figure 2c) to the overall reduction in NBP variability (Figure 2a). Regionally, direct soil moisture effects are found in both temperate and tropical biomes, while indirect effects occurring through the feedback on temperature and VPD are mostly concentrated in semi-arid and tropical regions. Our sensitivity analysis also shows that most of the reduction in NBP variability found in ExpA occurs because of a reduction in the variance of the climatological drivers, rather than because of a change in the sensitivity of NBP to these drivers (Extended Data Fig. 4). These findings demonstrate that soil moisture can impact carbon uptake variability in two different and equally important ways. First, soil moisture variability has direct effects on NBP, mostly because plant photosynthesis is reduced when soils become dry below a certain threshold (Figure 2b), second, it enhances temperature and VPD anomalies through land-atmosphere coupling, thus leading to indirect effects on NBP (Figure 2c, Extended Data Fig. 5). Importantly, some regions can be more sensitive to indirect effects (i.e. the SM feedbacks on T and VPD) than to direct SM effects (Extended Data Fig. 6). We note that because disentangling the individual contributions of T and VPD to NBP variability is not straightforward, only their joint contribution is reported here (see Methods for a discussion).

When aggregating these results to the global scale (Figure 3a), we find that indirect effects alone are on average (across models) responsible for most (60%) of the global NBP IAV, whereas direct SM effects account for only 20%. Suppressing direct and indirect effects together leads to a net decrease in NBP variance of about 90% (consistent with Figure 1) as a result of the positive covariance between the direct and indirect effects (Supplementary Tables 2-3). Finally, the temperature and VPD effects that are independent from soil moisture conditions and still persist in ExpA ($NBP^{T\&VPD\ NonLAC}$) only account for 9% of the overall global NBP variability, while radiation effects account for the remaining 11%. As a result of spatial aggregation (Figure 3b), indirect effects also tend to increase in relative importance as they are spatially more coherent (likely due to atmospheric mixing) and do not average out as fast as the direct effects[2]. In summary, the largest fraction of the global mean NBP IAV is driven by anomalies in temperature and VPD that represent an indirect response to soil moisture variability (since they do not occur in its absence, as demonstrated by the experiment). This finding reconciles opposing perspectives on the roles of temperature versus water availability[2-5], as the apparent importance of either driver actually depends on whether the indirect (feedback) effects are attributed to temperature or soil moisture (see Extended Data Fig. 7, Supplementary Fig. 5). While it is not possible to replicate the factorial experiment with observations (this would require manipulating soil moisture everywhere on the planet), we assess the degree to which the reference simulations reflect real observations. Evaluating the control simulations against observational estimates, we find that the modelled sensitivity of global NBP IAV to the different meteorological drivers (Figure 3) agrees well with two independent observational products (Extended Data Fig. 8). Taking into account the uncertainty of these observations, the spatial patterns of NBP IAV simulated by the models are also in reasonable agreement with real-world variability (Supplementary Fig. 6, see discussion in Methods).

More generally, our results show that the areas where NBP IAV is the largest overall (Fig. 4a) often correspond to those where the reduction of T and VPD variability due to prescribing soil moisture is the strongest (Fig. 4b-c). In other words, NBP variability tends to be larger where LAC is stronger (Fig. 4d). These known hotspots of LAC[36] match well with earlier studies that suggested that semi-arid regions dominate global NBP IAV[37,38], even though our analysis refines these previous findings (Extended Data Fig. 9) by also including regions usually classified as temperate or humid, but which are affected by LAC for only a few dry months during the year (e.g. Eastern Europe[22], Amazon basin[39]).

These results also bring a novel understanding of the sensitivity of land carbon uptake IAV to tropical mean temperature[40,41], which has been used to constrain coupled climate model projections[7,42]. Here, we find that the IAV of mean tropical land temperature is barely changed in the experiment with prescribed soil moisture (Extended Data Fig. 10). This is because suppressing soil moisture anomalies reduces temperature extremes only in a couple of hotspot regions (Figure 4b, Extended Data Fig. 3) with little impact on the overall tropical mean. Thus, while IAV in global land carbon uptake has been empirically found to be sensitive to tropical mean temperature in numerous studies[5,41], our results suggest that this sensitivity does not represent a strong mechanistic link, and thus might not necessarily represent the most adequate model constraint. In fact, the El Niño Southern Oscillation and SST in general may be the confounding driver of both tropical mean temperature and the precipitation patterns which cause the SM anomalies leading to NBP variability.

In conclusion, we show that the IAV in land carbon uptake simulated by Earth system models is primarily driven by anomalies in temperature and VPD which are themselves controlled by soil moisture variability. These indirect soil moisture effects occur through LAC and account for 60% (±18%) of the simulated global land carbon uptake IAV. They explain why the simulated global NBP variability 1) mainly arises from tropical and semi-arid regions[37,38] which are known hotspots of LAC[6,36,43], 2) is predominantly a temperature and VPD response (at the global scale) according to land surface models and empirical sensitivity analyses[2,5], and 3) is also largely dependent on soil moisture variability according to coupled climate models[4]. Our results reveal that soil moisture–atmosphere feedbacks represent a dominant source of variability in global carbon uptake and thus reconcile previous conflicting assessments[2-5]. To some extent, we note that these findings might be symptomatic of how land surface models were developed in the first place. Parameterizing a strong sensitivity of carbon uptake to observed VPD or temperature can constitute a simpler way for a land-surface model to achieve good skill, especially when soil water stress and soil moisture dynamics are only represented approximately. As a result, even though models strongly agree that direct and indirect soil moisture effects together dominate land carbon uptake variability, the actual partitioning between direct and indirect effects may be more dependent on modelling approaches. More generally, our results illustrate the importance of differentiating estimates of ecosystem sensitivity to natural droughts as opposed to artificial droughts (e.g. rainfall exclusion experiments), since only the former incorporates LAC and its impact on temperature and humidity. Because soil and atmospheric dryness do not equally respond to climate change[27,44], the direct and indirect soil moisture effects identified here might impact future NBP in different ways. As current climate models have a large spread in their representation of vegetation response to dryness[45] and of LAC strength[46], this could introduce uncertainties in the feedbacks that are difficult to diagnose from offline land surface model evaluation efforts[47], with potentially large impacts on carbon fluxes as demonstrated here. We also note that long-term changes in vegetation structure and composition might alter the ecosystem's future response[4] to and control[9,48,49] of soil moisture–atmosphere feedbacks. Thus, more physical and holistic representations of the vegetation response to soil and atmospheric dryness might have a strong potential to reduce key uncertainties in current projections of future terrestrial carbon fluxes.

References:

1 Friedlingstein, P. *et al.* Global Carbon Budget 2019. *Earth Syst Sci Data* **11**, 1783-1838, doi:10.5194/essd-11-1783-2019 (2019).

2 Jung, M. *et al.* Compensatory water effects link yearly global land CO2 sink changes to temperature. *Nature* **541**, 516-520, doi:10.1038/nature20780 (2017).

3 Humphrey, V. *et al.* Sensitivity of atmospheric CO2 growth rate to observed changes in terrestrial water storage. *Nature* **560**, 628-631, doi:10.1038/s41586-018-0424-4 (2018).

4 Green, J. K. *et al.* Large influence of soil moisture on long-term terrestrial carbon uptake. *Nature* **565**, 476-479 (2019).

5 Piao, S. *et al.* Interannual variation of terrestrial carbon cycle: Issues and perspectives. *Global Change Biology*, doi:10.1111/gcb.14884 (2019).

6 Seneviratne, S. I. *et al.* Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment. *Geophysical Research Letters* **40**, 5212-5217 (2013).

7 Cox, P. M. *et al.* Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature* **494**, 341-344, doi:10.1038/nature11882 (2013).

8 Novick, K. A. *et al.* The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. *Nature Climate Change* **6**, 1023-1027, doi:10.1038/nclimate3114 (2016).

9 Anderegg, W. R. L., Trugman, A. T., Bowling, D. R., Salvucci, G. & Tuttle, S. E. Plant functional traits and climate influence drought intensification and land–atmosphere feedbacks. *Proceedings of the National Academy of Sciences* **116**, 14071-14076, doi:10.1073/pnas.1904747116 (2019).

10 Ciais, P. *et al.* in *Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* 465-570 (Cambridge University Press, 2014).

11 Sitch, S. *et al.* Recent trends and drivers of regional sources and sinks of carbon dioxide. *Biogeosciences* **12**, 653-679, doi:10.5194/bg-12-653-2015 (2015).

12 Jones, C. D. *et al.* C4MIP – The Coupled Climate–Carbon Cycle Model Intercomparison Project: experimental protocol for CMIP6. *Geosci Model Dev* **9**, 2853-2880, doi:10.5194/gmd-9-2853-2016 (2016).

13 Tramontana, G. *et al.* Predicting carbon dioxide and energy fluxes across global FLUXNET sites with regression algorithms. *Biogeosciences* **13**, 4291-4313, doi:10.5194/bg-13-4291-2016 (2016).

14 Lawrence, D. M. *et al.* Parameterization Improvements and Functional and Structural Advances in Version 4 of the Community Land Model. *J Adv Model Earth Sy* **3** (2011).

15 Kennedy, D. *et al.* Implementing Plant Hydraulics in the Community Land Model, Version 5. *J Adv Model Earth Sy* **11**, 485-513, doi:10.1029/2018ms001500 (2019).

16 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. *Bulletin of the American Meteorological Society* **82**, 2415-2434 (2001).

17 Wunch, D. *et al.* The Total Carbon Column Observing Network. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **369**, 2087-2112, doi:10.1098/rsta.2010.0240 (2011).

18 Schimel, D. *et al.* Observing terrestrial ecosystems and the carbon cycle from space. *Global Change Biology* **21**, 1762-1776 (2015).

19 Friedlingstein, P. *et al.* Uncertainties in CMIP5 Climate Projections due to Carbon Cycle Feedbacks. *Journal of Climate* **27**, 511-526, doi:10.1175/JCLI-D-12-00579.1 (2014).

20 Arora, V. K. *et al.* Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models. *Biogeosciences* **17**, 4173-4222, doi:10.5194/bg-17-4173-2020 (2020).

21 Mercado, L. M. *et al.* Impact of changes in diffuse radiation on the global land carbon sink. *Nature* **458**, 1014-1017, doi:10.1038/nature07949 (2009).

22 Seneviratne, S. I., Luthi, D., Litschi, M. & Schar, C. Land-atmosphere coupling and climate change in Europe. *Nature* **443**, 205-209 (2006).

23 Hirschi, M., Mueller, B., Dorigo, W. & Seneviratne, S. I. Using remotely sensed soil moisture for land-atmosphere coupling diagnostics: The role of surface vs. root-zone soil moisture variability. *Remote Sensing of Environment* **154**, 246-252 (2014).

24 Yin, D., Roderick, M. L., Leech, G., Sun, F. & Huang, Y. The contribution of reduction in evaporative cooling to higher surface air temperatures during drought. *Geophysical Research Letters* **41**, 7891-7897, doi:10.1002/2014gl062039 (2014).

25 Miralles, D. G., Teuling, A. J., van Heerwaarden, C. C. & Vila-Guerau de Arellano, J. Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation. *Nature Geosci* **7**, 345-349 (2014).

26 Bateni, S. M. & Entekhabi, D. Relative efficiency of land surface energy balance components. *Water Resources Research* **48**, doi:10.1029/2011wr011357 (2012).

27 Zhou, S. *et al.* Land–atmosphere feedbacks exacerbate concurrent soil drought and atmospheric aridity. *Proceedings of the National Academy of Sciences* **116**, 18848-18853, doi:10.1073/pnas.1904955116 (2019).

28 Hirschi, M. *et al.* Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. *Nature Geosci* **4**, 17-21 (2011).

29 Wehrli, K., Guillod, B. P., Hauser, M., Leclair, M. & Seneviratne, Sonia I. Identifying Key Driving Processes of Major Recent Heat Waves. *Journal of Geophysical Research: Atmospheres* **124**, 11746-11765, doi:10.1029/2019jd030635 (2019).

30 Sellers, P. J. *et al.* A Revised Land Surface Parameterization (SiB2) for Atmospheric GCMS. Part I: Model Formulation. *Journal of Climate* **9**, 676-705, doi:10.1175/1520-0442(1996)009<0676:arlspf>2.0.co;2 (1996).

31 Leuning, R. A critical appraisal of a combined stomatal-photosynthesis model for C3 plants. *Plant, Cell and Environment* **18**, 339-355, doi:10.1111/j.1365-3040.1995.tb00370.x (1995).

32 Medlyn, B. E. *et al.* Reconciling the optimal and empirical approaches to modelling stomatal conductance. *Global Change Biology* **17**, 2134-2144, doi:10.1111/j.1365-2486.2010.02375.x (2011).

33 Yan, Z. *et al.* A moisture function of soil heterotrophic respiration that incorporates microscale processes. *Nature Communications* **9**, doi:10.1038/s41467-018-04971-6 (2018).

34 Metcalfe, D. B. *et al.* Shifts in plant respiration and carbon use efficiency at a large-scale drought experiment in the eastern Amazon. *New Phytologist* **187**, 608-621, doi:10.1111/j.1469-8137.2010.03319.x (2010).

35 Berg, A. *et al.* Interannual Coupling between Summertime Surface Temperature and Precipitation over Land: Processes and Implications for Climate Change. *Journal of Climate* **28**, 1308-1328, doi:10.1175/jcli-d-14-00324.1 (2015).

36 Dirmeyer, P. A. The terrestrial segment of soil moisture -climate coupling. *Geophysical Research Letters* **38**, - (2011).
37 Ahlstrom, A. *et al.* The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. *Science* **348**, 895-899, doi:10.1126/science.aaa1668 (2015).
38 Poulter, B. *et al.* Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature* **509**, 600-603, doi:10.1038/nature13376 (2014).
39 Levine, P. A. *et al.* Soil Moisture Variability Intensifies and Prolongs Eastern Amazon Temperature and Carbon Cycle Response to El Niño–Southern Oscillation. *Journal of Climate* **32**, 1273-1292, doi:10.1175/jcli-d-18-0150.1 (2019).
40 Keeling, C. D., Whorf, T. P., Wahlen, M. & Vanderplicht, J. Interannual Extremes in the Rate of Rise of Atmospheric Carbon-Dioxide since 1980. *Nature* **375**, 666-670, doi:10.1038/375666a0 (1995).
41 Wang, X. *et al.* A two-fold increase of carbon cycle sensitivity to tropical temperature variations. *Nature* **506**, 212-215, doi:10.1038/nature12915 (2014).
42 Huntzinger, D. N. *et al.* Uncertainty in the response of terrestrial carbon sink to environmental drivers undermines carbon-climate feedback predictions. *Sci Rep-Uk* **7**, doi:10.1038/s41598-017-03818-2 (2017).
43 Koster, R. D. *et al.* GLACE: The Global Land-Atmosphere Coupling Experiment. Part I: Overview. *J. Hydrometeor* **7**, 590-610 (2006).
44 Cook, B. I. *et al.* Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios. *Earth's Future* **8**, doi:10.1029/2019ef001461 (2020).
45 Trugman, A. T., Medvigy, D., Mankin, J. S. & Anderegg, W. R. L. Soil Moisture Stress as a Major Driver of Carbon Cycle Uncertainty. *Geophysical Research Letters* **45**, 6495-6503, doi:10.1029/2018gl078131 (2018).
46 Berg, A. & Sheffield, J. Soil Moisture–Evapotranspiration Coupling in CMIP5 Models: Relationship with Simulated Climate and Projections. *Journal of Climate* **31**, 4865-4878, doi:10.1175/jcli-d-17-0757.1 (2018).
47 Collier, N. *et al.* The International Land Model Benchmarking (ILAMB) System: Design, Theory, and Implementation. *J Adv Model Earth Sy* **10**, 2731-2754, doi:10.1029/2018ms001354 (2018).
48 De Kauwe, M. G. *et al.* Forest water use and water use efficiency at elevated CO2: a model-data intercomparison at two contrasting temperate forest FACE sites. *Global Change Biology* **19**, 1759-1779, doi:10.1111/gcb.12164 (2013).
49 Swann, A. L. S., Hoffman, F. M., Koven, C. D. & Randerson, J. T. Plant responses to increasing CO2 reduce estimates of climate impacts on drought severity. *Proceedings of the National Academy of Sciences* **113**, 10019-10024, doi:10.1073/pnas.1604581113 (2016).

Figure legends:

Figure 1. Carbon fluxes in CTL and ExpA. a) *Inter-annual variability (IAV) in global mean NBP (centered and de-trended) as simulated by four Earth system models (CCSM4, ECHAM6, GFDL and IPSL) in coupled model experiments with (CTL) and without (ExpA) anomalies in soil moisture. Positive NBP indicates carbon uptake.* ***b)*** *Standard deviations of global mean NBP, GPP and ReD in the two experiments.* ***c)*** *Drivers of change in global mean NBP variance (Supplementary Methods S1). Global*

mean NBP variance decreases in the experiment with prescribed seasonal soil moisture mainly because GPP variance is reduced. GPP and ReD fluxes are not available for the IPSL model.

***Figure 2. Direct and indirect SM effects on NBP variability**. **a)** Change in annual NBP standard deviation (ΔSD) when prescribing seasonal soil moisture. **b)** Change caused by a direct response to the suppressed soil moisture variability. **c)** Change caused by the reduced variability of temperature and VPD (i.e. the indirect effects of suppressing SM variability). Negative values in **(a-c)** indicate a decrease of the variability in ExpA compared to CTL. The median across the four models is shown.*

***Figure 3. Drivers of inter-annual NBP variability.** Contribution of meteorological drivers to the inter-annual variance of NBP: direct soil moisture effects (NBP^{SM}), indirect LAC-dependent temperature and VPD effects ($NBP^{T\&VPD\ LAC}$), non LAC-dependent temperature and VPD effects ($NBP^{T\&VPD\ NonLAC}$), and radiation effects (NBP^{R}). **a)** globally (mean of the four models ± 1 SD), and **b)** from local to global scales.*

***Figure 4. NBP variability and LAC hotspots. a)** Median simulated NBP IAV in the control simulation. **b)** Change in the standard deviation of temperature and **(c)** VPD when suppressing non-seasonal soil moisture variability (SD in ExpA minus SD in CTL). **d)** is a combined representation of all the grid points in (a-c). The overall IAV of NBP (colorscale) tends to be higher in regions that have a strong land-atmosphere coupling effect. For visualization purposes, arbitrary thresholds in **d)** are used to highlight hotspots of land-atmosphere coupling in **(a-c)**.*

Methods:

<u>Model experiment</u>

The presented results are based on the Global Land-Atmosphere Coupling Experiment – Coupled Model Intercomparison Project phase 5 (GLACE-CMIP5) numerical experiment[6]. This model experiment was originally designed to investigate soil moisture – climate feedbacks under historical and future scenarios, and notably their impact on extreme heat events[6]. Its experimental design is inspired from the original GLACE experiment[43], which focused on the role of soil moisture in seasonal weather predictability. Six Earth System Models were used for global climate simulations: the Community Climate System Model 4 (CCSM4), the European community Earth-System Model (EC-Earth), the European Centre/Hamburg Model 6 (ECHAM6), the Geophysical Fluid Dynamics Laboratory model (GFDL), the Institut Pierre-Simon Laplace model (IPSL), and the Australian Community Climate and Earth System Simulator (ACCESS). Model outputs for carbon fluxes are only available for 4 models (CCSM4, ECHAM6, GFDL, and IPSL), and the availability of certain variables is limited in some cases (Supplementary Table 4), which explains why some analyses cannot be conducted with all models (e.g. Figure 1c).

The control (CTL) and the soil moisture experiments (ExpA) consist of *coupled* atmosphere/land simulations (Extended Data Fig. 2) using prescribed sea surface temperatures (SST), sea ice, land use and atmospheric CO_2 concentrations from each of the model's fully coupled reference CMIP5 runs (except for CCSM4, where the reference CMIP5 run itself is used as the control simulation). Unlike so-called "offline" simulations where a land surface model is driven by a fixed meteorological forcing, a *coupled* simulation resolves water and energy exchanges between both the land and the atmosphere, allowing land processes to feed back to the atmosphere and influence it locally. The model simulations cover the historical period since 1950 and the 21st century (RCP8.5 scenario). Further details documenting the control experiment, including the description of the atmospheric and land model components, can be found in Seneviratne, et al. [6]. The only forced difference between the CTL and ExpA simulations is the soil moisture variability. In ExpA, soil moisture is prescribed to a reference climatology (seasonal cycle) calculated from the control run over the period 1971-2000 (Extended Data Fig. 1). Thus, the main difference (on a climatological time scale) between the two simulations is related to the change in soil moisture. It is worth noting that at finer, meteorological, time scales (e.g. daily time series), the internal variability inherent to general circulation models will also lead to differences between the two simulations.

Prescribing soil moisture implies that the water balance is not necessarily conserved. An investigation of this imbalance with the Community Earth System Model[50] showed a positive net imbalance (i.e. the sum of all water additions and subtractions) on the order of +8% globally (relative to the annual mean precipitation), associated with an overall increase in land evapotranspiration. We note that in some specific regions, less water may be added than is removed (negative imbalance), and that temperature extremes are found to be reduced in both cases (positive or negative imbalance) as a result of the suppressed land-atmosphere coupling. While there is no apparent impact on global mean precipitation[50], there are some changes in the distribution of precipitation (e.g. an increase in extreme events over the tropics[51]). We do not expect changes in precipitation between CTL and ExpA to have any impact on carbon fluxes (since soil moisture is prescribed).

To enable a consistent comparison, we re-grid all model outputs to a common resolution of 2 degrees using conservative re-gridding and compute monthly averages. The entire analysis presented in this paper is focused on inter-annual variability over the period 1960-2005. We note that VPD is first calculated from daily averages of temperature and relative humidity and only then averaged to monthly means. Inter-annual variability corresponds to the signal remaining after removing the seasonal cycle as well as any long-term linear trend on a monthly basis (the long-term trend of each month is subtracted). For the ECHAM6 model, two grid cells located in the Tibetan plateau are discarded from the whole analysis, as spurious spikes are present in heterotrophic respiration for ExpA. We also discard Greenland and Antarctica to maintain a comparable spatial coverage among all models. Although this paper focuses on the anomalies (i.e. deviations from the seasonal cycle), we also illustrate the seasonal cycles of NBP, GPP and ReD simulated in CTL and ExpA in Supplementary Fig. 7. For completeness, we also provide time series of global mean SM, T, VPD and R IAV (similar to Figure 1) in Supplementary Fig. 8.

<u>Comparison of the control simulations with observational estimates</u>

We evaluate simulated IAV of NBP, soil moisture, temperature, and VPD against available observations in Supplementary Figs. 6 and 9-11. For NBP IAV (Supplementary Fig. 6), we note that while observational estimates of NBP variability exist, they do not agree well with each other, reflecting our limited knowledge of net carbon fluxes globally[52,53] (Supplementary Fig. 6g, "obs vs obs"). To focus on time periods where these observational datasets are more reliable globally, we use the period 1980-2010 for the FLUXCOM RS+METEO dataset and the period 2000-2018 for the CAMS atmospheric CO_2 inversion. We show that models correlate with these observational estimates as much as the observations themselves correlate with each other (Supplementary Fig. 6g, "models vs obs"). We also find that there is little consensus on the overall (de-trended) NBP IAV amplitude. The global mean NBP standard deviation of the different models ranges from 0.86 PgC yr^{-1} for CCSM4 to 2.76 PgC yr^{-1} for GFDL. When compared with observational products (Supplementary Fig. 6h), we find that, excluding FLUXCOM RS+METEO, which is known to underestimate the global NBP IAV[52], the CAMS atmospheric CO_2 inversion[53] suggests a value of 0.68 PgC yr^{-1}, while dynamic vegetation models used for the Global Carbon Project[1] suggest a range of 0.53 to 1.50 PgC yr^{-1}. Thus, some models (GFDL in particular) seem to overestimate the overall NBP variability. However, regardless of how close they are to observations or other estimates, all models are unanimous that the global NBP variance is reduced by about 90% when prescribing soil moisture and that indirect effects dominate this response (Figures 1 and 3).

We evaluate spatial patterns of IAV for soil moisture, temperature and VPD against available observational datasets in Supplementary Figs. 9-11. The simulated soil moisture IAV patterns agree reasonably well with total soil moisture from the ERA5-Land reanalysis[54] and with satellite observations of shallow soil moisture (5-10 cm depth) from the ESA CCI Combined product v4.5[55] (Supplementary Fig. 9). Regarding temperature and VPD IAV, we find that models and observational sources[56,57] are in reasonable agreement (Supplementary Figs. 10-11). Finally, we also evaluate spatial patterns of global long-term mean GPP, which is arguably better constrained by observations than long-term mean NBP. We find that the models agree very well with the observational data[52,58] in terms of spatial patterns (Supplementary Fig. 12). For global mean GPP, two models produce a relatively high global mean GPP (of about 150 PgC yr^{-1}). However, such values are not entirely unrealistic according to other satellite-based estimates (e.g. Joiner et al. 2018[59] report 140 PgC yr^{-1}).

<u>Sensitivity analysis</u>

In Figures 2 and 3, we reproduce the approach by Jung, et al. [2], which consists of a local month-wise linear regression of the NBP model output against the main meteorological drivers (which are also deseasonalized and detrended):

$$NBP^*_{s,m} = \beta^{SM}_{s,m} \cdot SM_{s,m} + \beta^{T}_{s,m} \cdot T_{s,m} + \beta^{VPD}_{s,m} \cdot VPD_{s,m} + \beta^{R}_{s,m} \cdot R_{s,m} \qquad \text{Eq. 1}$$

s: spatial index (grid point)
m: month index (1 to 12)
β : regression coefficients
NBP: net biome production anomaly
SM: total soil moisture anomaly
T: 2m air temperature anomaly
VPD: vapour pressure deficit anomaly
R: surface downward solar radiation anomaly

In the text, the four components of Eq. 1 are referred to using the more compact notation:

$$\mathrm{NBP}^* = \mathrm{NBP}^{\mathrm{SM}} + \mathrm{NBP}^{\mathrm{T}} + \mathrm{NBP}^{\mathrm{VPD}} + \mathrm{NBP}^{\mathrm{R}} \qquad \text{Eq. 2}$$

where $\mathrm{NBP}^{\mathrm{SM}}$, $\mathrm{NBP}^{\mathrm{T}}$, $\mathrm{NBP}^{\mathrm{VPD}}$, $\mathrm{NBP}^{\mathrm{R}}$, correspond to the soil moisture–driven, temperature–driven, vapour pressure deficit–driven and radiation–driven NBP respectively, and NBP* is the overall result of the regression. This regression is applied to the CTL and ExpA simulations separately (each regression is referred to using the appropriate notation $\mathrm{NBP}^*_{\mathrm{CTL}}$ or $\mathrm{NBP}^*_{\mathrm{ExpA}}$). In Figure 2b-c, the difference in annual NBP variability is calculated by subtracting the standard deviation of the components of Eq. 2 from both experiments (e.g. $\Delta SD(NBP^{SM}) = SD(NBP^{SM}_{ExpA}) - SD(NBP^{SM}_{CTL})$).

Because this statistical approach does not incorporate other potential sources of NBP variability as explanatory variables (ecosystem memory in particular, but also fires) and can only capture linear relationships within a given month, it should not be expected to capture the full complexity of ESM outputs. Our evaluation shows that this approach is able to reproduce a correct NBP inter-annual variability at the global (Supplementary Figs. 1-2) and local scales (Supplementary Fig. 3), although the overall NBP variability is generally underestimated due to the reasons mentioned above. We also apply this statistical approach to two fully independent observational estimates of NBP fluxes. We use the FLUXCOM RS+METEO dataset (GSWP3 version) over the period 1981-2010[52], which is a machine-learning-based upscaling of flux tower measurements and the CAMS v18r3 dataset[53], which is an atmospheric CO_2 inversion, over the period 2000-2018. We find that the overall partitioning of global NBP IAV between the different drivers is similar to what models are suggesting (Extended Data Fig. 8). The ability of the regression to reproduce these observational estimates is shown in Supplementary Fig. 13. For FLUXCOM, the sensitivity analysis is able to capture the variability almost perfectly. This is only possible because we use the same predictors as the ones used by the machine learning algorithms (i.e. the GSWP3 meteorological forcing[60]). As a result, there is a perfect internal consistency between

FLUXCOM NEE and its predictors. For the CAMS inversion however, such internal consistency does not exist. Using ERA5-Land[54] soil moisture, temperature, VPD and radiation as predictors, we find that the sensitivity analysis agrees relatively well with the models, even though it underestimates the magnitude of CAMS NBP anomalies at the global scale. Locally, this regression performs moderately well (Supplementary Fig. 13f), which is nonetheless a reasonable result when considering the very high uncertainty of regional NBP anomalies when derived from CO_2 inversions at sub-continental scale[53].

Of particular interest to this paper is the difference in NBP variance between CTL and ExpA (e.g. Figure 2a). We find that this difference can be reproduced very well by the sensitivity analysis for three out of the four models (Supplementary Fig. 4). Differences are underestimated for the CESM model, but this seems to occur rather uniformly and most spatial patterns are preserved (the ratio in NBP variance between CTL and ExpA estimated from the regression is thus close to the actual one, see Supplementary Table 3). Closer inspection of the regression residuals suggests that ecosystem memory and lag effects (which cannot be captured by Eq. 1) might be particularly important for this model. It is interesting to note that for some models (e.g. GFDL), the NBP variance can also locally increase when seasonal soil moisture is prescribed (Supplementary Fig. 4). This only occurs in a few arid regions which have almost no NBP variability in the control simulation and where soil moisture is extremely low except during occasional wet years. Prescribing a mean seasonal soil moisture in those regions causes small amounts of soil water to be available every year (instead of every few years), which increases the overall NBP variability.

Finally, we note that several alternative formulations to Eq. 1 were tested. The chosen formulation (Eq. 1) is the one that best reproduces the model NBP outputs. Potential alternative formulations may consist in 1) using only soil moisture, temperature and radiation, as in Jung et al.[2], 2) including an interaction term between temperature and soil moisture in place of VPD, 3) replacing VPD by relative humidity (RH). Using any of these three alternative formulations does not impact the main finding of the study that most of the global NBP variability is driven by indirect soil moisture effects (see Supplementary Figs 5 and 14-15).

Joint analysis of T and VPD effects

In Figures 2 and 3, the contributions of temperature and VPD are represented as a sum ($NBP^{T\&VPD} = NBP^{T}+NBP^{VPD}$). This is because temperature and VPD are correlated to some extent (VPD is calculated from temperature and relative humidity), so that the ability of the sensitivity analysis to attribute NBP anomalies to either one of these two variables (i.e. temperature versus VPD) might be limited in some cases. We recognize this potential limitation by analysing the joint contribution of these two variables. For completeness, individual contributions are also illustrated in Extended Data Figs, 4-5. With the caveats mentioned above, Extended Data Fig. 4 shows that VPD has a much larger role than T in the reduction of NBP variability occurring between CTL and ExpA. However, this does not mean that T is less sensitive than VPD to prescribing soil moisture. Rather, Extended Data Fig. 5 shows that the sensitivity analysis attributes more NBP variability to VPD to begin with but that both the VPD-driven and T-driven NBP variability are reduced in ExpA.

Variance contributions at different levels of aggregation

In Figure 3, Extended Data Fig. 7, and Supplementary Figs. 14-16, the contribution of different drivers to NBP_{CTL} variance is computed at different levels of spatial aggregation. The different levels of aggregation are the following (in degrees): 2, 3, 4, 5, 6, 7.5, 9, 10, 12, 15, 18, 20, 22.5, 30, 36, 45, 60, 90, 180, 360 (i.e. global). Contributions are calculated as follows. Similarly to Jung et al.[2], the different NBP time series (NBP^{SM}, $NBP^{T\&VPD}$, and NBP^{R}) are first aggregated to the given spatial resolution. After aggregation, the variance of the time series (i.e. $\sigma^2\left(NBP_{CTL}^{SM}\right)$, etc.) are computed at each grid point. Then, the variance of the T&VPD contribution $\sigma^2\left(NBP_{CTL}^{T\&VPD}\right)$ is decomposed at each grid point into an LAC-dependent and non LAC-dependent contribution as explained in the Supplementary Methods S2 section. After that and similar to Jung et al.[2], the global spatial average of the variances is calculated for each of the four contributions (e.g. $\overline{\sigma^2\left(NBP_{CTL}^{SM}\right)}$, etc.). The relative contribution of a component at a given level of spatial aggregation (as shown in Figure 3b) is then calculated by normalizing that global spatial average against the sum of all components:

$$Contribution(NBP^{SM}) = \frac{\overline{\sigma^2(\mathrm{NBP}_{\mathrm{CTL}}^{\mathrm{SM}})}}{\overline{\sigma^2(\mathrm{NBP}_{\mathrm{CTL}}^{\mathrm{SM}})+\sigma^2(\mathrm{NBP}_{\mathrm{CTL}}^{\mathrm{T\&VPD\ LAC}})+\sigma^2(\mathrm{NBP}_{\mathrm{CTL}}^{\mathrm{T\&VPD\ NonLAC}})+\sigma^2(\mathrm{NBP}_{\mathrm{CTL}}^{\mathrm{R}})}} \qquad \text{(Eq. 3)}$$

Identically to Jung et al.[2], the spread in the contributions estimated by the four different models shown in Extended Data Fig. 7 is reported in two different ways. The outer uncertainty bounds represent the standard deviation of the contribution estimated by the four models. The inner uncertainty bounds represent the standard deviation between the four estimates, but after removing each model's mean contribution across all levels of aggregation. Thus, the inner uncertainty bounds show the uncertainty in the tendency of the contribution (its change from regional to global scale).

Online-only references:

50 Hauser, M., Orth, R. & Seneviratne, S. I. Investigating soil moisture–climate interactions with prescribed soil moisture experiments: an assessment with the Community Earth System Model (version 1.2). *Geosci Model Dev* **10**, 1665-1677, doi:10.5194/gmd-10-1665-2017 (2017).

51 Lorenz, R. *et al.* Influence of land-atmosphere feedbacks on temperature and precipitation extremes in the GLACE-CMIP5 ensemble. *Journal of Geophysical Research: Atmospheres* **121**, 607-623, doi:10.1002/2015jd024053 (2016).

52 Jung, M. *et al.* Scaling carbon fluxes from eddy covariance sites to globe: synthesis and evaluation of the FLUXCOM approach. *Biogeosciences* **17**, 1343-1365, doi:10.5194/bg-17-1343-2020 (2020).

53 Chevallier, F. *et al.* Objective evaluation of surface- and satellite-driven carbon dioxide atmospheric inversions. *Atmospheric Chemistry and Physics* **19**, 14233-14251, doi:10.5194/acp-19-14233-2019 (2019).

54 C3S. C3S ERA5-Land reanalysis. doi:10.24381/cds.e2161bac (2019).

55 Gruber, A., Scanlon, T., van der Schalie, R., Wagner, W. & Dorigo, W. Evolution of the ESA CCI Soil Moisture climate data records and their underlying merging methodology. *Earth Syst Sci Data* **11**, 717-739, doi:10.5194/essd-11-717-2019 (2019).

56 Hersbach, H. *et al.* The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society* **146**, 1999-2049, doi:10.1002/qj.3803 (2020).

57 Harris, I., Osborn, T. J., Jones, P. & Lister, D. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data* **7**, doi:10.1038/s41597-020-0453-3 (2020).

58 Zhang, Y. *et al.* A global moderate resolution dataset of gross primary production of vegetation for 2000–2016. *Scientific Data* **4**, doi:10.1038/sdata.2017.165 (2017).

59 Joiner, J. *et al.* Estimation of Terrestrial Global Gross Primary Production (GPP) with Satellite Data-Driven Models and Eddy Covariance Flux Data. *Remote Sensing* **10**, 1346, doi:10.3390/rs10091346 (2018).

60 Kim, H. J. Global Soil Wetness Project Phase 3 Atmospheric Boundary Counditions (Experiment 1). doi:10.20783/DIAS.501 (2017).

Data availability:
GLACE-CMIP5 model outputs can be obtained from Sonia Seneviratne (sonia.seneviratne@ethz.ch). FluxCom data is available at http://www.fluxcom.org/CF-Download/. CAMS data is available from the Atmosphere Data Store at https://atmosphere.copernicus.eu/data. ERA5 and ERA5Land data is available from the Climate Data Store at https://cds.climate.copernicus.eu. VPM-GPP is available at https://doi.org/10.6084/m9.figshare.c.3789814. ESA CCI Soil Moisture is available from

https://www.esa-soilmoisture-cci.org. CRU TS data is available from https://crudata.uea.ac.uk/cru/data/hrg/. GSWP3 data is available from http://dx.doi.org/10.20783/DIAS.501.

Code availability:
Code and documentation for CCSM4 is publicly available at https://www.cesm.ucar.edu/models/ccsm4.0/. Code and documentation for ECHAM6 (MPI-ESM) is available for scientific users at https://mpimet.mpg.de/en/science/modeling-with-icon/code-availability. Code and documentation for the GFDL model is publicly available at https://www.gfdl.noaa.gov/modeling-systems-group-public-releases/. Code and documentation for the IPSL model is publicly available at https://cmc.ipsl.fr/ipsl-climate-models/ipsl-cm5/. Model outputs were processed using the software Matlab 2019a.

Acknowledgements: This research was funded by a Postdoc.Mobility fellowship of the Swiss National Science Foundation (P400P2_180784). C.F. acknowledges funding through the NASA IDS grant 80NSSC17K0687. P.G. acknowledges funding from NASA 80NSSC18K0998 and European Research Council synergy grant USMILE ERC CU18-3746. We thank all modelling groups who participated in the GLACE-CMIP5 experiments and conducted the model runs, in particular Frédérique Cheruy, Stefan Hagemann and Dave Lawrence. We also thank Gordon Bonan, Julia K. Green, Martin Hirschi, Dave Lawrence, Diego Miralles, Ulrich Weber, and Yi Yin for comments on the analyses, the data availability, or the manuscript.

Author contributions: V.H. designed and conducted the study. S.I.S. designed and coordinated the GLACE-CMIP5 climate model experiment. A.B., P.C., P.G., M.J., M.R., S.I.S. and C.F., provided feedback on the analyses, the figures, and the manuscript.

Competing interests: The authors declare no competing interests.

Additional information:
Extended data is available for this paper
Supplementary information is available for this paper

Extended Data figure legends:
*Extended Data Figure 1. **Soil moisture treatments in the CTL and the ExpA simulations**. At each grid point, the seasonal cycle calculated from the control experiment (CTL) is prescribed into the factorial experiment (ExpA). These example times series are taken from the CCSM4 model at 2°N and 58°W (North-East Amazon region).*

*Extended Data Figure 2. **Concept of the Global Land-Atmosphere Coupling Experiment (GLACE).** Setup of the control simulation (left) and the experiment with prescribed seasonal soil moisture (right).*

*Extended Data Figure 3. **Temperature and VPD extremes influenced by land-atmosphere coupling.** Change in the 95th percentile between the distributions of de-seasoned, de-trended temperature (a) and VPD (b) between CTL (the control run) and ExpA ($\Delta Q_{95} = Q_{95}^{ExpA} - Q_{95}^{CTL}$). The median ΔQ_{95} of all models is reported. Suppressing non-seasonal soil moisture variability in ExpA reduces temperature and VPD extremes, demonstrating the role of land-atmosphere coupling.*

*Extended Data Figure 4. **Change in annual NBP variability between CTL and ExpA**. Evaluation of the change in the latitudinal NBP standard deviation (SD) between CTL and ExpA, decomposed by meteorological driver according to the sensitivity analysis (i.e. Δ corresponds to the difference $SD(NBP^*_{ExpA}) - SD(NBP^*_{CTL})$). Negative values indicate a decrease of the NBP variability in ExpA compared to CTL. The middle and right columns indicate how much of this change is due to a change in the variance of the meteorological driver between ExpA and CTL, or due to a change in the sensitivity of NBP to that driver respectively (also see Eq. 1). Results for each model are normalized* *by the model's NBP standard deviation (calculated across the entire space-time domain) and the median across models is depicted. Black dots indicate that at least one model disagrees on the sign of the change.*

Extended Data Figure 5. ***NBP anomalies in CTL and ExpA.*** *Distributions (all grid points, at all time steps) of modelled NBP anomalies (left column), and their decomposition into meteorological drivers with the sensitivity analysis (other columns) for the the control experiment (CTL) and the experiment with only seasonal soil moisture (ExpA). Rows correspond to each of the four climate models. Note the logarithmic scale on the y-axis. By construction, there are no soil moisture – driven NBP anomalies in ExpA for the second column (as seasonal soil moisture is prescribed in this experiment). The magnitude of the temperature-driven and VPD-driven NBP anomalies (third and fourth columns) is substantially reduced in ExpA (as a result of soil moisture–atmosphere feedbacks).*

Extended Data Figure 6. ***Comparison of direct versus indirect effects.*** *Difference between the magnitudes of direct effects (Figure 2b) versus indirect (feedback) effects occurring through T and VPD (Figure 2c).*

Extended Data Figure 7. ***Opposing perspectives on drivers of NBP IAV reconciled by soil moisture-atmosphere feedbacks. a)*** *Relative magnitude of individual NBP components across spatial scales (same as Figure 3b).* ***b-c)*** *The apparent relative importance of the meteorological drivers depends on how the indirect effects of SM on T & VPD are viewed. Outer uncertainty bounds indicate the model spread (ensemble mean ± 1 SD), inner uncertainty bounds indicate the spread (± 1 SD) in the tendency (i.e. the relative change from local to global scale, see Methods).*

Extended Data Figure 8. ***Sensitivity analysis compared to observational estimates. a)*** *Contribution of the different meteorological drivers to global NBP IAV as estimated from the control simulations and from two independent observational products. Here, $NBP^{T\&VPD}$ is not separated into a LAC and non LAC contribution as done in Figure 3b (because this cannot be done with the observational datasets).* ***b)*** *same as Figure 3b, but based on FLUXCOM.* ***c)*** *same as Figure 3b, but based on CAMS.*

Extended Data Figure 9. ***Contribution of LAC hotspots to global NBP IAV.*** *Global NBP IAV from the control experiment (CTL) calculated over all land grid cells versus only over the land-atmosphere coupling hotspots identified in Figure 4.*

Extended Data Figure 10. ***Tropical temperature in CTL vs ExpA. a)*** *Inter-annual variability in tropical mean land temperature, in model experiments with and without variability in soil moisture (similar to Figure 1a for NBP).* ***b)*** *Apparent sensitivity of global mean NBP to tropical mean temperature in CTL and ExpA.*