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No constraint on long-term tropical land carbon-climate feedback uncertainties from interannual variability

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Unraveling drivers of the interannual variability of tropical land carbon cycle is critical for understanding land carbon-climate feedbacks. Here we utilize two generations of factorial model experiments to show that interannual variability of tropical land carbon uptake under both present and future climate is consistently dominated by terrestrial water availability variations in Earth system models. The magnitude of this interannual sensitivity of tropical land carbon uptake to water availability variations under future climate shows a large spread across the latest 16 models (2.3 ± 1.5 PgC/yr/Tt H_2O), which is constrained to 1.3 ± 0.8 PgC/yr/Tt H_2O using observations and the emergent constraint methodology. However, the long-term tropical land carbon-climate feedback uncertainties in the latest models can no longer be directly constrained by interannual variability compared with previous models, given that additional important processes are not well reflected in interannual variability but could determine long-term land carbon storage. Our results highlight the limited implication of interannual variability for long-term tropical land carbon-climate feedbacks and help isolate remaining uncertainties with respect to water limitations on tropical land carbon sink in Earth system models.

Climate change and its variability can affect the carbon cycle, which in turn can feedback to climate through changing carbon cycle and then radiative forcing (carbon-climate feedbacks)[1]. The interannual variability (IAV) of the land carbon cycle is mainly driven by climate variations, so understanding underpinning mechanisms is considered useful for quantifying carbon-climate feedbacks[2]. The latest sixth Intergovernmental Panel on Climate Change assessment report (IPCC AR6) states that the magnitude of carbon-climate feedbacks becomes larger but also more uncertain in higher CO_2 emissions scenarios (very high confidence), hindering the full assessment of climate mitigation strategies[3]. In particular, tropical land is projected to release large amounts of carbon into the atmosphere as a result of unprecedented warming and drought, standing out as a hotspot of positive carbon-climate feedback globally. Although Earth system models (ESMs) generally agree on the sign of tropical land carbon-climate feedback, the broad range of its magnitude contributes to the reported uncertainties of climate change projections[3,4].

Tropical mean temperature has been proposed as a primary driver for the IAV of tropical land carbon sink over past decades[5–7]. Based on a significant empirical multi-model relationship between the sensitivity of the tropical land carbon sink (proxied by atmospheric CO_2 growth rate) to tropical temperature interannual variations during 1960–2010 and the long-term sensitivity of tropical land carbon storage to climate warming, the resulting emerging constraint (EC) lowers the mean and spread of tropical land carbon-climate feedbacks across the previous ensemble of C4MIP models by about 23% and 56%, respectively[8].

However, recent research has raised questions about the mechanistic interpretation of the empirical sensitivity of CO_2 growth rate (CGR) to tropical mean temperature on the interannual scale. This is because observations show that extreme drought events can strongly weaken the tropical land sink[9,10] and CGR is also significantly sensitive to terrestrial water storage (TWS) anomalies on the interannual scale during 2002–2017[11]. Using factorial experiments to isolate soil moisture impacts on CGR or land carbon

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uptake in four CMIP5 ESMs, Humphrey et al.[12] showed that, despite tropical mean temperature IAV is kept unchanged, suppressing soil moisture IAV can reduce by about 90% of land carbon uptake variability during 1960–2005. Liu et al.[13] further demonstrated that droughts have an increasing impact on tropical land carbon uptake over the past six decades. Given the identified large influence of water limitations on tropical land carbon cycle[14–16], the research objectives of this study are twofold: i) to what extent is tropical land carbon sink IAV related to terrestrial water in state-of-the-art ESMs? ii) can interannual variability still be able to constrain long-term tropical carbon-climate feedback uncertainties in state-of-the-art ESMs?

Results

Present-to-future tropical land NBP IAV dominated by water variations in models

To investigate the impact of terrestrial water variability on land carbon cycle IAV, we utilize the latest Global Land-Atmosphere Climate Experiment - Coupled Model Intercomparison Project phase 6 (GLACE-CMIP6 experiment) and extend the investigated period of present climate in a previous GLACE-CMIP5 study[12] to the future climate, i.e., until the end of this century (Methods). Model experiment results show that, without soil moisture IAV, present-to-future yearly tropical averaged net biome production (NBP) variances in CMIP5 (1970–2100) and CMIP6 models (1985–2099) are reduced by about 92 ± 8% and 84 ± 12%, respectively (Fig. 1a, b). The spatial patterns of NBP variance reductions confirm that tropical lands are the main region impacted by the removal of soil moisture IAV (Fig. 1c, d). We note that removing soil moisture IAV will not only directly remove soil moisture limitations on the carbon cycle (e.g., less water supply for photosynthesis) but also indirectly reduce the impacts of some atmospheric extremes on the carbon cycle due to dampened land-atmospheric feedbacks[17,18]. When decomposing NBP into the carbon uptake (GPP, gross primary production) and carbon release (RED, respiration and other disturbance carbon fluxes), the reduction of NBP variance caused by soil moisture IAV removal is largely contributed by GPP (Supplementary Table 1), in alignment with previous studies[19]. These results show that CMIP6 models confirm earlier results obtained from CMIP5 and further suggest that water-driven ecosystem processes dominating tropical NBP IAV under present climate are evident under a climate with very high levels of global warming in models (about 4 °C at the end of the 21st century). Therefore, the IAV of tropical NBP can provide valuable information on the sensitivity of NBP to water variations on the interannual scale ($\gamma_{IAV,W}$) under future climate in models.

Interannual sensitivity of tropical land carbon uptake to water variations in models

Given many tropical regions with high carbon density, such as Amazonia, Southern Africa, and Australia[20], are projected to experience substantial drying and more droughts, differences in $\gamma_{IAV,W}$ among the latest CMIP6 ESMs are anticipated to contribute to uncertainties in future land carbon sink efficiency. To investigate the spread of the interannual sensitivity of tropical NBP to water variations ($\gamma_{IAV,W}$) under present climate and future climate across a large ensemble of latest ESMs, we, therefore, utilize "historical" and "1pctCO$_2$-rad" experiments for which 16 CMIP6 ESMs have relevant outputs. "1pctCO$_2$-rad" experiments isolate the elevated CO_2 effects on carbon cycle and allow to investigate long-term carbon-climate feedbacks alone. For the present climate, we utilize 20yrs of recent data (1995–2014) from the "historical" experiment and observations. For future climate, we utilize the period of 35 to 140 years after the start of the "1pctCO$_2$-rad" simulation to represent the climate after the year 2014. $\gamma_{IAV,W}$ is approximated as the univariate linear regression slope between tropical NBP IAV and tropical water IAV (Methods). We acknowledge that some parts of NBP are driven by other climatic factors; however, we use this univariate regression to avoid underestimation of $\gamma_{IAV,W,}$ as the indirect effects of water variations on NBP IAV by land-atmospheric feedbacks will be attributed to other climatic drivers when using a multiple linear regression[12]. Since year-to-year variation of tropical land carbon uptake is a relatively "fast" flux process, mainly including photosynthesis and respiration, we expect the sensitivity of tropical NBP to water variations on the interannual scale under future climate could be driven by similar processes, and thus be related to variation under present climate in models. Indeed, we find that there is a significant emergent relationship between $\gamma_{IAV,W}$ under future climate (y variable) and $\gamma_{IAV,W}$ under present climate (x variable) across 16 CMIP6 models ($R^2 = 0.76$) (Fig. 2). This significant emergent relationship offers an opportunity to constrain $\gamma_{IAV,W}$ under a future

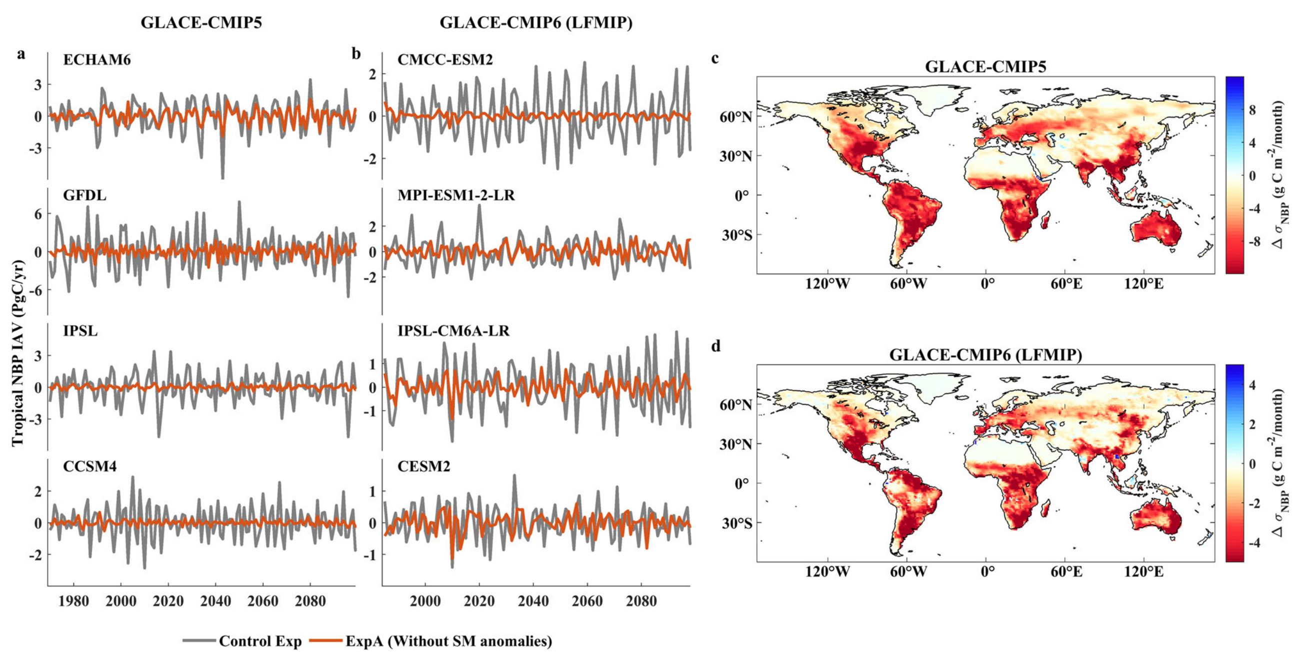

Fig. 1 | Present-to-future NBP IAV in model experiments. Detrended year-to-year variations in tropical NBP from present to future in experiments with and without soil moisture (SM) anomalies, obtained from (**a**) GLACE-CMIP5 and (**b**) GLACE-CMIP6 (LFMIP). Spatial distributions of the reduction of tropical NBP standard deviation caused by suppressing SM anomalies in (**c**) GLACE-CMIP5 and (**d**) GLACE-CMIP6 (LFMIP).

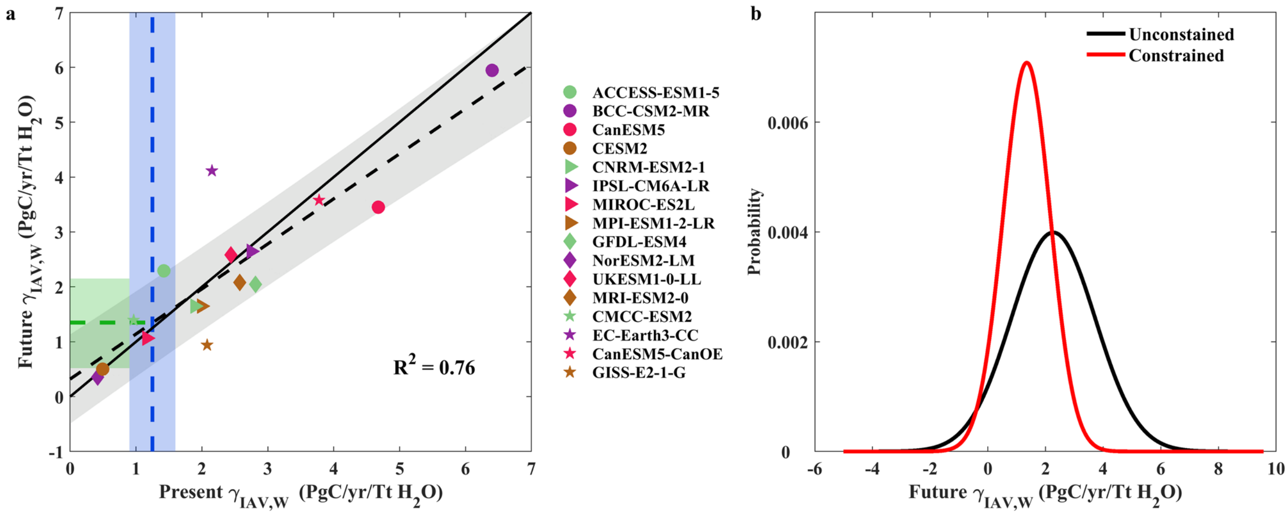

Fig. 2 | Relationship between the interannual sensitivity of tropical land carbon to water variations under present climate and future warmer climate in CMIP6. **a** Interannual sensitivity of tropical land carbon uptake to water variations ($\gamma_{IAV,W}$) under a future warmer climate (y-axis) versus present climate (x-axis). Each symbol represents a single ESM simulation, the grey shade represents the emergent relationship between the y variable and the x variable, the blue shade represents the observational estimate of the x variable, and the green shade represents the resulting emergent constraint on the y variable. The thicknesses represent ± one standard error. The solid black line indicates the 1:1 line. **b** Probability distributions of unconstrained and constrained interannual sensitivity of tropical land carbon uptake to water variations under a future warmer climate.

warmer climate, if combined with observations. Combining observed CO_2 growth rate (the proxy for tropical land carbon sink) and TWS during 1995–2014, the resulting emergent constraint (EC) shows that, compared with the unconstrained ensemble of CMIP6 models (2.3 ± 1.5 PgC/yr/Tt H_2O), the mean and spread of future $\gamma_{IAV,W}$ are reduced by about 41% and 44%, respectively (1.3 ± 0.8 PgC/yr/Tt H_2O). In addition, we use the data for the period of 1960–2014 to derive x variable and find that the strong linear relationship between x and y remains robust. However, the constraint on y variable could be less robust in this case because most of data used to estimate x variable are not directly observed (Supplementary Fig. 1). We also use the sum of modelled global land and ocean carbon fluxes to match observed CO_2 growth rate more accurately, we find that it would worsen the strength of the emergent relationships to some degree ($R^2 = 0.36$) and thus the constraint on future $\gamma_{IAV,W}$ is less strict (1.8 ± 1.3 PgC/yr/Tt H_2O) (Supplementary Fig. 2). This could be expected because the physical link between the y and x variables is most consistent when using modelled tropical NBP. Overall, our results suggest that simulated variability in the tropical land sink in unconstrained ESMs appears to be too sensitive to water variations on average on the interannual scale.

Relationships between interannual variability and long-term sensitivity in models

Short-term (interannual scale in this study) system variability in the land carbon cycle has been proposed as a means to constrain the long-term system sensitivity in the context of climate-carbon cycle feedbacks[21,22]. We then investigate can interannual variability still be able to constrain long-term tropical carbon-climate feedbacks (γ_{LT}) in CMIP6 models? Following the previous approach[8,23,24], and using simulations of 16 models from the "1pctCO$_2$", "1pctCO$_2$-bgc" and "historical" experiments in CMIP6 and observations during 1960–2014 (Methods), we first test whether a previously documented EC on γ_{LT} relying on IAV of CGR and temperature still holds in CMIP6. We find that the strength of the emergent relationship between γ_{LT} and $\gamma_{IAV,T}$ ($R^2 = 0.40$) is much weaker than previously reported (e.g., $R^2 = 0.96$)[8], and that the resulting EC does not substantially affect the mean and spread of γ_{LT} relative to the unconstrained ensemble across these 16 models (− 29.1 ± 24.6 PgC/K changed to − 32.3 ± 22.3 PgC/K) (Fig. 3a, b). In addition, if we alternatively use the sum of modelled global land and ocean carbon fluxes, rather than modelled tropical land sink to derive x variable (allowing more direct comparison with the atmospheric CO_2 growth rate), the EC still does not hold (Supplementary Fig. 3). Then, we test whether modelled present $\gamma_{IAV,W}$ could be used to directly constrain γ_{LT}. We find that the correlation here is very weak ($R^2 = 0.15$) and using the present-day $\gamma_{IAV,W}$ as a tentative constraint on γ_{LT} yields unsatisfactory results (Fig. 3c, d). Therefore, we find that both $\gamma_{IAV,T}$ and $\gamma_{IAV,W}$ alone are not able to constrain the large spread of γ_{LT} across the latest 16 CMIP6 models. These results suggest that uncertainties in longer-term tropical carbon-climate feedbacks across a large ensemble of CMIP6 models cannot be directly constrained from interannual variability of land carbon cycle and climate.

Discussion and conclusion

This study utilizes the latest GLACE-CMIP6 and previous GLACE-CMIP5 experiments to demonstrate that present-to-future tropical NBP IAV is consistently dominated by soil moisture variations in ESMs. This indicates that tropical land carbon uptake IAV mainly reflects water availability impacts on tropical land carbon in models. However, models do not capture the increasing water-carbon coupling during the last six decades[13]. The broad spread of $\gamma_{IAV,W}$ also highlights large uncertainties on the magnitude of sensitivity of land carbon fluxes to drought in latest CMIP6 ESMs. This could be largely caused by discrepancies in their representations of water stress on vegetation[25,26]. A common approach is to use an empirical reduction factor (β) ranging from 0 to 1 to regulate plant photosynthesis under drought conditions; however, models disagree on specific functional relationships between β and soil moisture content and whether β should regulate some critical parameters, e.g., the maximum carboxylation rate of Rubisco (V_{cmax})[27,28]. Recently, some models begun to employ plant hydraulics instead because it represents some key physiological processes; however, there could be additional uncertainties due to more unvalidated parameters. For instance, CESM2 (CLM5) directly simulates plant hydraulics and predicts the β factor as a function of leaf water potential[29]. This allows greater physiological realism (by virtue of simulating more variability in the depth of water uptake from soils) but degrades performance on interannual variability of land carbon cycle[30]. In addition, drought could indirectly impact land carbon fluxes by triggering temperature extremes and high vapor pressure deficit (VPD) by land-atmosphere feedbacks[12,31], suggesting that uncertainties in drought sensitivity of land carbon fluxes across models may also originate from their differences in plant responses to atmospheric conditions[28].

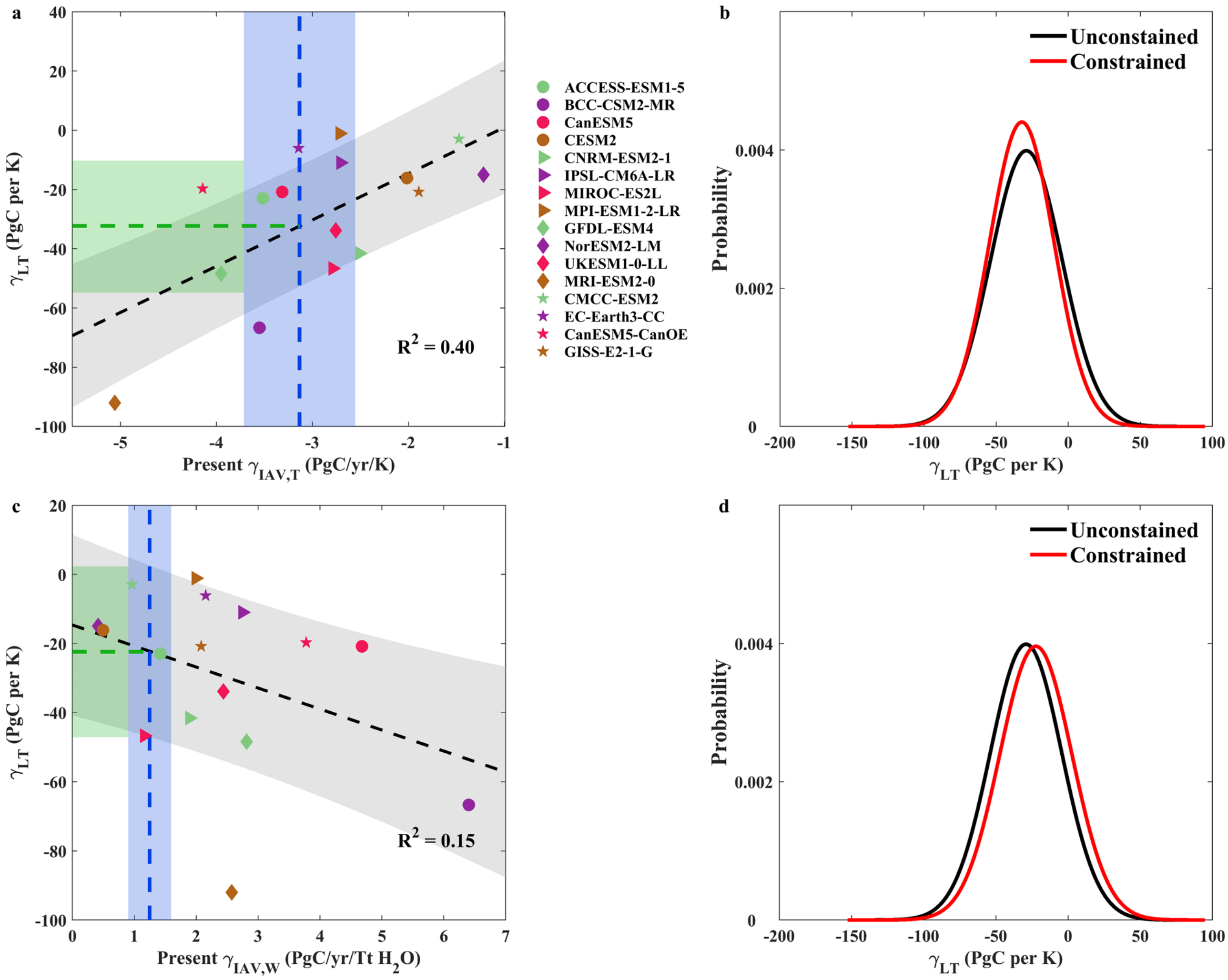

Fig. 3 | Relationship between the long-term tropical land carbon-climate feedbacks and the interannual sensitivity of tropical land carbon uptake to climate in CMIP6. a Long-term sensitivity of tropical land carbon storage to climate change (y variable, γ_{LT}) versus interannual sensitivity of tropical land carbon uptake to temperature variations (x variable, $\gamma_{IAV,T}$). Each symbol represents a single ESM simulation, the grey shade represents the emergent relationship between the y variable and the x variable, the blue shade represents the observational estimate of the x variable, and the green shade represents the resulting emergent constraint on the y-axis variable. The thicknesses represent ± one standard error. **b** Probability distributions of unconstrained and constrained γ_{LT}. (**c**, **d**) Same as **a** and **b**, but replacing $\gamma_{IAV,T}$ with $\gamma_{IAV,W}$ derived from the period of 1960–2014.

Furthermore, the interannual sensitivity of tropical land carbon to water variations ($\gamma_{IAV,W}$) under present and future climate show a significant emergent relationship across 16 latest CMIP6 models. This indicates that models' present biases in simulating sensitivity of tropical land uptake to water persists into to the future. Our proposed alternative constraint on future $\gamma_{IAV,W}$ falls into a category called 'bias persistence' in the general EC framework proposed by Sanderson, et al.[32], where the measured (x variable) and unknown quantities (y variable) are of the same nature, and the EC results from the persistence of each model's bias in response to a forcing from the present into the future. This suggests that better calibration of representations of IAV in contemporary carbon-water processes (e.g., using GRACE observations) in models could directly benefit future projections. At the tropical scale, combined with the observational constraint of CGR and TWS, $\gamma_{IAV,W}$ under future climate is estimated to have a much smaller mean and spread compared to the unconstrained model ensemble. However, this result does not provide a process-based or bottom-up solution for model improvements. It is recommended to coordinate comparisons between model simulations and accurate observations within the soil-plant-atmosphere continuum to evaluate and improve model representations of climate-carbon coupling. For instance, new measurements of air columns profiles by aircraft are helping to measure the response of local carbon fluxes to drought and fire at finer temporal and spatial scales, including the lagged effects[33–37]. Better representation of fires, often triggered by droughts, and their impacts on carbon cycle are also essential to improve net land carbon uptake modelling[38–40]. This is anticipated to reduce uncertainties in climate change projections given the projected substantial drying and increasing frequency of droughts in tropical lands.

The IAV of tropical land carbon cycle was used to directly constrain long-term tropical land carbon-climate feedbacks (γ_{LT}) in previous generations of ESMs[8,23] and 7 CMIP6 ESMs[24]. However, here we find that both $\gamma_{IAV,W}$ and the previously established observational constraint ($\gamma_{IAV,T}$) do not place an efficient EC on γ_{LT} across 16 CMIP6 ESMs. This failure of utilizing IAV to constrain long-term tropical land carbon-climate feedback is not unexpected. As we have shown, tropical land carbon uptake IAV is mainly driven by soil moisture variations, while climate change at longer timescales also includes overall warming. Warming has direct influences on leaf level photosynthetic capacity and autotrophic/heterotrophic respiration, representations of which (in particular, how they acclimate as temperatures change) vary substantially between models[28,41,42]. Prediction of long-term carbon cycle dynamics is also affected by a host of processes orthogonal to those that control IAV, such as changes in ecosystem nutrient status[43], vegetation structure and demographic changes[44–46] and rising tropical tree mortality[47,48].

Our results also highlight the importance of recommended out-of-sample testing for validating previously diagnosed EC[49]. If the EC still works in a new and larger ensemble of ESMs, this is useful evidence of the robustness of EC and indicates the probability the EC emerged by chance is very low; otherwise, this strongly suggests the EC cannot be confirmed. The original constraint relied on the so-called 'frequency substitution' approach[8,32], whereby the future response to a given forcing (all aspects of long-term climate change) is constrained using the response of the system to a different forcing (only interannual climate variations) and using the correlation in the model ensembles as the primary line of evidence for the constraint. Sanderson, et al.[32] also argued that this type of constraint is subject to the problem if models share structural assumptions with few free degrees of freedom, e.g., previous CMIP5 models share simple temperature-scaling assumptions for soil respiration[50]. Another type of 'bias persistence' EC used on future $\gamma_{IAV,W}$ are fundamentally less prone underlying structural assumptions of the ensemble. In addition to the γ_{LT} here, Schlund, et al.[51] found multiple ECs on equilibrium climate sensitivity diagnosed or confirmed in CMIP5 do not hold on in CMIP6. They also proposed a possible explanation that multiple processes dominate the targeted y variable in the more complex CMIP6 models, while the single process (x variable) originally found in CMIP5 or in a smaller ensemble of models is not sufficient in CMIP6. This also supports our previous interpretation that uncertainties of γ_{LT} in a large ensemble of CMIP6 ESMs are determined by multiple processes, some of which do not come into play at the interannual time scale.

In summary, this study unravels the climatic drivers of the tropical land carbon cycle IAV and clarifies its limited implications for the long-term tropical land carbon-climate feedback in ESMs. Our results demonstrate that terrestrial water variations dominate interannual variability of tropical land carbon cycle under both present climate and a future much warmer climate in ESMs. The large spread on the magnitude of interannual sensitivity of tropical land carbon fluxes to terrestrial water variations under future climate in latest 16 CMIP6 ESMs could be constrained to a best estimate of 1.3 ± 0.8 PgC/yr/Tt H_2O. The IAV of tropical land carbon cycle can no longer directly constrain future tropical land carbon-climate feedback uncertainties in latest ESMs. This is largely because there are additional complex processes that are not well represented in IAV but can determine long-term tropical carbon storage. Calibrating model process representations to a wider range of observed features of the terrestrial biosphere is recommended to systematically improve modeled climate-carbon coupling and constrain long-term tropical carbon-climate feedbacks, thereby reducing uncertainty in climate change projections.

Methods

Model experiments

GLACE-CMIP5 and GLACE-CMIP6 (LFMIP). GLACE-CMIP5 stands for Global Land-Atmosphere Climate Experiment - Coupled Model Intercomparison Project phase 5[52]. We name here "GLACE-CMIP6" the Land Feedback MIP (LFMIP) of the CMIP6-based Land Surface, Snow and Soil Moisture Multimodel Intercomparison Project[53]. These two generations of experiments share a similar protocol to investigate land-atmospheric feedbacks under present and future climate. In GLACE-CMIP5, the control experiment (CTL) is the combination of CMIP5 "historical" and "RCP 8.5" simulations. Experiment A (ExpA) imposes a historical seasonal cycle of soil moisture, prescribed from 1971–2000 climatology from the CMIP5 "historical" simulations. ExpA uses the same prescribed SSTs, sea ice, land use, and atmospheric CO_2 concentrations from each model's CTL. In GLACE-CMIP6, CTL is the combination of CMIP6 "historical" and "SSP585" simulations. ExpA (i.e., LFMIP-pdLC) controls the seasonal cycle of soil moisture prescribed as 1980–2014 climatology from CMIP6 "historical" simulations. ExpA comprises the prescribed forcing of sea surface temperature and sea ice derived from the CTL. Therefore, CTL and ExpA only differ in soil moisture interannual variability (IAV), and their comparisons, therefore, allow us to investigate impacts of soil moisture IAV on global carbon cycle. For GLACE-CMIP5, relevant outputs are available from 4 models, including: ECHAM6, GFDL, IPSL, CCSM4. For GLACE-CMIP6, relevant outputs are available from 4 models, including: CESM2, IPSL-CM6A-LR, MPI-ESM1-2-LR, CMCC-ESM2.

1pctCO$_2$, 1pctCO$_2$-rad, 1pctCO$_2$-bgc. "1pctCO$_2$" means atmospheric CO_2 concentration increases at a rate of 1% per year from its preindustrial level (~ 285 ppm) until it quadruples over a 140-yr period, which is the combination of "1pctCO$_2$-rad" and "1pctCO$_2$-bgc". "1pctCO$_2$-rad" means increasing atmospheric CO_2 affects the radiative transfer processes in the atmosphere and hence climate but not the biogeochemical processes directly over land and ocean, for which the preindustrial value of atmospheric CO_2 concentration is prescribed. As a result, the dynamics of terrestrial carbon fluxes are directly driven by climate change. "1pctCO$_2$-bgc" means increasing atmospheric CO_2 directly affects biogeochemical processes over land and ocean, while the radiative transfer processes in the atmosphere is forced by the preindustrial value of atmospheric CO_2 concentration. As a result, the dynamics of terrestrial carbon fluxes are directly driven by increasing CO_2, despite there could be some climatic changes caused by vegetation changes or plant physiological responses to increasing CO_2[4]. Therefore, these experiments can be utilized to investigate carbon-concentration and carbon-climate feedbacks, separately[4].

historical. "historical" experiment is driven by all historical forcings, such as anthropogenic greenhouse gas emission, land use change, etc. Therefore, it can be used to analyze historical interannual carbon-climate relationships in models.

In this study, we analyze the monthly tropical land carbon uptake, global land carbon uptake, global ocean carbon uptake, total soil moisture, snow, air temperature outputs from these simulations.

Observations

CO_2 growth rate. Interannual variations of CO_2 growth rate (CGR) are shown to be dominated by tropical land sink[19]. We use annual global atmospheric CO_2 growth rate from the Greenhouse Gas Marine Boundary Layer Reference of the National Oceanic and Atmospheric Administration (NOAA/ESRL).

Land climate. For observational terrestrial water availability records, we use Gravity Recovery and Climate Experiment (GRACE) satellite observations of terrestrial water storage (TWS) anomaly, which provides monthly data from 2002 to now with a spatial resolution of $3° \times 3°$[54]. We also use 7 years of GRACE reconstruction spanning from 1995 to 2001[55] to complement a 20-yr dataset to represent present climate. For near-surface air temperature, we use the Climate Research Unit (CRU) TS4.01 temperature dataset, which provides monthly data from 1901 to 2018 with a spatial resolution of $0.5° \times 0.5°$.

Diagnostics of carbon-climate relationships

To derive the IAV of land carbon cycle and climate, we detrend data under the present climate linearly due to short time periods (20-yr) but detrend data under future climate (> 100-yr) with a 11-yr running mean to avoid non-linear trends, with the residuals defining the IAV. The interannual sensitivity of carbon cycle to temperature variations ($\gamma_{IAV,T}$) is estimated as the univariate linear regression slope between tropical NBP IAV and tropical land temperature IAV. Similarly, the interannual sensitivity of the carbon cycle to variations in water ($\gamma_{IAV,W}$) is approximated as the univariate linear regression slope between tropical NBP IAV and tropical water IAV. Whether 'water' refers to soil moisture or terrestrial water storage depends on the specific case. For present climate, the years following the eruption of Mount Agung (1962,1963), El Chichón (1982,1983) and Mount Pinatubo (1991,1992) are also excluded from analyses to avoid potential radiation-driven perturbations of carbon flux anomalies[56].

To derive the long-term tropical carbon-climate feedbacks in CMIP6 ESMs, we follow the linear feedback approach[1] by utilizing experiments of

$1pctCO_2$ and $1pctCO_2$-bgc to calculate γ_{LT}, which is the long-term tropical land carbon-climate feedback, indicating changes in tropical land carbon storage per unit increase (1 °C) of tropical temperature.

$$\gamma_{LT} = \frac{\Delta C_{LT}^{COU} - \Delta C_{LT}^{BGC}}{\triangle T_{LT}^{COU} - \triangle T_{LT}^{BGC}} \quad (1)$$

Where $\triangle C_{LT}^{COU}$ is the change in tropical land carbon storage from year 35 to year 140 in the $1pctCO_2$ experiment, where the simulation is fully coupled (both biogeochemically and radiatively); $\triangle C_{LT}^{BGC}$ is the change in tropical land carbon storage from year 35 to year 140 in the $1pctCO_2$-bgc experiment, where the simulation is biogeochemically coupled; $\triangle T_{LT}^{COU}$ and $\triangle T_{LT}^{BGC}$ represent the corresponding changes in average tropical land near-surface temperature. The tropical land here spans from 30°S to 30°N, following Cox, et al.[8].

Emergent constraint

The emergent constraint (EC) is a method developed over the past two decades to constrain future quantities of interest projected by ESMs[49,57]. The basic concept is that elements of present and future climate (x and y, respectively) can be significantly correlated across an ensemble of ESMs because of their consistent underpinning physical relationships. The difference in x and y among ESMs could be large; however, if x can be measured with observations, the spread of y in ESMs can, under some circumstances[32], be "constrained" based on the emergent relationship between x and y.

In this study, x could be the interannual sensitivity of tropical land carbon uptake to either water or temperature variations under present climate, y is either the interannual sensitivity of tropical land carbon uptake to water under future climate, or long-term tropical land carbon-climate feedbacks under future climate. We note that, since only TWS rather than total soil moisture is available from observations, and not all ESMs have output of TWS, to keep consistency between models and observations in the water proxy, we follow Wu, et al.[58] to sum up all water bodies on land from model output (mainly total soil moisture and snow) as the proxy for TWS. In this situation, there could be some potential small biases in the comparisons between observation and models and we suggest next generations of ESMs, where possible, provide TWS as outputs. For the unconstrained ensemble of models, we assume all models are equal and calculate probability density functions (PDFs) of the future climate element (y) using a Gaussian distribution. After applying our emergent constraints, we calculate constrained PDFs of y following the methodology[8,22]. The PDFs of the observational constraints under present climate (x) are defined as:

$$P(x) = \frac{1}{\sqrt{2\pi\sigma_x^2}} \exp\left\{\frac{(x - \bar{x})^2}{2\sigma_x^2}\right\} \quad (2)$$

Where $\bar{x}$ is the least-squares linear regression coefficient of tropical NBP or CGR against tropical temperature or water and σ_x is the corresponding standard error.

The "prediction error" of the emergent multi-model linear regression ($\sigma_{f(x)}$) defines contours of equal probability density around the multi-model linear regression, which indicate the probability density of y given x:

$$P(y|x) = \frac{1}{\sqrt{2\pi\sigma_f^2}} \exp\left\{\frac{(x - f(x))^2}{2\sigma_f^2}\right\} \quad (3)$$

Where $\sigma_f = \sigma_{f(x)}$.

Given the PDFs of $P\{y|x\}$ and $P\{x\}$, the observationally constrained PDF for y is:

$$P(y) = \int_{-\infty}^{+\infty} P\{y|x\}P(x)dx \quad (4)$$

Data availability

All the datasets used here are publicly available. Atmospheric CO2 observations are available at https://gml.noaa.gov/ccgg/; GRACE observations of terrestrial water storage are available at https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/; GRACE-REC terrestrial water storage are available at https://doi.org/10.6084/m9.figshare.7670849; Climate model simulations are publicly available from Earth System Grid Federation: https://esgf-node.llnl.gov/search/cmip6/.

Code availability

Codes are available through Zenodo at https://doi.org/10.5281/zenodo.10435247.

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References

1. Friedlingstein, P. et al. Climate–Carbon Cycle Feedback Analysis: Results from the C4MIP Model Intercomparison. *J. Clim.* **19**, 3337–3353 (2006).
2. Keeling, C. D., Whorf, T. P., Wahlen, M. & van der Plichtt, J. Interannual extremes in the rate of rise of atmospheric carbon dioxide since 1980. *Nature* **375**, 666–670 (1995).
3. Canadell, J. G. et al. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte et al.) 673–816 (Cambridge University Press, 2021).
4. Arora, V. K. et al. Carbon-concentration and carbon-climate feedbacks in CMIP6 models and their comparison to CMIP5 models. *Biogeosciences* **17**, 4173–4222 (2020).
5. Wang, W. L. et al. Variations in atmospheric CO2 growth rates coupled with tropical temperature. *Proc. Natl. Acad. Sci. USA* **110**, 13061–13066 (2013).
6. Wang, J., Zeng, N. & Wang, M. R. Interannual variability of the atmospheric CO2 growth rate: roles of precipitation and temperature. *Biogeosciences* **13**, 2339–2352 (2016).
7. Wang, X. H. et al. A two-fold increase of carbon cycle sensitivity to tropical temperature variations. *Nature* **506**, 212-+ (2014).
8. Cox, P. M. et al. Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability. *Nature* **494**, 341–344 (2013).
9. Phillips, O. L. et al. Drought Sensitivity of the Amazon Rainforest. *Science* **323**, 1344–1347 (2009).
10. Lewis, S. L., Brando, P. M., Phillips, O. L., van der Heijden, G. M. F. & Nepstad, D. The 2010 Amazon Drought. *Science* **331**, 554–554 (2011).
11. Humphrey, V. et al. Sensitivity of atmospheric CO2 growth rate to observed changes in terrestrial water storage. *Nature* **560**, 628-+ (2018).
12. Humphrey, V. et al. Soil moisture–atmosphere feedback dominates land carbon uptake variability. *Nature* **592**, 65–69 (2021).
13. Liu, L. et al. Increasingly negative tropical water–interannual CO2 growth rate coupling. *Nature* **618**, 755–760 (2023).
14. Green, J. K. et al. Large influence of soil moisture on long-term terrestrial carbon uptake. *Nature* **565**, 476-+ (2019).
15. Liu, L. et al. Soil moisture dominates dryness stress on ecosystem production globally. *Nat. Commun.* **11**, 4892 (2020).
16. Padrón, R. S., Gudmundsson, L., Liu, L., Humphrey, V. & Seneviratne, S. I. Drivers of intermodel uncertainty in land carbon sink projections. *Biogeosciences* **19**, 5435–5448 (2022).
17. Seneviratne, S. I. et al. Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Sci. Rev.* **99**, 125–161 (2010).
18. Vogel, M. M. et al. Regional amplification of projected changes in extreme temperatures strongly controlled by soil moisture-temperature feedbacks. *Geophys. Res. Lett.* **44**, 1511–1519 (2017).
19. Piao, S. L. et al. Interannual variation of terrestrial carbon cycle: Issues and perspectives. *Glob. Change Biol.* **26**, 300–318 (2020).

20. Seneviratne, S.I. et al. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds V. Masson-Delmotte et al.) 1513–1766 (Cambridge University Press, 2021).
21. Cox, P. M. Emergent Constraints on Climate-Carbon Cycle Feedbacks. *Curr. Clim. Change Rep.* **5**, 275–281 (2019).
22. Kwiatkowski, L. et al. Emergent constraints on projections of declining primary production in the tropical oceans. *Nat. Clim. Change* **7**, 355-+ (2017).
23. Wenzel, S., Cox, P. M., Eyring, V. & Friedlingstein, P. Emergent constraints on climate-carbon cycle feedbacks in the CMIP5 Earth system models. *J. Geophys. Res-Biogeo* **119**, 794–807 (2014).
24. Zechlau, S., Schlund, M., Cox, P. M., Friedlingstein, P. & Eyring, V. Do Emergent Constraints on Carbon Cycle Feedbacks Hold in CMIP6? *J. Geophys. Res.: Biogeosci.* **127**, e2022JG006985 (2022).
25. Trugman, A. T., Medvigy, D., Mankin, J. S. & Anderegg, W. R. L. Soil Moisture Stress as a Major Driver of Carbon Cycle Uncertainty. *Geophys Res. Lett.* **45**, 6495–6503 (2018).
26. Liu, L. B. et al. Broad Consistency Between Satellite and Vegetation Model Estimates of Net Primary Productivity Across Global and Regional Scales. *J. Geophys Res-Biogeo* **123**, 3603–3616 (2018).
27. 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. *Glob. Change Biol.* **19**, 1759–1779 (2013).
28. Rogers, A. et al. A roadmap for improving the representation of photosynthesis in Earth system models. *N. Phytol.* **213**, 22–42 (2017).
29. Kennedy, D. et al. Implementing Plant Hydraulics in the Community Land Model, Version 5. *J. Adv. Model Earth Syst.* **11**, 485–513 (2019).
30. Lawrence, D. M. et al. The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty. *J. Adv. Model Earth Sy* **11**, 4245–4287 (2019).
31. Barkhordarian, A., Bowman, K. W., Cressie, N., Jewell, J. & Liu, J. Emergent constraints on tropical atmospheric aridity—carbon feedbacks and the future of carbon sequestration. *Environ. Res. Lett.* **16**, 114008 (2021).
32. Sanderson, B. M. et al. The potential for structural errors in emergent constraints. *Earth Syst. Dynam* **12**, 899–918 (2021).
33. Gatti, L. V. et al. Drought sensitivity of Amazonian carbon balance revealed by atmospheric measurements. *Nature* **506**, 76–80 (2014).
34. Saatchi, S. et al. Persistent effects of a severe drought on Amazonian forest canopy. *Proc. Natl. Acad. Sci.* **110**, 565–570 (2013).
35. Worden, J. et al. Satellite Observations of the Tropical Terrestrial Carbon Balance and Interactions With the Water Cycle During the 21st Century. *Rev. Geophys.* **59**, e2020RG000711 (2021).
36. Bloom, A. A. et al. Lagged effects regulate the inter-annual variability of the tropical carbon balance. *Biogeosciences* **17**, 6393–6422 (2020).
37. Liu, L., Zhang, Y., Wu, S., Li, S. & Qin, D. Water memory effects and their impacts on global vegetation productivity and resilience. *Sci. Rep.* **8**, 2962 (2018).
38. Schimel, D. & Baker, D. The wildfire factor. *Nature* **420**, 29–30 (2002).
39. Liu, J. et al. Contrasting carbon cycle responses of the tropical continents to the 2015–2016 El Niño. *Science* **358**, eaam5690 (2017).
40. Murdiyarso, D. & Adiningsih, E. S. Climate anomalies, Indonesian vegetation fires and terrestrial carbon emissions. *Mitig. Adapt. Strateg. Glob. Change* **12**, 101–112 (2007).
41. Oliver, R. J. et al. Improved representation of plant physiology in the JULES-vn5.6 land surface model: photosynthesis, stomatal conductance and thermal acclimation. *Geosci. Model Dev.* **15**, 5567–5592 (2022).
42. Bond-Lamberty, B., Bailey, V. L., Chen, M., Gough, C. M. & Vargas, R. Globally rising soil heterotrophic respiration over recent decades. *Nature* **560**, 80-+ (2018).
43. Fleischer, K. et al. Amazon forest response to CO2 fertilization dependent on plant phosphorus acquisition. *Nat. Geosci.* **12**, 736-+ (2019).
44. Friend, A. D. et al. Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO2. *Proc. Natl. Acad. Sci. USA* **111**, 3280–3285 (2014).
45. Needham, J. F., Chambers, J., Fisher, R., Knox, R. & Koven, C. D. Forest responses to simulated elevated CO2 under alternate hypotheses of size- and age-dependent mortality. *Glob. Change Biol.* **26**, 5734–5753 (2020).
46. Longo, M. et al. Impacts of Degradation on Water, Energy, and Carbon Cycling of the Amazon Tropical Forests. *J. Geophys. Res.: Biogeosci.* **125**, e2020JG005677 (2020).
47. Bauman, D. et al. Tropical tree mortality has increased with rising atmospheric water stress. *Nature* **608**, 528-+ (2022).
48. Hubau, W. et al. Asynchronous carbon sink saturation in African and Amazonian tropical forests. *Nature* **579**, 80-+ (2020).
49. Hall, A., Cox, P., Huntingford, C. & Klein, S. Progressing emergent constraints on future climate change. *Nat. Clim. Change* **9**, 269–278 (2019).
50. Shao, P., Zeng, X., Moore, D. J. P. & Zeng, X. Soil microbial respiration from observations and Earth System Models. *Environ. Res. Lett.* **8**, 034034 (2013).
51. Schlund, M., Lauer, A., Gentine, P., Sherwood, S. C. & Eyring, V. Emergent constraints on equilibrium climate sensitivity in CMIP5: do they mid for CMIP6? *Earth Syst. Dynam* **11**, 1233–1258 (2020).
52. Seneviratne, S. I. et al. Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment. *Geophys. Res. Lett.* **40**, 5212–5217 (2013).
53. van den Hurk, B. et al. LS3MIP (v1.0) contribution to CMIP6: the Land Surface, Snow and Soil moisture Model Intercomparison Project - aims, setup and expected outcome. *Geosci. Model Dev.* **9**, 2809–2832 (2016).
54. Tapley, B. D., Bettadpur, S., Ries, J. C., Thompson, P. F. & Watkins, M. M. GRACE measurements of mass variability in the Earth system. *Science* **305**, 503–505 (2004).
55. Humphrey, V. & Gudmundsson, L. GRACE-REC: a reconstruction of climate-driven water storage changes over the last century. *Earth Syst. Sci. Data* **11**, 1153–1170 (2019).
56. Mercado, L. M. et al. Impact of changes in diffuse radiation on the global land carbon sink. *Nature* **458**, 1014–U1087 (2009).
57. Qu, X. & Hall, A. What controls the strength of snow-albedo feedback? *J. Clim.* **20**, 3971–3981 (2007).
58. Wu, R.-J., Lo, M.-H. & Scanlon, B. R. The annual cycle of terrestrial water storage anomalies in CMIP6 models evaluated against GRACE data. *J. Clim*. **34**, 8205–8217 (2021).

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Author contributions

L.L. conceived the original idea. L.L. and S.I.S. designed the research. L.L., S.I.S., R.F., H.D., and R.S.P performed the research. L.L. carried out analyses. L.L. wrote the paper with contributions from R.F., H.D., R.S.P., S.I.S., A.B., J.M., A.A., and H.K.

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