

Modeling Resilience of the Earth System Under Climate Change Mitigation

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List of abbreviations

- AMOC** atlantic meridional overturning circulation. 12, 14, 15
- AOD** aerosol optical depth. 18
- BECCS** bioenergy with carbon capture and storage. 12, 13, 109
- CCS** carbon capture and storage. 13
- CCU** carbon capture and utilization. 13
- CDR** carbon dioxide removal. 5–7, 9, 11–14, 21, 23, 101, 103–111, 113
- CESM2** Community Earth System Model. 112
- CMIP** Coupled Model Intercomparison Project. 10, 19, 102, 104, 112
- CO₂** carbon dioxide. v, 1, 3, 5–7, 10–13, 15–17, 20–23, 99–106, 108–111, 113
- DACCS** direct air carbon capture and storage. 12, 13, 101
- ESM** Earth system model. 1, 6–12, 14, 17–24, 99–105, 107–109, 111–113
- GPP** gross primary production. 6, 23, 100, 104, 112
- IAM** integrated assessment model. 10–13, 101, 102, 109
- IMP** illustrative mitigation pathway. 10
- IPCC** Intergovernmental Panel on Climate Change. 6, 7, 10, 20, 21, 109
- LCA** life cycle assessment. 109
- LSM** land surface model. 18, 19, 103, 108
- MPI-ESM** Max Planck Institute for Meteorology Earth System Model. 11, 99, 102, 104, 108, 112, 113
- MPI-GE** Max Planck Institute for Meteorology Grand Ensemble. 11
- MRV** monitoring, reporting, and verification. 13, 109
- PFT** plant functional type. 18, 19
- SAI** stratospheric aerosol injection. 6, 15, 16, 21, 106
- ScenarioMIP** Scenario Model Intercomparison Project. 10, 11, 21, 109, 110
- sDACCS** sun-powered direct air capture with (electro)chemical conversion of captured CO₂ into sink products for storage. 23, 99, 101, 106, 109, 111
- SO₂** sulfur dioxide. 14
- SSP** shared socioeconomic pathway. 10, 11, 13, 14, 21, 102, 106
- VolMIP** Volcanic Forcings Model Intercomparison Project. 110
- VPD** vapor pressure deficit. 16
- WRCP** World Climate Research Programme. 10

Human livelihoods rely on the ability of the Earth system to buffer greenhouse gas emissions and recover from externally forced and internal disturbances to a dynamic equilibrium. Anthropogenic climate change and human action challenge this resilience of climate, carbon cycle, and ecosystems to disturbances. Therefore, assessing how they affect the future trajectory of the Earth system is critical for adaptation and mitigation planning. Comprehensive Earth system projections are foundational for these assessments. However, they mostly neglect the explicit effects of anthropogenic interventions for stabilizing global climate like artificial carbon dioxide (CO₂) removal and deliberate stratospheric aerosol injections. The projections also rarely account for impacts of varying volcanic aerosol levels on climate and carbon cycle. Their accuracy in simulating repercussions of climate extremes on vegetation productivity, an essential carbon sink, also remains unclear. These shortcomings compromise the reliability of long-term risk assessments.

This dissertation, based on three manuscripts, explores ways to better represent vegetation resilience, disturbances from volcanic eruptions, and human interventions in projections of climate change mitigation scenarios. To this end, the work includes model development, statistical emulation, and comparisons of models and observations. As part of this work, Earth system model simulations with an explicitly represented, renewable-powered approach for CO₂ removal and conversion corroborate the absence of unintended side effects that would substantially offset its removal potential. However, the results also reveal fundamental land use constraints that could cause target conflicts between large-scale CO₂ removal, agriculture, and ecosystem services. Further, model emulations with varying volcanic aerosol levels demonstrate that representing this intermittent forcing realistically increases global and regional temperature uncertainty relative to a constant approach commonly applied in climate change assessments. The results suggest a substantial share of this uncertainty propagates to natural carbon sinks. This significantly increases uncertainty about when planetary temperatures may stabilize, and net-zero emissions may be reached, making it vital to better account for varying aerosol levels in future risk assessments. Finally, comparing statistical relationships between temperature–moisture and vegetation productivity extremes in observations and two Earth system models provides confidence in modeled vegetation resilience at regional to global scales. Both models perform worse locally and struggle to match the observed timing between hydroclimatic drivers and vegetation responses. Recalibrating and improving process models could reduce these discrepancies which may be caused by high biases in soil moisture rates of change.

Findings from the studies are limited by uncertain and ambiguous scenarios of socio-economic development and future reliance on deliberate interventions, as well as model shortcomings. Future work could expand explicit modeling to more CO₂ removal approaches and explore their interactions within a portfolio of measures. Additional research on simulated soil moisture and carbon cycling is needed to address the observed biases. Overall, the insights from this work advance modeling capabilities for understanding impacts of human action and natural variability on our living environment. These advances expand the range of future scenarios that can be examined, and support the development of next-generation Earth system models and climate change mitigation strategies.

Kurzfassung

Die Fähigkeit des Erdsystems, Treibhausgasemissionen abzuf puffern und sich nach Störungen wieder in einem dynamischen Gleichgewicht zu stabilisieren, ist essenziell für die menschlichen Lebensgrundlagen. Der anthropogene Klimawandel stellt diese Resilienz von Klimasystem, Kohlenstoffkreislauf und Ökosystemen auf die Probe. Daher ist es für die Planung von Anpassungs- und Klimaschutzmaßnahmen entscheidend, den Einfluss menschlichen Handelns auf den künftigen Verlauf des Erdsystems zu bewerten. Modellbasierte Projektionen der Erdsystemdynamik bilden hierfür die Grundlage. Allerdings vernachlässigen sie meist die expliziten Auswirkungen anthropogener Eingriffe zur Klimastabilisierung, wie künstliche CO₂-Entnahme und Aerosolinjektionen in die Stratosphäre. Zudem berücksichtigen die Projektionen nur selten Auswirkungen schwankender vulkanischer Aerosole. Auch die Genauigkeit simulierter Auswirkungen von Klimaextremen auf Vegetation ist unklar. Diese Mängel beeinträchtigen langfristige Risikobewertungen.

Auf Basis von drei Manuskripten untersucht diese Dissertation Möglichkeiten, Vegetationsresilienz, Störungen durch stratosphärische Aerosole und menschliche Interventionen in Prognosen von Klimaszenarien besser zu berücksichtigen. Im Rahmen der Arbeit bestätigen Erdsystemmodell-Simulationen mit einer explizit implementierten, auf erneuerbaren Energien basierenden CO₂-Entnahme und -Umwandlungsmethode das Fehlen unbeabsichtigter Nebenwirkungen, die das Netto-Entnahmepotential erheblich schmälern würden. Diese Studie zeigt jedoch grundlegende Einschränkungen der Landnutzung auf, die zu Zielkonflikten zwischen großskaliger CO₂-Entnahme, Landwirtschaft und Ökosystemleistungen führen könnten. Darüber hinaus zeigen Modellemulationen mit variierenden Aerosolkonzentrationen, dass realistischere Darstellungen dieses Treibers Temperaturunsicherheiten im Vergleich zu üblichen Simulationsansätzen erhöhen. Die Ergebnisse deuten darauf hin, dass sich diese Unsicherheit teils in natürliche Kohlenstoffsenken überträgt. Dies reduziert die Gewissheit darüber, wann globale Temperaturen stabilisiert und Netto-Null-Emissionen erreicht werden können, erheblich. Risikobewertungen sollten schwankende Aerosolniveaus deshalb besser berücksichtigen. Schließlich untermauert ein Modell-Daten-Vergleich der Zusammenhänge zwischen Temperatur-Bodenfeuchte-Extremen und Vegetationsproduktivität die Robustheit modellierter Vegetationsresilienz auf regionaler bis globaler Ebene. Die Modelle schneiden lokal jedoch schlechter ab. Rekalisierung und Verbesserung der Prozessmodelle könnten diese Diskrepanzen verringern, möglicherweise durch Anpassung bei Änderungsraten der Bodenfeuchte.

Die Ergebnisse der Studien sind limitiert durch ungewisse, teils mehrdeutige Szenarien von sozioökonomischer Entwicklung und gezielten Eingriffen ins Erdsystem, sowie durch Modelleinschränkungen. Weitere Ansätze zur CO₂-Entnahme könnten künftig ebenfalls explizit modelliert und Wechselwirkungen innerhalb eines Maßnahmenportfolios untersucht werden. Darüber hinaus sind weitere Studien zur modellierten Bodenfeuchte und zum Kohlenstoffkreislauf erforderlich, um die beobachteten Verzerrungen zu beheben. Insgesamt tragen die Erkenntnisse dieser Arbeit dazu bei, Modellfähigkeiten zum Verständnis der Auswirkungen menschlichen Handelns und natürlicher Schwankungen auf unsere Lebensumwelt zu verbessern. Diese Fortschritte erweitern die Bandbreite untersuchbarer Zukunftsszenarien und fließen in die Entwicklung von Erdsystemmodellen der nächsten Generation sowie Strategien zur Klimawandeleindämmung ein.

2 | List of manuscripts

P1 M. Adam, T. Kleinen, M. M. May, and K. Rehfeld (2025). “Land conversions not climate effects are the dominant indirect consequence of sun-driven CO₂ capture, conversion, and sequestration”. *Environmental Research Letters* 20.3, 034011. DOI: [10.1088/1748-9326/ada971](https://doi.org/10.1088/1748-9326/ada971).

P2 M. Adam, T. Schürmann, and K. Rehfeld (2026b). “Future volcanic eruptions shift the timing of net-zero emissions”. *EarthArXiv [preprint, accepted: PLOS Climate]*. DOI: [10.31223/X5946V](https://doi.org/10.31223/X5946V)

P3 M. Adam, E. Ziegler, B. Gonzalez, N. Weitzel, and K. Rehfeld (2026a). “Earth system models might overestimate the local plant productivity response to temperature–moisture extremes”. *EGUsphere [preprint, under review]*. DOI: [10.5194/egusphere-2026-626](https://doi.org/10.5194/egusphere-2026-626)

Hereafter, the manuscripts Adam et al. (2025), Adam et al. (2026a), and Adam et al. (2026b) are referenced as **P1**, **P2**, and **P3**, respectively. They are included as separate chapters (Chapt. 6–8). Author contributions are detailed at the beginning of each of these chapters. Supplementary materials corresponding to **P1–P3** are printed in Appendix A–C.

3 | Data and code availability

Data and code to reproduce the findings from **P1–P3** are publicly available as permanent [Zenodo \(zenodo.org\)](https://zenodo.org) repositories, at the latest upon publication of each manuscript. Refer to the README.md file of each repository and the data and code availability statements of **P1–P3** for specific instructions.

P1 DOI: [10.5281/zenodo.14803902](https://doi.org/10.5281/zenodo.14803902)

P2 DOI: [10.5281/zenodo.18404077](https://doi.org/10.5281/zenodo.18404077)

P3 DOI: [10.5281/zenodo.18468113](https://doi.org/10.5281/zenodo.18468113)

Anthropogenic greenhouse gas emissions from fossil fuel burning and extensive land use induce global warming and environmental change (Pathak et al., 2022; Riahi et al., 2017). Current rates of this planetary change are historically unparalleled (Ruddiman, 2013), even sparking debates to define a new geological era, the “Anthropocene” (Crutzen, 2002; Lewis and Maslin, 2015; Malhi, 2017; Ruddiman, 2013). With their success in utilizing fossil resources, modern humans have concomitantly put their livelihoods at stake. An increasing frequency, intensity, and duration of weather extremes and natural disasters bears risks for human health, agriculture, infrastructure, and natural carbon sinks (Bastos et al., 2023; Bell et al., 2024; Clarke et al., 2022; Reichstein et al., 2013). Shifting climate zones, environmental pollution, and land use conflicts threaten ecosystem services which are at the basis of supply chains from food production to construction (Fu et al., 2015; Hurtt et al., 2020; Lambin and Meyfroidt, 2011). Committed sea level of 0.5 meters or more until the end of the century, mainly induced by ice sheet melt, puts around 800 million people at elevated risks of flooding or forces them to move away from the coast (C. McMichael et al., 2020; Nauels et al., 2025; UCCRN, 2018). On top of the anthropogenic forcing, the Earth system and its climate are highly variable, further adding uncertainty to the planet’s future trajectory (Hawkins and Sutton, 2009; Huybers and Curry, 2006).

While the consequences of unrestrained climate change and an ongoing biodiversity crisis are alarming, exit strategies are clear and result from long-standing scientific evidence (IPCC, 1990; Pathak et al., 2022). Economic prosperity and human livelihoods must decouple from fossil fuel exploitation (IPCC, 2023). To a moderate extent, some economic sectors have gradually started to do so through renewable energies and lowered material footprints (Infante-Amate et al., 2024; Papież et al., 2022). Land use practices also need to target net-zero emissions, for example, by improved nutrient and manure management, reduced land conversion and degradation, and shifting diets (Popp et al., 2017; S. Roe et al., 2019). This imperative of decarbonization builds on endorsement from societies around the globe, with 72 % of people globally supporting turning away from fossil fuels quickly (UNDP, 2024). Yet, past and current efforts for decarbonization have been insufficient to achieve the Paris Climate Agreement’s target of limiting global warming below 1.5 °C by 2100 (Friedlingstein et al., 2026; Matthews and Wynes, 2022). Under current efforts it is unlikely the target of 2 °C will be met (Jiang et al., 2025; van Soest et al., 2021).

Given the struggles to deliver a sufficiently ambitious decarbonization, implementation of yet *additional* anthropogenic interventions into the Earth system for climate change mitigation is becoming likely or even unavoidable (de Coninck et al., 2018; Fuss et al., 2014; Gasser et al., 2015; Low and Buck, 2020; Riahi et al., 2021; S. M. Smith et al., 2024). Carbon dioxide removal (CDR), that is artificial drawdown of atmospheric CO₂ into long-lived carbon sinks, could supplement the insufficient greenhouse gas emission reductions (Babiker et al., 2022; IPCC, 2005; Riahi et al., 2022). In addition, aerosol injections into the stratosphere have been suggested as an intervention into the planetary energy budget to counterbalance the radiative forcing of greenhouse gas emissions (Crutzen, 2006; de Coninck et al., 2018). *Climate engineering* through CDR or intervention into the planet’s radiative balance is no direct replacement of emission reductions and is contested for multiple reasons. CDR, no matter if supplied by biomass conversion or purely technological

process chains, demands large amounts of energy and natural resources (Fuss et al., 2018; P. Smith et al., 2016). It could alter nutrient flows and conflict with land use for food production and other ecosystem services (Lambin and Meyfroidt, 2011; Popp et al., 2017; P. Smith et al., 2016). Whether CDR methods could reach high technological readiness on a large-scale early enough in this century is also unclear (Nemet et al., 2024; Nemet et al., 2018). CDR also faces non-linearities and pathway dependencies of the Earth system, rendering it impossible to directly revert the biogeophysical effects of greenhouse gas emissions with removals. Next to committed sea level change through ice sheet melt (Hinkel et al., 2014), asymmetric efficiencies of natural carbon uptake under rising and declining atmospheric CO₂ levels are a prominent example for these non-linearities (Koven et al., 2022; Zickfeld et al., 2021).

As with CDR, environmental side effects of stratospheric aerosol injections (SAIs) are uncertain and hard to quantify in advance to prospective real-world application (Futerman et al., 2025). In contrast to many proposed CDR approaches, with aerosols emissions from volcanic eruptions there is a natural analog to deliberate aerosol injections. However, to what extent insights into the Earth system's response to volcanic eruptions can be transferred to SAI is debated, for example, due to aerosol characteristics (Pope et al., 2012). Unlike CDR methods, SAIs do not address the root cause of anthropogenic climate change, that is greenhouse gas emissions, but the symptom of global warming. Because of inherent non-linearities of the climate system, attenuating the warming effect of greenhouse gases alone would not fully revert climate change (K. L. Ricke et al., 2010). On top of that, SAIs could, for example, alter precipitation patterns compared to the counterfactual world with consequences for water supply, food production, and regional vegetation productivity (K. L. Ricke et al., 2010). However, vegetation would still experience beneficial CO₂ fertilization effects (Bonan, 2008). Interactions of aerosol injections with natural carbon uptake and prospective CO₂ removals are mostly unclear (Vaughan and Lenton, 2012).

In addition to the uncertainties surrounding prospective anthropogenic interventions for climate change mitigation, the Earth system trajectory is by itself inherently uncertain. Both internal and externally forced climate variability translate into uncertainty of future temperature and circulation (Ellerhoff et al., 2022; Hawkins and Sutton, 2009). Eventually, anthropogenic disturbances, interventions, and natural climate variability may impact gross primary production (GPP) and capacities of the terrestrial biosphere to sequester atmospheric CO₂. For climate change mitigation, GPP resilience, that is the ability of vegetation productivity to recover from disturbances, is pivotal. However, vegetation is tightly linked with hydroclimate and susceptible to temperature–moisture extremes (Bonan, 2008; Zscheischler et al., 2014a). It is unclear, if an increasing likelihood of these extremes will substantially damage the land carbon sink or if CO₂ fertilization, species migration, and hydroclimate changes can outweigh the damaging effects (Mahecha et al., 2022; Reichstein et al., 2013).

Given the unknowns and ambiguities of CDR and SAI, combined with additional uncertainties originating from natural forcings and vegetation resilience, a new generation of impact assessments is urgently needed to inform policymakers and climate change mitigation strategies (Bastos et al., 2023; Rickels et al., 2019; N. P. Simpson et al., 2021; Zickfeld et al., 2023). Projections of future Earth system trajectories with comprehensive Earth system models (ESMs) are a key component of such assessments, in particular by contributing to the scientific backbone of the Intergovernmental Panel on Climate

Change (IPCC) (Ciais et al., 2013; Pathak et al., 2022). However, these models have not originally been conceived with future anthropogenic interventions in mind. This is why they lack a spatially explicit and temporarily evolving representation of CDR (Zickfeld et al., 2023). Joint modeling efforts underpinning IPCC assessments also do not include large simulation ensembles of varying natural forcings, in particular through volcanic aerosols (Aubry et al., 2025; Chim et al., 2025). Further, the ability of state-of-the-art ESMs to accurately represent the biosphere's varying response to natural and anthropogenic disturbances is often disregarded (Bonan et al., 2024; Sharma et al., 2023), even though the terrestrial biosphere buffers around a fourth of current anthropogenic CO₂ emissions (Friedlingstein et al., 2025). All of these shortcomings motivate testing the necessity for expanded modeling capabilities and advancing the level of detail represented in Earth system projections.

In the context of these research needs, the guiding objective of this dissertation is to explore benefits and opportunities of enhanced ESM capabilities for future projections and to contribute methodological advancements to the wider modeling community. To this end, three case studies are conducted on (i) explicit modeling of technological CDR, (ii) representing climate and carbon cycle uncertainty induced by realistically varying stratospheric aerosols from volcanic eruptions, and (iii) gauging the simulated resilience of vegetation productivity to temperature–moisture extremes. This chapter provides scientific background for these topical studies. First, it introduces key uncertainties of the future Earth system trajectory, also touching upon potential effects of anthropogenic interventions on Earth system resilience and upon scenario and model building for future projections (Sect. 4.1). With ESMs being the main methodological tool and a research subject at the same time, it then details concepts of Earth system modeling (Sect. 4.2). Finally, it discusses the deficiencies of current climate projections which motivate this work (Sect. 4.3). The subsequent chapters present the guiding research objectives of this dissertation (Chapt. 5), contain the three case studies (Chapt. 6–8), and discuss results (Sect. 9.1), limitations (Sect. 9.2), and implications of them (Sect. 9.3, Chapt. 10). Further context, methodological details, and detailed discussions of individual findings are provided in **P1–P3** (Chapt. 6–8) and the corresponding supplementary materials (App. A–C).

4.1 The (un)certain future trajectory of the Earth system

The Earth system comprises our planet's oceans (hydrosphere) and atmosphere, nutrient cycles of the marine and terrestrial biosphere, soil systems (pedosphere), vegetation (biosphere), ice sheets (cryosphere) and other freshwater reservoirs (hydrosphere), and geological-scale stores of minerals and fossil biomass (litosphere) (Ruddiman, 2008, Fig. 4.1). All of these compartments interact, leading to non-linear and complex behaviour of the system as a whole (Feldl and G. H. Roe, 2013; Flato, 2011; Zickfeld et al., 2011). Earth system compartments are deeply intertwined with human livelihoods and essentially constitute humanity's living environment. For example, weather and climate dynamics determine the background conditions the human body and human-made infrastructure have to withstand (e.g., A. J. McMichael et al., 2006; Meierrieks, 2021; Patz et al., 2005; Verschuur et al., 2024). High thermodynamic inertia and radiative feedbacks of oceans and the cryosphere moderate these dynamics (Erb et al., 2013; Fyke et al., 2018; T. Li et al.,

2000; Ruddiman, 2008). Precipitation and runoff are essential for supplying freshwater and supporting agriculture (Banwart et al., 2016). Nutrients in the soils co-determine agricultural yields (Banwart et al., 2016). And the geosphere (pedosphere and lithosphere) supplies fossil fuels, metals, minerals, and space for settlements and infrastructure (Desonie, 2007). At the same time as being reliant on the Earth system, human activities also disturb the Earth system’s dynamic equilibrium on local to global scales. Foremost, anthropogenic emissions and land use shift the radiative balance and threaten essential ecosystem services by destroying biodiversity and diminishing capacities for natural carbon sequestration (IPCC, 2023). These and similar existential dependencies of humanity on the Earth system motivate studying the fundamental processes that shape our environment and influence everyday life.

The dependency of human livelihoods on the Earth system also drives the desire to foresee the system’s future evolution. However, in contrast to many other scientific disciplines which can isolate specific dynamics on a lab-scale, this is often impossible for interactions across Earth system compartments because of the system’s size and complexity. Instead, assessing the future trajectory of the Earth system and its resilience to anthropogenic interventions requires model building based on field experiments, in-situ measurements, satellite observations, paleoclimate archives, and fundamental principles (Flato, 2011; Ruddiman, 2008). Early on, scientists started to leverage their observational insights into fundamental physical phenomena of weather and climate, biogeochemical processes involved in carbon cycling, and non-linear behaviour in complex systems for building predictive power. The famous first general circulation model by Manabe et al. (1965) allowed the numerical description of temperature and moisture distributions around the planet. And Hasselmann (1976)’s stochastic energy balance model enabled differentiating between natural fluctuations and anthropogenic warming. Two other prime examples for early models in Earth system sciences are Walker, Hays, and Kasting’s description of the geological thermostat through silicate weathering (Walker et al., 1981) and various approximations of bi- or multi-stable ecological systems with mathematical models (Hirota et al., 2011; R. M. May, 1977). Since these early models were formulated, a growing stock of observational and paleoclimate data compilations as well as powerful computational resources facilitated integration and mutual coupling of numerous process models into comprehensive Earth system models (Sect. 4.2). State-of-the-art ESMs now cover major compartments from atmosphere to anthroposphere and include processes from vegetation dynamics to soil carbon cycling (Fig. 4.1). Further integrations emerge continuously. The most recent advancements incorporate dynamic ice sheets, aerosol chemistry, atmospheric eddies at a kilometer-scale resolution, and vegetation demography (Andernach et al., 2026; Fisher et al., 2018; Goelzer et al., 2025; Sherwood et al., 2014).

Even though Earth system science now integrates more than 60 years of model building, *forecasting* socioeconomic evolution and prospective anthropogenic interventions based on first principles is still fundamentally out of reach. Climate *projections* work around this constraint by bracketing known uncertainties with “What if?” scenarios and extrapolating the system’s evolution along plausible storylines (Riahi et al., 2017; K. Ricke et al., 2023; Rougier and Goldstein, 2014; Shepherd et al., 2018). Typically, multiple different storylines are constructed around self-consistent political and socioeconomic assumptions (Shepherd et al., 2018, Sect. 4.1.1). This sets climate change projections apart from *forecasts*. Forecasting, as applied, for example, in numerical weather prediction, aims to *predict* a future

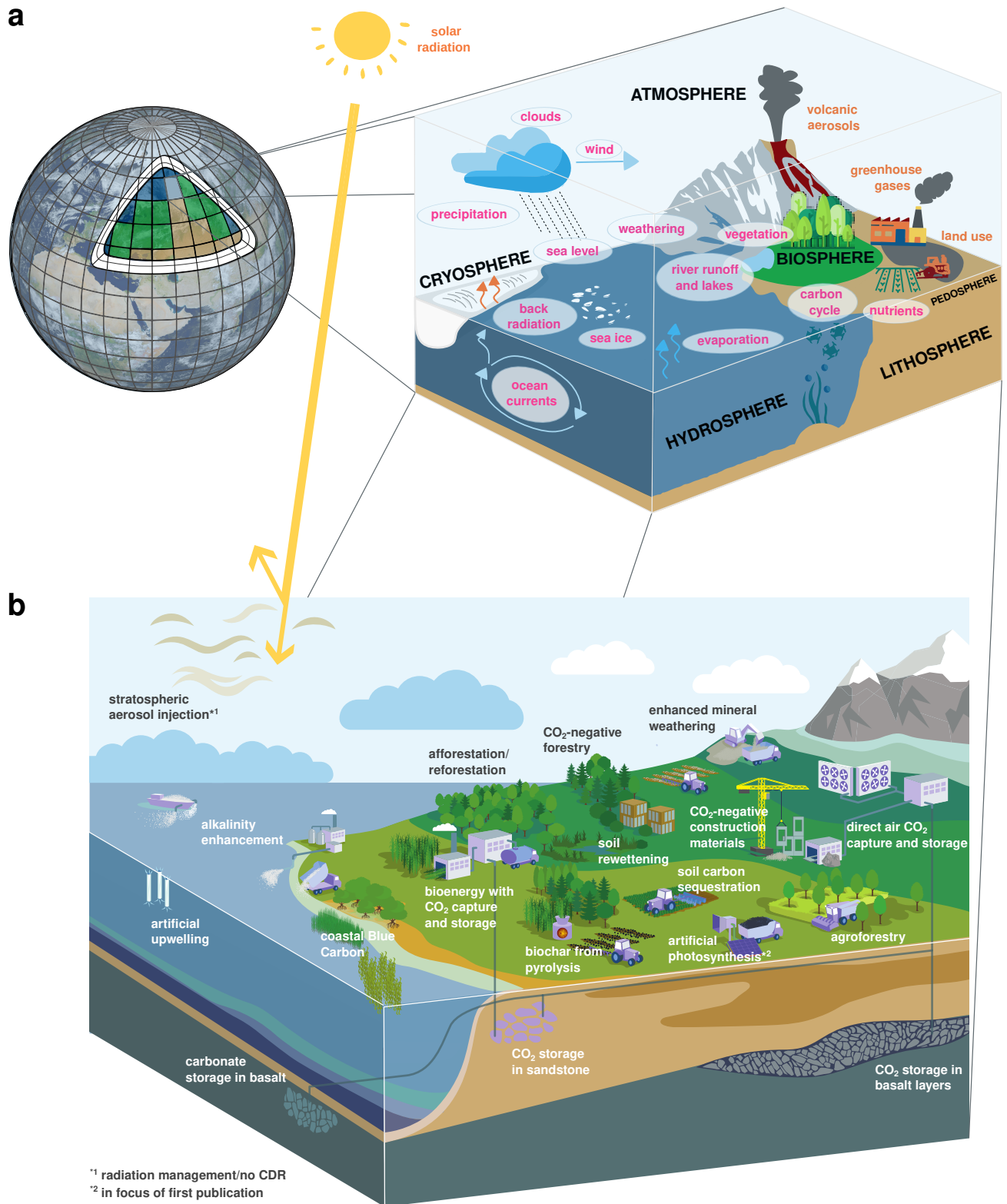


Figure 4.1: Conceptual overview of (a) key Earth system compartments represented in ESMs and (b) proposed anthropogenic interventions for climate change mitigation. (a) ESMs discretize the Earth system on spherical grids and describe drivers (orange), dynamics (pink), and interactions across the system. The figure is modified from Ellerhoff (2023), drawing on Mengis et al. (2020). Image of planet Earth: ESA/Copernicus/Sentinel-2/NASA. (b) Suggested marine, terrestrial, and atmospheric interventions for stabilizing planetary climate through CDR and stratospheric aerosol injections (non-extensive visualization of proposed approaches). The figure is modified from CDRterra (2023)/B. Maier.

system state based on an initial state and boundary conditions. *Projections* along scenarios also start out from an initial state defined on the basis of reality through observations but need to be interpreted in context of each scenario's assumptions and the differences between scenarios (Dellink et al., 2017; Riahi et al., 2022; Shepherd et al., 2018). This approach avoids the need for explicit sociopolitical modeling, but still allows to identify key system transitions, bottlenecks or pitfalls that limit achieving climate change mitigation.

4.1.1 CO₂ emission and removal scenarios

The framework of shared socioeconomic pathways (SSPs) (Riahi et al., 2017) is the most widely applied storyline approach in Earth system projections during recent years. It defined the boundary conditions for the Scenario Model Intercomparison Project (ScenarioMIP) exercises of the sixth Coupled Model Intercomparison Project (CMIP) cycle under the umbrella of the World Climate Research Programme (WRCP) that fed into the recent Intergovernmental Panel on Climate Change (IPCC) assessments (O'Neill et al., 2016; Tebaldi et al., 2021). CMIP and CMIP-endorsed efforts like ScenarioMIP are coordinated simulation projects of multiple modeling groups with common initial and boundary conditions that are defined by storylines. Such model intercomparisons are essential for determining the confidence in future projections and identifying priorities for model development. The IPCC's most recent sixth assessment report applied an additional classification of these storylines as illustrative mitigation pathways (IMPs) (Riahi et al., 2022) and the upcoming ScenarioMIP simulations as part of CMIP7 further expand and improve the scenarios (van Vuuren et al., 2025).

SSPs provide modeling constraints on future energy demand, carbon pricing, land use practices, and greenhouse gas emissions and removals. Drawing on integrated assessment models (IAMs), that is macroeconomic cost-optimization models, these constraints yield emission and land use boundary conditions for ESMs (Fig. 4.2a). The underlying storylines cover, for example, global progression towards sustainable economies and reduced inequality (SSP1), moderate improvements to sustainability but continued pressure on environmental systems (SSP2), conflicts and nationalism that lead to deprioritization of globally distributed prosperity (SSP3), and ongoing extensive growth of global economy fueled by fossil resources (SSP5) (Dellink et al., 2017; Riahi et al., 2017). A couple of *marker scenarios* (Fig. 4.2b) are particularly relevant because they bracket much of the qualitative spread of the IAMs. These marker scenarios result in anthropogenic radiative forcings by the end of the century of 1.9 W m^{-2} (SSP1-1.9), 2.6 W m^{-2} (SSP1-2.6), 4.5 W m^{-2} (SSP2-4.5), and 7.0 W m^{-2} (SSP3-7.0). They correspond to limiting global mean temperatures in the 21st century to 1.5°C (at $> 50\%$ likelihood), 2°C ($> 67\%$), 3°C ($> 50\%$), and 4°C ($> 50\%$) compared to pre-industrial levels, respectively (Fig. 4.2; Riahi et al., 2022). The extreme case is $+8.5 \text{ W m}^{-2}$ radiative forcing (SSP5-8.5), which leads to global warming in excess of 4°C at $> 50\%$ likelihood (Riahi et al., 2022). Current policies and measurements align closely with SSP3-7.0 (Riahi et al., 2022).

A key differentiating factor between the marker scenarios are levels of greenhouse gas emissions and artificial removals (Fig. 4.2b). The description here is limited to CO₂, since it contributes most of the anthropogenic greenhouse effect due to its large emitted volume compared to other anthropogenic greenhouse gases like methane, nitrous oxide, and fluorocarbons. Over the past decade, annual anthropogenic CO₂ emissions from fossil

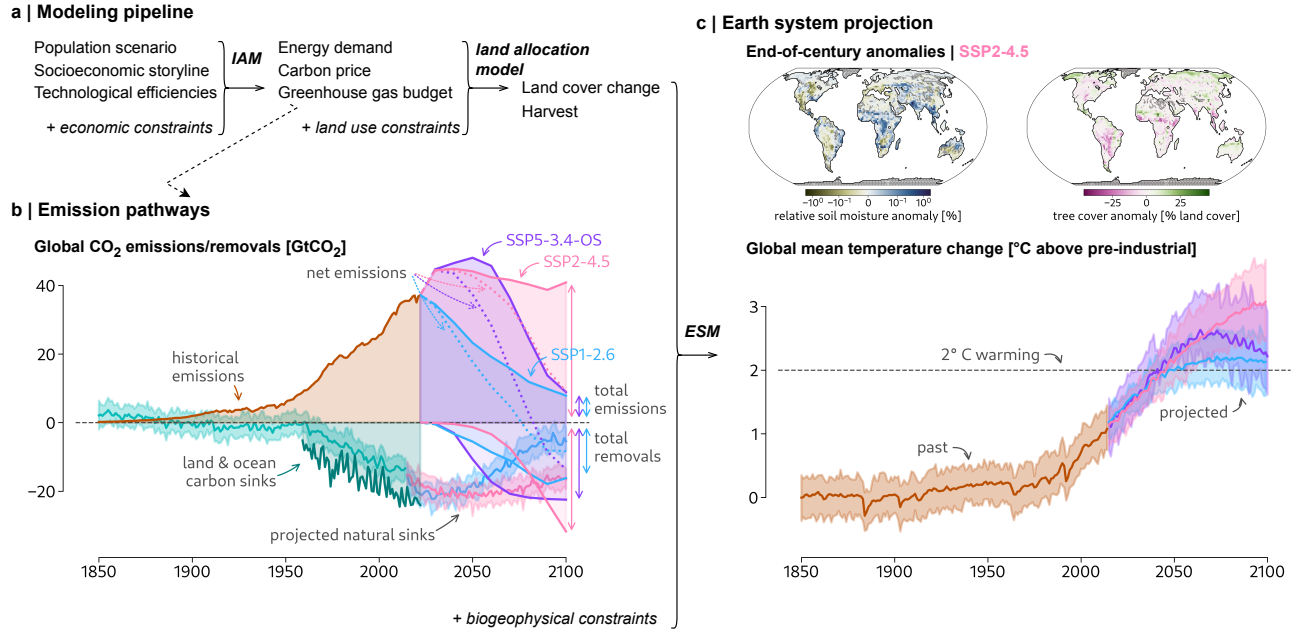


Figure 4.2: Scenario building for Earth system projections. (a–c) Inputs, outputs, and constraints of integrated assessment models (IAMs), land allocation models, and Earth system models (ESMs). Each bracket represents a major modeling step. (b) Historical annual CO₂ emission rates (Friedlingstein et al., 2023), natural carbon uptake from observations and bookkeeping (dark green) (Friedlingstein et al., 2023) and from coupled ESM simulations (light green) (Wieners et al., 2019a), and future emissions and removals (Riahi et al., 2017) along with projected natural carbon sinks (Wieners et al., 2019b) for the SSP marker scenarios SSP1-2.6 and SSP2-4.5. Shadings indicate 25th–to–75th percentile ranges of each ensemble. Modeled carbon sinks draw on the Max Planck Institute for Meteorology Grand Ensemble (MPI-GE) (Olonscheck et al., 2023) obtained with the Max Planck Institute for Meteorology Earth System Model (MPI-ESM). Note that standard ScenarioMIP output for SSP5-3.4-OS is generally limited and has not been produced for MPI-ESM. Refer to P2 for additional simulations of this scenario. (c) Exemplary results of the MPI-GE (top; Olonscheck et al., 2023; Wieners et al., 2019b) and ScenarioMIP Earth system projections (bottom; Tebaldi et al., 2021). Maps depict relative decadal average ensemble mean anomalies between 2099–2089 and 2015–2025 for (top left) full column soil moisture and (top right) absolute anomalies of tree cover under SSP2-4.5. Positive values indicate higher values at the end of the century. (bottom) Historical and projected ScenarioMIP ensemble mean and 25th–to–75th percentile ranges (shaded) corresponding to the scenarios shown in panel (b). Note that the model ensemble depicted here is not identical with Tebaldi et al. (2021) due to data availability. As a result, the ensemble’s mean climate sensitivity here is slightly higher, reflected in more pronounced warming.

fuels ($35.6 \pm 1.8 \text{ GtCO}_2 \text{ yr}^{-1}$) and land use change ($4.4 \pm 2.6 \text{ GtCO}_2 \text{ yr}^{-1}$) amounted to $40.0 \pm 3.2 \text{ GtCO}_2 \text{ yr}^{-1}$ on average (Friedlingstein et al., 2026). In a world with moderate decarbonization like SSP2-4.5, net CO₂ emissions peak at slightly above $40 \text{ GtCO}_2 \text{ yr}^{-1}$ in the 2030s and slowly decline over the 21 century (Fig. 4.2b). In this scenario, net CO₂ emissions in 2100 are still at about a quarter of today, that is $\sim 10 \text{ GtCO}_2 \text{ yr}^{-1}$. In contrast, a more ambitious scenario like SSP1-2.6 peaks at present day emission levels, reaches net-zero CO₂ emissions in the mid-2070’s, and attenuates the effects of previous emissions with net-negative emissions in the order of -5 to -7 GtCO_2 over the following decades (Fig. 4.2b) using carbon dioxide removals (Riahi et al., 2022). CDR in scenarios that likely limit planetary warming below 2°C cumulates to 630 GtCO_2 (95 % confidence 440 to 1.100 GtCO_2) over the course of this century (S. M. Smith et al., 2023).

The SSPs marker scenarios described above all lead to monotonously rising global mean temperature until the end of the century (Fig. 4.2b). However, emission trajectories with a non-monotonous global mean temperature response are also compatible with present policies. This type of scenario is often referred to as an *overshoot scenario* or *temperature overshoot*. Global mean temperature in an overshoot scenario temporarily exceeds the warming targets set out in the Paris Climate Agreement, before subsequently achieving a

limited global warming below 2 °C or 1.5 °C. CDR is a key factor for driving the climate system to warming levels that are compatible with the Paris Agreement. A blueprint overshoot scenario is SSP5-3.4-OS (O'Neill et al., 2016). This scenario follows an emission-intensive pathway until 2040, before rapidly transitioning to net-negative emissions around 2060 (Fig. 4.2b). This is achieved with cumulative CO₂ removals of more than 1.100 GtCO₂ at annual net-negative CO₂ emission rates of up to $-14.0 \text{ GtCO}_2 \text{ yr}^{-1}$ (Melnikova et al., 2021; O'Neill et al., 2016). Without delving into detailed differences in the energy sector, land partitioning, or CDR portfolio, the disparate emission pathways resulting from SSP1-2.6, SSP2-4.5, and SSP5-3.5-OS already highlight the large uncertainty of the Earth system trajectory in light of possible anthropogenic forcings and interventions.

Temperature overshoot trajectories require a lower rate of decarbonization in the near-term future than monotonous emission pathways. However, this comes at the expense of immense amounts of CDR towards the end of the century. These CO₂ removals entail substantial drawbacks due to non-linearities of the Earth system. Marine and terrestrial carbon sinks, which, at present, buffer approximately half of the anthropogenic CO₂ emissions into the atmosphere, re-equilibrate during periods of lower positive or net-negative emissions (Koven et al., 2022). This rebound effect is asymmetric, with more CO₂ released than buffered before (Melnikova et al., 2021; Zickfeld et al., 2021). Given the high projected monetary and environmental costs of large-scale CDR, this asymmetry is a reason why avoided greenhouse gas emissions are preferable over CO₂ removals. In contrast to the asymmetric carbon cycle response, from the perspective of some other Earth system compartments, a short-lived temperature overshoot might be tolerable. For example, ESM simulations suggest that a slow-down of the atlantic meridional overturning circulation (AMOC) during an overshoot would only be temporary and melting of permafrost could at least partially recover after the overshoot (Schwinger et al., 2022a). However, these simulations do not consider irreversible emissions from thawing permafrost and exhibit overcompensation dynamics which could induce strong temporary decadal cooling after a temperature overshoot (Schwinger et al., 2022b). Overshooting a warming target of 1.5 °C might also increase the likelihood for non-linear state transitions that are irreversible on a short to mid term (“tipping elements”) (Ritchie et al., 2026; Wunderling et al., 2023). Such an emission trajectory would also risk prolonged consequences on biodiversity that extend well beyond the duration of the actual overshoot, particularly in tropical key biodiversity areas (Meyer et al., 2022). Land use change for deploying CDR would be an additional risk for ecosystems (Meyer et al., 2022; L. J. Smith and Torn, 2013).

No matter if an emission scenario leads to a monotonous global mean temperature trajectory or an overshoot, macroeconomic IAMs typically allocate a majority of CO₂ removals to bioenergy with carbon capture and storage (BECCS) and direct air carbon capture and storage (DACCS), albeit at different scales (Babiker et al., 2022; Riahi et al., 2022; Rosen, 2018). BECCS relies on large-scale plantations of fast-growing biomass assimilating CO₂ through natural photosynthesis. Subsequently, energy is produced from this biomass and CO₂ from point-source exhaust gases is captured for storage. Major drawbacks of this approach arise from competition with agriculture for food production over nutrients, water, and land. In contrast to BECCS, DACCS employs fully technological process chains to withdraw CO₂ from the atmosphere. Permanent storage of captured CO₂ is supposed to be achieved by underground and undersea storage in both cases. DACCS demands substantial amounts of energy for capturing and processing atmospheric CO₂, which has

to be renewably sourced to achieve carbon neutrality of the process chain. Conversion into durable sink products has also been proposed (M. M. May and Rehfeld, 2019). Converting captured CO₂ into usable products, particularly fuels is also an active field of research (Dowell et al., 2017; Gabrielli et al., 2020). However, this carbon capture and utilization (CCU) withdraws CO₂ from the atmosphere only momentarily before it gets re-released. Therefore, it does not qualify as a method for CO₂ removal (Geden et al., 2024).

Integrated assessment models suggest large scale-up of BECCS to start in the 2030's and DACCS being deployed from the 2070's and onwards, reflecting their current technological readiness. In this context, both are considered as upcoming or *novel CDR* methods (Geden et al., 2024). Most of the remaining removals are supposed to be realized by *conventional CDR* (Geden et al., 2024), which involves improved carbon sequestration in agriculture and forestry through land and forest management practices as well as afforestation and wetland restoration (Babiker et al., 2022; Geden et al., 2024). The high suggested contribution of BECCS and DACCS is mainly due to their high theoretical removal potentials compared to other CDR methods, reaching 0.5 to 11 GtCO₂ yr⁻¹ and 5 to 40 GtCO₂ yr⁻¹, respectively (S. M. Smith et al., 2023). Potential means of marine CDR (Boyd et al., 2024; Doney et al., 2025) are not covered by the scenarios. The scenarios are also not granular regarding terrestrial removals besides BECCS and DACCS (Rickels et al., 2019).

The IAM scenarios assume a quickly increasing technological readiness of efficient CDR methods over the next decades, which is a core uncertainty of CDR (Nemet et al., 2018). In addition, large-scale CDR is cost-intensive (Ozkan, 2021; Strefler et al., 2021a) as research and development and initial scale-up need to be facilitated by subsidies and a voluntary carbon removal market (Fuss et al., 2024). Currently, all novel CDR methods brought forward are still in development, with an increasing number of demonstrators built. Novel CDR delivered 1.35 MtCO₂ yr⁻¹ in 2024 (Pongratz et al., 2024), while company announcements already cumulate to 120 MtCO₂ yr⁻¹ for 2030 (Nemet et al., 2024). The 3 to 4 orders of magnitude difference of current removals to theoretical potentials and storylines demand annual growth rates of 40 % or more starting from around 2030, which is at least as ambitious as recent growth rates of photovoltaics (Nemet et al., 2024).

Storylines such as the SSPs assume CO₂ removals to be permanent. However, depending on the specific method, CDR likely faces leaks along the removal process chain and during storage. Likewise, it is challenging to quantify net CO₂ removals achieved at a certain time and location. Therefore, a future carbon removal market will have to be accompanied by *monitoring, reporting, and verification (MRV)* to ensure carbon removal credits are valid, accurate, and credible (Schulte et al., 2024). Monitoring efficacy and durability of removals is particularly challenging for conventional CDR approaches, because they engage with the complex carbon cycling in soils and vegetation. Tracing net removals in these open systems demands field measurements and local to global modeling. However, durability issues could also occur for novel CDR methods, for example, because the number of safe storage sites for gaseous CO₂ from CCS is limited (Fuss et al., 2018).

Even if a portfolio of different methods (Mühlbauer et al., 2025; Strefler et al., 2021b) reaches market maturity, bears its costs, and achieves permanent and measurable carbon removals, CDR risks incentivizing prolonged fossil fuel emissions (Buck, 2020; Carton et al., 2020; Dowell et al., 2017; Fuss et al., 2014; Ozkan, 2021). Large-scale terrestrial CDR might still cause target conflicts with sustainable use of land, water, and nutrients

(Heck et al., 2018; Popp et al., 2017; P. Smith et al., 2016) and might eventually feed back into weather and climate dynamics through physical land–atmosphere interactions. For example, simulations of high-latitude afforestation demonstrate that regional warming would have to be expected due to albedo feedback effects (Betts, 2000; Loughran et al., 2023). At the same time, reforestation in the tropics would benefit regional climate change mitigation thanks to additional latent heat release from evapotranspiration (Betts, 2000; Peng et al., 2014; Windisch et al., 2021). Similarly, (bio-)physical feedbacks could occur through changes in land management (De Hertog et al., 2022) and renewable energy harvest for technological carbon sequestration (Hu et al., 2016; Y. Li et al., 2018). Particularly for novel approaches, in-situ observations and modeling studies of these interactions are rare. In this context, ESMs are limited by their insufficient abilities of explicitly representing novel CDR approaches and the associated energy harvest (Rickels et al., 2019; Zickfeld et al., 2023). However, they are critical for assessing environmental risks and burdens of the scenarios tuned for economic cost-optimality.

4.1.2 Stratospheric sulfate aerosols and volcanically forced climate variability

Some future uncertainties of socioeconomic origin can be approximated with the SSP framework. However, greenhouse gas emissions and (bio-)physical land–atmosphere interactions from land cover change are just two of many sources of uncertainty for the future trajectory of the Earth system. Deliberate aerosol injections into the stratosphere and natural aerosol forcing through volcanic eruptions add to the scenario uncertainty from greenhouse gas emissions and land use (Fig. 4.1). This work focuses on sulfate aerosols as they represent the dominant stratospheric aerosol species among many others including solid compounds of volcanic, meteoric or organic origin, and non-sulfurous volcanic gases (Kremser et al., 2016).

Sulfate aerosols are nanometer to micrometer-scale droplets of dissolved sulfuric acid which form from sulfur dioxide (SO_2) gas through various chemical pathways (Kremser et al., 2016; Whitby, 2007). These aerosols increase planetary reflectivity within the lower stratosphere, that is in atmospheric layers between ~ 15 and ~ 25 km above the ground (Junge and Manson, 1961; Kremser et al., 2016). In turn, this shifts the Earth’s radiative balance and leads to relative cooling and climatic changes. The climatic effects include shifts in atmospheric circulation and declining overall precipitation (Zanchettin et al., 2022), a higher likelihood for decadal-scale AMOC disturbances and for El Niño/La Niña-type climate modes, as well as an increase in Arctic sea ice cover (Illing et al., 2018; Pausata et al., 2015). The magnitude of implications is conditional on the system state at the time of an eruption for many of these climatic phenomena (Illing et al., 2018).

At present, stratospheric sulfate aerosols predominantly stem from natural sources, with the main contribution made by large volcanic eruptions through SO_2 injections (Kremser et al., 2016). However, cooling effects of sulfate aerosols could also be leveraged for climate change mitigation with deliberate injections (Crutzen, 2006; de Coninck et al., 2018). Within limitations, observations and climate model simulations of past volcanic eruptions can serve as testbeds and analogs for studying consequences of such an anthropogenic intervention on the Earth system (de Coninck et al., 2018; Pope et al., 2012; K. Ricke et al., 2023; K. E. Trenberth and Dai, 2007). Analogies might be limited, though, because deliberate

aerosol injections could rely on other aerosol species than the sulfate aerosols from volcanic outbreaks (Pope et al., 2012). Whether eruptions are suitable as an analog also depends on the injection scenario. Different types of scenarios are imaginable, including storylines with gradual and abrupt changes in aerosol injections (de Coninck et al., 2018; Keith and MacMartin, 2015). Given these scenario uncertainties, the Earth system's response to volcanic variability may generally serve as pointer rather than as precise analogy to anthropogenic SAIs.

Aerosol-induced cooling may attenuate or slow some repercussions of anthropogenic climate change. However, it cannot fully reverse climate change and greenhouse gas effects, and may risk additional adverse consequences for the biosphere. Uncertainties are substantial, as are options to design deliberate injections (IPCC, 2023; Määttä et al., 2024; MacMartin et al., 2016; Zarnetske et al., 2021). SAIs would reduce the likelihood for temperature and precipitation extremes along with lowered surface temperature, but cannot stabilize regional climate everywhere at once because of non-linear pathway dependencies (K. L. Ricke et al., 2010; Tilmes et al., 2013). Similar hysteresis dynamics with partially compensated or slowed down climate change impacts are also expected in the context of ice sheet melting, forest dieback, or AMOC slowdown (Futerman et al., 2025; Tilmes et al., 2020).

More gradual rates of climate change and, for example, avoided temperature overshoots could benefit vegetation resilience and biodiversity conservation (Futerman et al., 2025; Trisos et al., 2018). At the same time, tropical forest biome and taxa distributions would likely shift due to changes in circulation and water cycling under sustained aerosol-induced cooling (Zarnetske et al., 2021). Permafrost thawing could also be mitigated, implicating a significant reduction in CO₂ and methane emissions (Chen et al., 2023; Chen et al., 2020). However, if injections are not gradual or terminate suddenly, they would pose existential risks to many species and ecosystems, due to extraordinarily high rates of change of climatic niches (McCormack et al., 2016; Trisos et al., 2018; Zarnetske et al., 2021). Even with gradually changing radiative forcing, anthropogenic climate change would leave irreversible legacies on terrestrial plant biomes and high-latitude herbivores (Zarnetske et al., 2021). For marine ecosystem, legacy effects could potentially be pronounced, given the ocean's high thermodynamic inertia (Zarnetske et al., 2021). Aerosol injections have no direct effect on atmospheric CO₂ levels, since they only mitigate an effect of anthropogenic climate change, not its causes. As such, aerosol injections cannot counteract the negative consequences of ocean acidification on calcifying marine organisms, because they have little effects on atmospheric CO₂ (Zarnetske et al., 2021).

Large volcanic eruptions raise sulfate aerosol load in the lower stratosphere by an order of magnitude or more. The 1991 Pinatubo eruption, for example, temporarily increased aerosols by a factor of 30 to 60 above the long-term background (Kremser et al., 2016) with peak sulfur aerosol loads between 14 and 22 Tg (Bluth et al., 1992; Guo et al., 2004; Quaglia et al., 2022). A peak global mean cooling of around -0.8°C can be attributed to the radiative effects of this particular outbreak, followed by a gradual return to pre-eruption levels over the following two to three years (Kremser et al., 2016; Zanchettin et al., 2022). This example highlights that next to immediate climatic consequences, volcanic forcing adds significant regional to global temperature variability (Ellerhoff et al., 2022). Enhancements in global mean temperature variability due to varying volcanic forcing extend up to time scales of a couple of decades (Ellerhoff et al., 2022; Schillinger et al., 2022). Thus, sporadic volcanic

events are a source of uncertainty for the future trajectory of the Earth system (Bethke et al., 2017; Chim et al., 2025; van Dijk et al., 2024). It is unclear, whether this variability could destabilize or strengthen natural carbon sinks under climate change mitigation measures.

The net response of natural carbon uptake to stratospheric aerosol injections is the result of intricate dynamics. Aerosol injections affect cloud microphysics, increasing the proportion of diffuse irradiation (Gu et al., 2003). Even though overall insolation declines during the years following a major eruption like the one of Pinatubo in 1991, this stimulates photosynthesis and vegetation carbon uptake (Gu et al., 2003; Mercado et al., 2009; Zarnetske et al., 2021). Lower average temperatures through radiative cooling also reduce the vapor pressure deficit (VPD), reducing water stress on vegetation and further promoting productivity. Whether these stimulating effects actually enhance terrestrial carbon drawdown indirectly, is unclear (MacMartin et al., 2016). This is because the changes in radiative properties would also exacerbate losses of stratospheric ozone and increase ultraviolet surface irradiation significantly, with detrimental effects on photosynthesis but also human health (de Coninck et al., 2018; Zarnetske et al., 2021). Effects of stratospheric aerosols on marine carbon sinks are unclear, with estimates ranging from pathway dependent enhancements of the sinks to no effect (Reith et al., 2016; Tjiputra et al., 2016).

4.1.3 Vegetation productivity and resilience of terrestrial carbon stocks

Land carbon sinks take up close to a quarter of anthropogenic CO₂ emissions into the atmosphere (Friedlingstein et al., 2026). Vegetation carbon uptake through photosynthesis contributes the majority of this buffering effect, in particular through forests (Pan et al., 2011). On top of that, evapotranspiration effects from vegetation exert stabilizing feedbacks on climate by transporting latent heat from the surface to the troposphere, promoting cloud formation and surface cooling (Bonan, 2008; Fahrenbach et al., 2025). Evapotranspiration thus moderates local microclimate change and contributes to dampening weather extremes, such as extreme heat events.

Maintaining the dampening influence of vegetation on carbon cycle and climate in the future is essential for climate change mitigation. In this context, rising atmospheric CO₂ levels further stimulate plant growth and carbon sequestration (Norby et al., 2005; Tharammal et al., 2019), manifested by global greening over the recent decades (Zhu et al., 2016), but also in paleoclimate records (Gomes et al., 2025). Climate change stimulates vegetation growth by warming in boreal latitudes (Forkel et al., 2016) and increasing the duration of the growing season (Kolus et al., 2019; Sitch et al., 2014). Juxtaposing the stimulating effects of CO₂ fertilization and global warming on vegetation productivity, global warming enlarges the vapor pressure deficit (Johnston et al., 2025). This increases water stress experienced by plants and, eventually, reduces productivity. Shifting meridional temperature gradients and regional feedbacks alter circulation, which transforms and relocates climatic niches (Svenning and Sandel, 2013; Wiens et al., 2009). Deforestation and land cover change significantly diminish vegetation carbon stocks and biodiversity (Boysen et al., 2020; Ciais et al., 2013; Gatti et al., 2021). And increasing likelihoods of compounding temperature–moisture extremes and other disturbances may severely damage regional vegetation productivity with a persistent legacy (Anderegg et al., 2015; Kolus et al., 2019; J. Li et al., 2024; Mahecha et al., 2022; Ridder et al., 2022; Zscheischler et al., 2014a).

Estimating current and future net effects of climate change and CO₂ fertilization is complicated by the many vegetation–climate and vegetation–carbon cycle interactions and further dependencies of vegetation growth, for example, on nutrient availability (Piao et al., 2020; Wieder et al., 2015). On the one hand, CO₂ fertilization is non-linear and the stimulating effect gradually levels off with rising CO₂ levels (Collatz et al., 1992; Farquhar et al., 1980). On the other hand, there are robust signs of climate change damaging forest integrity and carbon uptake, for example, in the Amazon rainforest (Friedlingstein et al., 2026; Gatti et al., 2021; Hubau et al., 2020). From the early 2010s, this crucial carbon sink has partly turned into a net source (Gatti et al., 2021). This is not exclusively attributable to human actions like deforestation but a higher water stress and limited nutrients as well (Gatti et al., 2021; Wang et al., 2020). Climate change effects are also reflected in a slowing of global greening trends, which, however, also integrate human activity components (Piao et al., 2020). Eventually, critical state transitions or feedbacks of anthropogenic interventions on atmospheric circulation could lead to extensive rainforest dieback (Lenton et al., 2008; Lu et al., 2021; Wunderling et al., 2023), risking essential buffering capacities of anthropogenic greenhouse gas emissions.

Vegetation productivity and terrestrial carbon sequestration are highly variable on time scales from days to centuries (Friedlingstein et al., 2026; Willeit et al., 2014). Therefore, estimating and attributing changes in vegetation resilience under climate change mitigation scenarios, including those with deliberate interventions for temperature stabilization, is difficult. Resilient vegetation could recover from unusual disturbances, like extremely high or low temperatures and moisture availability. In contrast, low resilience is characterized by a continuously weakened ability to sustain photosynthesis and carbon sequestration (Hacke et al., 2001). In this case, the terrestrial biosphere eventually turns into a permanent carbon source due to qualitatively different climatic or environmental regimes (Schwalm et al., 2017). Under current greenhouse gas levels and climate, vegetation productivity is still predominantly resilient to weather extremes. However, extremes, especially compounding temperature–moisture extremes, shape the variability of land carbon uptake substantially (Zscheischler et al., 2014a; Zscheischler et al., 2014b). For example, extraordinarily high temperature and lack of moisture raise the likelihood for severe droughts, temporarily reducing net land carbon uptake. By contrast, particularly hot and wet conditions often promote growth and net carbon uptake. Impacts of temperature–moisture extremes can cumulate to the scale of the net global annual land sink, but are currently balanced over time (Reichstein et al., 2013; Zscheischler et al., 2013). However, whether this balanced relation will shift with an increased likelihood of extreme weather and climate in the future and result in more long-term legacy effects is unclear and demands accurate observations and Earth system models (Frank et al., 2015; Reichstein et al., 2013; Saatchi et al., 2013).

4.2 Earth system modeling concepts

Comprehensive projections of the Earth system under climate change mitigation rely on Earth system models. These are complex numerical tools with numerous subcomponents, process models, and simulated interdependencies (Donner and Large, 2008; Flato et al., 2013). ESMs aim to integrate as many relevant processes from biosphere, climate, carbon cycle, and anthroposphere as possible (Fig. 4.1), growing out of the need to represent

climate–carbon cycle dynamics under past, present, and future climate change (Ciais et al., 2013). This led to the integration and further development of previously independent atmosphere–ocean general circulation models, land surface models, and dynamic global vegetation models (Blyth et al., 2021; Flato, 2011; Port et al., 2012). However, ESMs remain approximations of reality. To remain tractable, they employ *discretizations* of fundamental laws and *parametrize* processes and interactions (Fig. 4.3). Accuracy and applicability of these approximations vary by model, process, Earth system compartment, and, crucially, application. ESM calibrations that deliver reliable results for one application do not necessarily perform well for another one, due to complex interactions, non-linear feedbacks, and the large number of degrees of freedom. Model approximations of real-world processes and phenomena fall onto an accuracy gradient, which is co-determined by the degree of fundamental process understanding, complexity of interactions to be represented, availability and quality of calibration data, and numerical tractability. Along this gradient, this section describes some of the main challenges when simulating the high-dimensional, complex Earth system and reviews essential strategies for coping with them.

Fundamental laws have inherent predictive power and fall on one side of the accuracy gradient. Their primary uncertainty arises from measurement precision of the relevant natural constants. The ideal gas law and the Navier–Stokes equation for fluid momentum transport on the planetary sphere are examples of fundamental physical laws. However, while real-world state variables vary continuously, in a model world, differential equations have to be discretized at non-infinitesimal resolution to keep them computationally manageable. As a result of spatial and temporal discretizations, unresolved, sub-scale quantities need to be aggregated to the resolved scale, where they serve as boundary conditions or diagnostics (Flato, 2011). To achieve this, ESMs apply numerous physically motivated or empirical *parametrizations* of sub-scale dynamics. Every additional parameter in these approximations adds a degree of freedom that has to be constrained by calibration or by design. In addition, while there are analytical solutions to fundamental laws like the ideal gas law and the Navier–Stokes equation in specific settings*, fluid dynamics on the sphere can only be numerically approximated, producing additional inaccuracies. Numerical inaccuracies demand careful selection of solver algorithms and sometimes bias corrections to guarantee mass and energy conservation (e.g., Rast et al., 2013; Reick et al., 2013; Stevens et al., 2013). Regularly, they also come with further parameters to be constrained.

*: The barometric formulas for vertical pressure gradients in a static atmosphere provide closed solutions for the ideal gas law. Models of geostrophic flow above the surface boundary layer of the atmosphere solve a simplified Navier–Stokes equation.

Parametrizations are essential for approximating sub-scale phenomena but also for complex dynamics that are too intricate to be modeled or not fully understood. This applies in particular to biophysical, (micro-)biological, and chemical processes of the Earth system. For example, most ESMs employ parametrizations building on the aggregated quantity of aerosol optical depth (AOD) to represent the net effect of aerosols on climate, instead of resolving complicated aerosol chemistry and cloud microphysics (Toohey et al., 2016). Land surface models (LSMs) contained in ESMs parametrize vegetation as plant functional types (PFTs) (Fig. 4.3a). The PFTs are high-level abstractions of vegetation biomes such as boreal needleleaf trees or C4-type croplands that perform photosynthesis and compete for resources and space (Blyth et al., 2021). These vegetation classes are characterized by parameters like canopy albedo, roughness, and rates for carboxylation and electron transport (Reick et al., 2013; Reick et al., 2021). *Bioclimatic limits* constrain the long-term climatological envelope a PFT can sustain as well as the timing of bud burst and leaf shedding (Blyth et al., 2021; Reick et al., 2013). Beyond vegetation growth and competitions, many other

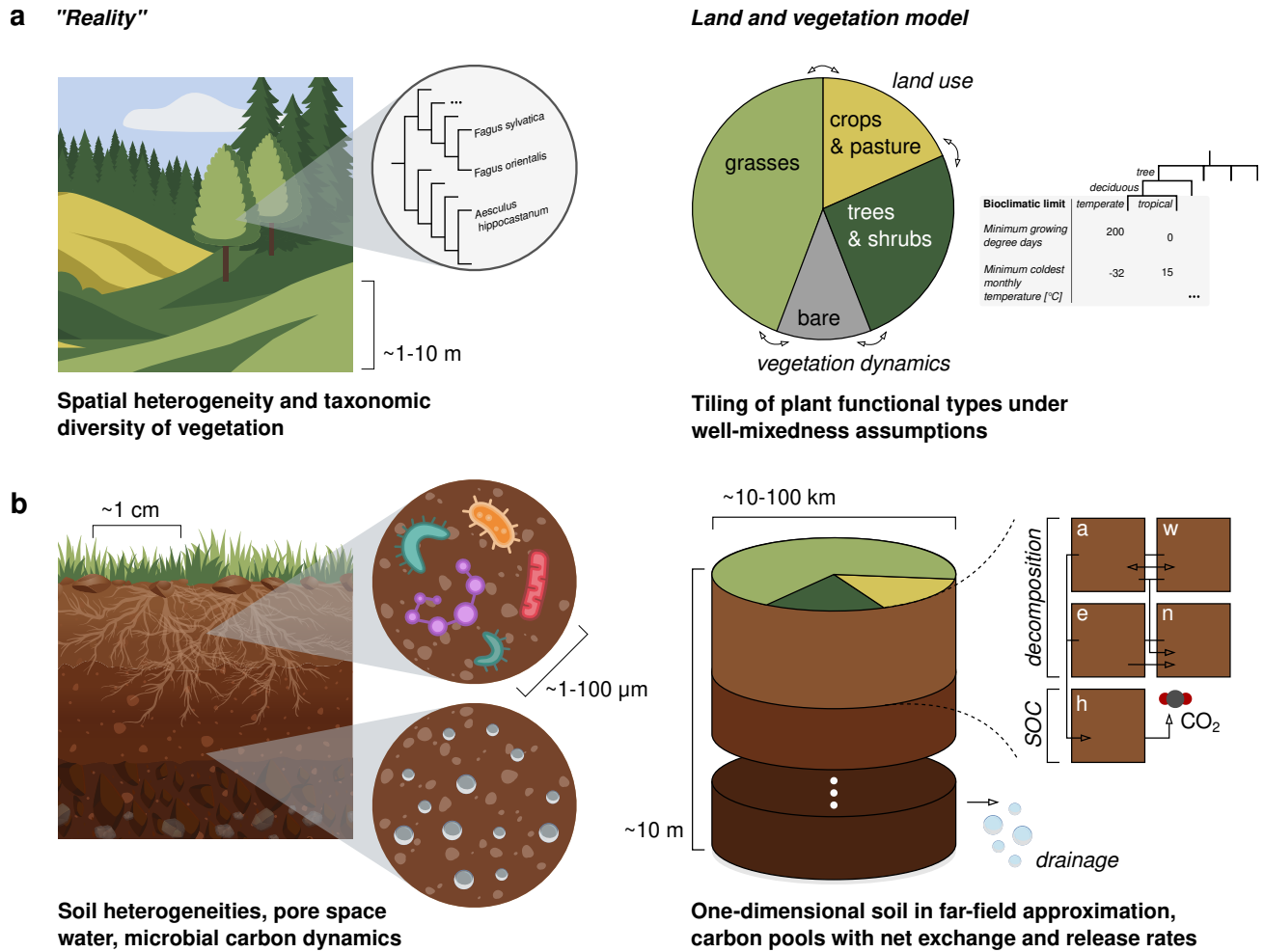


Figure 4.3: Conceptual examples for parametrizations and simplifications employed within a typical land surface model of the sixth CMIP cycle, JSBACH3.2 (Reick et al., 2013). (a) In the model, plant functional types cover the land surface and assimilate carbon through photosynthesis, but leave out almost every taxonomic detail. Local heterogeneities are assumed to level out at typical ESM resolutions of kilometers and above. Bioclimatic limit parameters approximate long-term climatic constraints for broad vegetation classes. (b) Similarly, sub-scale soil carbon dynamics and hydrology are aggregated to coarser resolutions. One-dimensional flow models parametrize the net water balance of the soil. Mineral and organic carbon cycling is handled in a pooling scheme with pools characterized by solubility and hydrolyzability. The sketches are partially inspired by Reick et al. (2013) and Reick et al. (2021), and contain elements designed by brgfx and Freepik on Magnific.com.

processes represented by land surface models (LSMs) are also parametrized, including soil carbon cycling (Fig. 4.3b), natural disturbances through wildfires and windfall, effects of a forest's vertical structure on radiation and momentum transport, and anthropogenic land use (Blyth et al., 2021; Bonan, 2008).

Comprehensive ESMs include several dozens to hundreds of tunable parameters (Shi et al., 2019). Therefore, model calibration has a large impact on model skill. However, running parameter ensembles to systematically calibrate all ESMs parameters (see below) is computationally expensive and limited even on modern supercomputers. As a result, ESM calibration involves a combination of quantitative and expert judgement to identify parameter ranges that are most appropriate for achieving a specific tuning target (e.g., Mauritsen et al., 2013; Schmidt et al., 2017). For projections of Earth system resilience under climate change scenarios, important metrics include the climate response to transient greenhouse gas forcing, size and spatial layout of natural carbon stocks, and the statistics

of temperature and hydroclimate extremes (Arora et al., 2020; Jeevanjee et al., 2025; I. R. Simpson et al., 2025).

Next to parameter calibration, accurately representing boundary conditions from external forcing has major effects on the simulation results (Rougier and Goldstein, 2014). Without changes in external forcing, the Earth system would eventually relax towards a dynamic equilibrium that depends on solar energy input and geological-scale carbon cycle dynamics (Archer et al., 2009; Budyko, 1969). However, solar insolation, volcanic aerosols, and human activity vary and are responsible for a large fraction of climate variability (Ellerhoff et al., 2022; Huybers and Curry, 2006).

Drawing meaningful conclusions about the non-linear Earth system from ESM simulations requires strategies for statistical replication and isolating causal mechanisms. In Earth system modeling, these two issues are approached with *simulation ensembles*, *reference simulations*, and *off-line simulations* of model components (Flato et al., 2013). There are four types of simulation ensembles, that is, sets of realizations that vary only along specified dimensions: (i) Parameter ensembles sample the effect of changing a single parameter or of interactions between several parameters on the system dynamics. They are mostly applied for model calibration. (ii) Initial condition ensembles slightly offset starting conditions of a simulation to produce temporarily decorrelated realizations along a single set of boundary conditions. Temporal decorrelation can, for example, be achieved by forcing a short-lived disturbance on the system or selecting sufficiently temporarily spaced states from a previous simulation as initial condition. Such an ensemble allows sampling the uncertainty arising from internal variability of the Earth system (e.g., Deser et al., 2020). (iii) Members of a boundary condition ensemble differ by realization of external forcings. The forcings can be different emission and land use scenarios, for example, or different realizations of stochastically varying stratospheric aerosol levels. (iv) Finally, multi-model ensembles incorporate results from multiple ESMs and may include weighting algorithms according to model interdependencies and skill measured against observations (Eyring et al., 2019; Flato et al., 2013). Multi-model ensembles are, for example, applied in the comprehensive IPCC assessments, as are initial condition ensembles (Flato et al., 2013).

Two strategies are commonly applied in Earth system modeling to infer causality, unforced reference simulations and off-line simulations of submodels (Flato et al., 2013). Comparing simulations to a *control simulation* singles out coupled responses of the whole Earth system to changes in boundary conditions, initial state, or parameter values. In contrast, off-line simulations of submodels with prescribed input from the rest of the ESM allow to isolate stages of a process without coupling feedbacks back into the system. For example, differentiating between climate change effects on carbon uptake and the whole Earth system response including CO₂ fertilization draws on a combination of off-line and *fully-coupled* simulations of carbon cycle dynamics (Ciais et al., 2013; Friedlingstein, 2015).

4.3 Deficiencies of climate projections and research gaps

Complex ESMs are essential for quantitative assessments of future Earth system resilience and risks of anthropogenic interventions for climate change mitigation. However, these models and their land components were not developed with novel types of interventions in mind. ESMs partly lack the technical ability to address all uncertainties laid out by

climate change mitigation scenarios. Current models also miss many key interactions of CDR with Earth system compartments. Simplifications in models and scenarios once considered reasonable might be inadequate for accounting for uncertainties caused by varying aerosol levels. And while resilient land carbon sinks are essential for climate change mitigation, comprehensive assessments of simulated vegetation extremes are sparse. Evaluating these deficiencies requires an integrated approach that simultaneously improves modeling capabilities and quantifies their impacts. This thesis applies such an approach and addresses three specific shortcomings:

1. Earth system projections miss spatially explicit, dynamic, and interactive representations of technological CDR process chains and associated energy harvest

Projections of climate change mitigation scenarios implicitly incorporate the effect of CO₂ removals on net emissions through the SSP boundary conditions (Sect. 4.1.1). This permits quantifying hysteretic and non-linear responses of the carbon cycle and climate to CDR deployment in general. However, CDR–Earth system interactions extend well beyond an altered net greenhouse gas forcing (Zickfeld et al., 2023). Studying implications of large-scale deployment of terrestrial CDR on the surface moisture and energy balance, as well as carbon stocks and land use, requires spatially explicit representations. Earth system projections also need to integrate additional constraints on CDR scenarios, such as CDR allocation among countries (Fyson et al., 2020; K. Lee et al., 2021) and renewable energy harvest associated with large-scale CDR. Recent attempts to include some spatial constraints and Earth system interactions target photosynthesis-based CDR, particularly afforestation, by leveraging existing vegetation modeling capabilities (Moustakis et al., 2024). Yet, projections with explicitly modeled large-scale deployment of fully technological CDR process chains do not exist.

2. Projections of climate change mitigation scenarios disregard consequences of realistically varying volcanic aerosols on climate and carbon cycle

Varying levels of sulfate aerosols may considerably raise uncertainty of the future climate trajectory (Bethke et al., 2017) and, potentially, of natural carbon uptake. However, they are only rarely considered in future projections, even though there is strong evidence that volcanic forcing strongly contributes to underestimated climate variability by ESMs on multi-annual to multi-decadal time scales (Ellerhoff et al., 2022; Laepple et al., 2023). For example, ScenarioMIP-endorsed experiments which undermine IPCC assessments along the lines of the SSPs only contain the long-term median effect of natural aerosol injections (Aubry et al., 2025), but not the variation in forcing strength over time that occurs in reality (Schindlbeck-Belo et al., 2023). Volcanic outbreaks multiply sulfate aerosol loads in the lower stratosphere by orders of magnitude (Sect. 4.1), tantamount to radiative forcings of up to several W/m² and global mean temperature drops in the order of a couple of tenths to several K (Kremser et al., 2016). Therefore, ScenarioMIP projections barely represent uncertainties originating from this externally forced climate variability (Sect. 4.3). IPCC storylines also do not include scenarios with varying anthropogenic SAI at this point. Within limitations (Sect. 4.1), simulations with sporadic volcanic eruptions can also serve as a testbed for these potential anthropogenic interventions.

3. Comprehensive comparisons among observations and ESMs of the statistical relation between temperature–moisture extremes and extremely low or high vegetation productivity are lacking

Projections of ecosystem resilience and carbon stock vulnerabilities are pivotal for climate change mitigation (Friedlingstein et al., 2026). Both temperature and moisture extremes will persist longer, become more frequent, and intensify with global warming. It is unclear to what extent this will put the CO₂ buffering capacities of vegetation under pressure (Reichstein et al., 2013) and whether this will change the statistical relationship between temperature–moisture and vegetation productivity extremes. However, observation–ESM comparisons that gauge this statistical link across regions and extreme types are sparse. Identifying strengths and weaknesses in ESM parametrizations of vegetation–climate responses can facilitate more accurate projections of vegetation resilience.

In total, substantial gaps in model and scenario design remain for comprehensive projections of Earth system resilience under climate change mitigation, especially to prospective anthropogenic interventions. Progress on the research priorities identified above can help close these gaps and expand the informative value of future projections. Therefore, this dissertation and **P1–P3** pursue four research objectives, which are presented in the subsequent chapter (Chapt. 5). Overall, this work identifies three opportunities to significantly advance ESM capabilities, leverages simulations and observations to quantify benefits of these advancements, and discusses implications for climate change mitigation strategies.

Research objectives | 5

This dissertation pursues four specific research objectives (**O1–O4**) with key findings reported in three manuscripts (**P1–P3**):

O1: To gauge Earth system interactions of a fully technological CO₂ removal approach in net-negative emission and temperature stabilization scenarios

Approach: ESM projections with a spatially explicit and dynamically coupled representation of solar-powered direct air capture with CO₂ conversion into sink products (sDACCCS).

↪ *Results:* Effects of land–atmosphere interactions on surface climate are negligible and temporary shifts in natural carbon uptake do not significantly offset the CO₂ removal potential (**P1**). Land conversions for CDR deployment and associated renewable energy generation can be significant, but are not considered a fundamentally limiting factor if and only if sufficiently high land use efficiency can be achieved (**P1**).

O2: To quantify uncertainties imposed by realistically varying volcanic aerosol forcing on future surface climate and carbon uptake

Approach: Spatiotemporal emulation of ESM simulations driven by varying, paleo-informed volcanic aerosol forcing along a temperature overshoot trajectory.

↪ *Results:* Intermittent aerosol forcing adds significant uncertainty to the timing of future temperature and emission trajectories, both globally and regionally (**P2**). Supplementary regional temperature uncertainties affect a substantial share of the world’s population. These may also propagate into more uncertain natural carbon uptake, reducing the temporal certainty of achieving net-zero emissions (**P2**).

O3: To assess the abilities of ESMs to represent effects of temperature–moisture extremes on vegetation productivity

Approach: Statistical analysis and comparison among observations, ESM simulations, and vegetation model output

↪ *Results:* ESMs can reproduce the characteristics of the statistical relation between temperature–moisture and gross primary production extremes (**P3**). The vegetation response is spatially coherent and agrees with observations (**P3**). However, ESMs likely oversimplify moisture retention in the soil system, which may lead to exaggerated productivity responses. Their predictive power is low at local sites (**P3**).

O4: To advance modeling capabilities of prospective anthropogenic interventions into the Earth system for climate change mitigation

Approach: Earth system model development, design and execution of climate projections, and model evaluation.

↪ *Results:* A scalable, spatially explicit, and scenario-compatible representation of technological CDR in a comprehensive ESM has been achieved (**P1**). Combining ESMs and spatially explicit emulation techniques enables incorporating supplementary uncertainties of external aerosol forcing into future climate projections (**P2**). Simulation protocols for future anthropogenic interventions in the Earth system lack precise boundary conditions for spatial configurations, efficiencies, and biogeophysical interaction mechanisms

(P1, P2). Simulations of biosphere resilience to external disturbances require careful selection of driver variables and further process model refinements **(P3).**

Exemplified by the fourth objective, the overarching goal of this work is to contribute to more detailed and comprehensive projections of future Earth system trajectories, including potential anthropogenic interventions for climate change mitigation. Collectively, the findings, as discussed subsequently, support the conclusion that shortcomings in the models, as well as unresolved anthropogenic interventions and external forcings, exclude substantial sources of uncertainty from simulated trajectories. This conclusion encourages the development of innovative ESM capabilities, novel calibration and boundary condition data, and extended modeling protocols.

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Share of author contributions:

Author	Author position	Scientific ideas (%)	Data generation / programming (%)	Analysis, interpretation, technical work (%)	Paper writing (%)
M. Adam	1	80	95	85	80
T. Kleinen	2	5	5	5	5
M. M. May	3	5	-	5	5
K. Rehfeld	4	10	-	5	10

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Land conversions not climate effects are the dominant indirect
consequence of sun-driven CO₂ capture, conversion, and
sequestrationMoritz Adam^{1,*} , Thomas Kleinen² , Matthias M May³ and Kira Rehfeld^{1,4,*} ¹ Department of Geosciences, University of Tübingen, Tübingen, Germany² Max Planck Institute for Meteorology, Hamburg, Germany³ Institute of Physical and Theoretical Chemistry, University of Tübingen, Tübingen, Germany⁴ Department of Physics, University of Tübingen, Tübingen, Germany

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E-mail: moritz.adam@uni-tuebingen.de and kira.rehfeld@uni-tuebingen.de**Keywords:** carbon dioxide removal, earth system modeling, CO₂ conversion, photoelectrochemistry, land surface model, CDR, carbon cycleSupplementary material for this article is available [online](#)**Abstract**

Removing carbon dioxide (CO₂) from the atmosphere is required for mitigating climate change. Large-scale direct air capture combined with injecting CO₂ into geological formations could retain carbon long-term, but demands a substantial amount of energy, pipeline infrastructure, and suitable sites for gaseous storage. Here, we study Earth system impacts of modular, sun-powered process chains, which combine direct air capture with (electro)chemical conversion of the captured CO₂ into liquid or solid sink products and subsequent product storage (sDACCS). Drawing on a novel explicit representation of CO₂ removal in a state-of-the-art Earth system model, we find that these process chains can be renewably powered and have minimal implications for the climate and carbon cycle. However, to stabilize the planetary temperature two degrees above pre-industrial levels, CO₂ capturing, conversion, and associated energy harvest demand up to 0.46% of the global land area in a high-efficiency scenario. This global land footprint increases to 2.82% when assuming present-day technology and pushing to the bounds of removal. Mitigating historical emission burdens within individual countries in this high-removal scenario requires converting an area equivalent to 40% of the European Union's agricultural land. Scenarios assuming successful technological development could halve this environmental burden, but it is uncertain to what degree they could materialize. Therefore, ambitious decarbonization is vital to reduce the risk of land use conflicts if efficiencies remain lower than expected.

1. Introduction

Current and pledged efforts to reduce greenhouse gas emissions are insufficient to achieve net-zero CO₂ emissions in 2050 and the Paris Agreement's target in 2100 [1, 2]. To avoid exceeding future carbon emission budgets, climate change mitigation scenarios heavily rely on artificial carbon dioxide removal (CDR) from the atmosphere [3]. Proposed CDR approaches on land include but are not limited to forestation, bioenergy production with carbon capture and sequestration (BECCS), changing agricultural practices, enhancing mineral weathering,

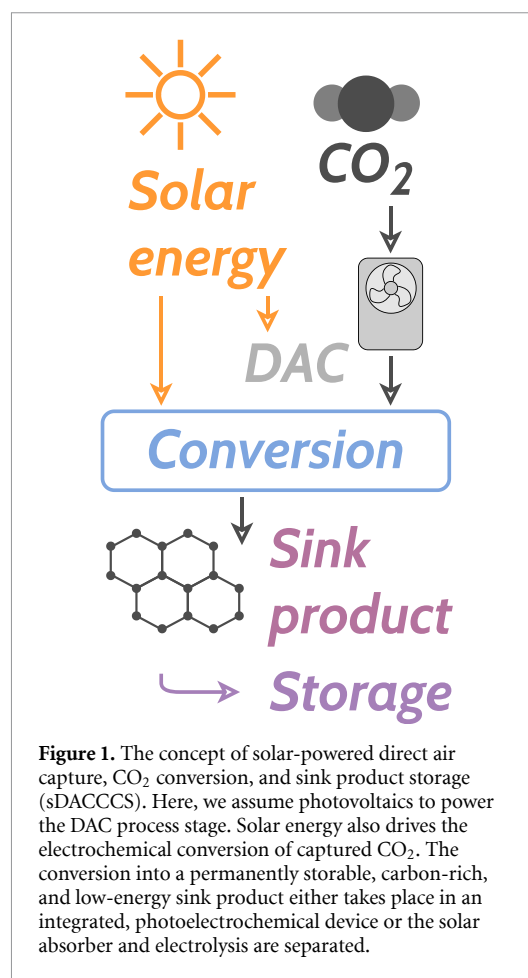
and different process chains which combine direct air capture (DAC) and subsequent carbon storage [4]. They differ in resource and cost efficiency, technological readiness, and environmental implications [5, 6]. Environmental consequences include pressure on land resources, biodiversity, and food, exacerbated by a growing population [7]. Therefore, a portfolio of CDR measures is most likely to emerge with continuously improving operability and scalability [8].

Removing CO₂ in the projected order of 10 gigatonnes per year or more [3, 6] will demand natural and economic resources [9]. CO₂ fixation based on natural processes, such as forestation, BECCS, or

enhanced weathering, is associated with high land and resource demand [8–10]. Biomass plantations also increase the use of freshwater and fertilizers and can offset their mitigation potential through biogeochemical and -physical effects [11, 12]. Given their constraints, meeting large-scale CDR targets exclusively with nature-based CDR is impossible within the planetary boundaries [6, 11, 12]. These deficits make large-scale CO₂ fixation with purely technological DAC attractive. DAC is often understood to deliver CDR as part of a process chain that injects the captured CO₂ gas into bedrock or abandoned oil and gas fields [4, 13]. However, process chains complementing DAC with (electro)chemical CO₂ conversion into sink products and storage of the products were also proposed (DACCS) and could be solar-powered (sDACCS, figure 1) [14, 15]. Carbon-rich but low-energy liquids or solids like formate or oxalate are particularly suitable for long-term CDR because they are easy to store and maximize removed carbon per unit of energy invested [14]. Production of elemental carbon is also an option [16] which could reduce interaction of the sink product with the environment to a minimum. However, costs and energy requirements of storing sink product volumes equivalent to gigatonnes of removed CO₂ are unclear, and life cycle assessments which include the environmental compatibility of different sink products are so far lacking.

DAC process chains promise higher land use efficiencies than, for example, biomass-based CDR, which may omit adverse climatological and biogeochemical effects [9]. Still, they are technologically immature, cost-intensive, and energy-demanding [5, 6, 17]. Environmental consequences, including land cover change, are often assumed to be low [17, 18]. The consequences are, however, poorly constrained from an Earth system perspective, especially for process chains requiring energy for CO₂ conversion [6, 19, 20]. Also, the number of safe storage sites is limited [6], and process chains building on direct gas injection for carbon storage could increase the profitability of fossil fuel exploitation [13, 21, 22]. Here, proposed process chains targeting carbon-rich solid or liquid sink products for permanent storage by (electro)chemically converting the captured CO₂ provide an alternative [14, 15]. This approach would avoid incentivizing hydrocarbon fuels because it maximizes the carbon and not the energy content in the sink products and expands the scope of suitable storage sites beyond sealed geological reservoirs.

Converting captured CO₂ into carbon-rich but low-energy sink products can be achieved with electrochemistry. The energy for the electrochemical CO₂ conversion can either be supplied externally, for example through photovoltaics, or by a solar absorber that integrates with the catalytic conversion reaction [14, 15]. At present, industrial-scale electrolysis would already be available for producing sink



products out of CO₂ and high conversion efficiencies have generally been demonstrated [23]. However, integrated, photoelectrochemical designs with a solar absorber in direct contact to the electrodes offer great benefits for conversion efficiencies [14, 15] and are actively developed on a lab scale. Conversion efficiencies promise more efficient use of land resources than natural photosynthesis, but have not been scrutinized in any scenario experiments. Aside from the sink product design that maximizes safe CO₂ removal per unit of energy invested, sDACCS can operate off the energy grid and neither requires the suitable sites and legal framework for gas injection nor extensive infrastructure for CO₂ transport. This modularity could facilitate fast scale-up. However, combining DAC-based process chains with a carbon-free energy supply is crucial for carbon-negativity, no matter if they achieve long-term carbon removal by storing CO₂ gas or a sink product [24–27]. Including this energy harvest in the assessment of DAC-based technology is essential because the technology could, otherwise, be carelessly perceived as a high-gain, low-side effect promise for reaching net-negative greenhouse gas emission budgets and offsetting residual emissions [8, 20, 28].

Modular DACCS process chains could be a strategic addition to future CDR portfolios. However, their requirements for natural resources

and monetary investments are uncertain [6]. Incorporating potential pitfalls like non-CO₂ effects within the Earth system into the design of CDR portfolios is equally important [29], especially if risks arise from CDR approaches falling short of high expectations. However, large-scale Earth system impacts of DACCS including the required renewable energy harvest have not yet been assessed. Therefore, we examine implications of exemplary DACCS process chains targeting a solid sink product within an Earth system model. We investigate CO₂ capture and conversion into formate (HCO₂⁻), a sink product with moderate conversion efficiencies, along two technological pathways, one building on present-day and one on hoped-for technology. To keep the scenarios comparable, we assume solar energy to drive the capturing and conversion stages in both of them. This on-site energy harvest is included in the sDACCS process chains' land demand without relying on grid electricity. To include pathway dependencies and achieve comparability with other Earth system simulations, we conduct model experiments with a time-dependent CDR target, emission forcing, and land use scenario.

Our simulations cover three pivotal uncertainty dimensions for Earth system implications sDACCS: (i) reliance on CDR, (ii) spatial deployment, and (iii) technological efficiency (table 1; further details on the scenario design in the methods section). Side effects typically scale with the need for CDR, the first uncertainty dimension. Our simulation ensemble covers a low and a high level of explicit CDR forcing, which both result in a net emission forcing compatible with the extended shared socioeconomic pathway [30, 31] (SSP) 1-2.6. Given the Earth system's heterogeneity, the localization of CDR can be relevant for its Earth system implications. Here, two stylized burden-sharing scenarios span the uncertainty space of potential sDACCS deployment locations. Finally, the energy efficiency of any terrestrial CDR process chain influences its land use efficiency [9, 26]. In our experiments, sDACCS efficiencies either correspond to a present-day technology state employing DAC with industrial-scale electrolysis or a state combining DAC with integrated photoelectrochemical CO₂ conversion. Both technology scenarios assume solar energy to power the whole sDACCS process chain.

We examine the impact of sDACCS on climate, land carbon stocks, and land cover at regional and global levels, utilizing a state-of-the-art Earth system model (ESM). To our knowledge, the framework, as described in the subsequent methods section, is the first explicit, interactive, and dynamic representation of a purely technological CDR approach in an ESM [see 12, 19, 37]. The implementation allows us to explicitly simulate first-order interactions of sDACCS with the climate and carbon cycle, including those induced by solar energy harvest,

physical surface modifications, and land use change. In emission-driven experiments spanning the three uncertainty dimensions identified above (Methods), we dynamically adjust the CDR cover in space and time in response to actual CO₂ removal. We can hereby establish a first estimate for the climatic impact and land footprint of the different sDACCS process chains and scenarios up to the year 2200. Within the limitations of our model, we find no significant and persistent non-CO₂ effects on the climate and terrestrial carbon cycle (Results, Discussion). However, depending on technological progress and spatial layout, the land conversions associated with sDACCS (Results) could co-determine if societies want to implement such highly efficient but costly CDR approaches (Discussion).

2. Methods

We employ a modified version of the Max Planck Institute for Meteorology Earth system model v1.2 (MPI-ESM) [38, 39] to quantify interactions of sDACCS within the Earth system. MPI-ESM is specifically calibrated to the anthropogenic warming [38] and contributes to IPCC's physical science basis through the coupled model intercomparison project (CMIP) phases 4–6 [19, 38, 40, 41]. The simulated land carbon cycle agrees well with observations [38] and its response to CO₂ forcing is close to the CMIP5 and 6 multi-model means [41]. MPI-ESM contains submodels of the atmosphere [42, 43], land surface [39], ocean and sea ice dynamics [44], and marine biogeochemistry [45]. Its land model JSBACH3.2 is the main interface for incorporating land-based sDACCS process chains as it provides radiative, momentum, moisture, and gas exchange with the atmosphere. Further, the land model parameterizes vegetation competition, photosynthetic productivity, vegetation–climate interactions, and anthropogenic land use change. Representing sDACCS in MPI-ESM also requires minor adjustments to the land–atmosphere coupling but they are restricted to passing additional variables between submodels and coupling explicit CDR to the atmospheric balances. We use a horizontal grid spacing of approximately 200 km for atmosphere and land (T63 spectral truncation) and about 150 km for the ocean [38].

The representation of sDACCS process chains within JSBACH has five primary goals: (i) predict their land use requirements under different irradiation conditions, (ii) simulate their impacts on the surface balances that are associated with changes in the physical surface properties, (iii) parametrize the CO₂ sequestration under technological uncertainty, (iv) model changes in sDACCS land cover and consequences for land-stored carbon interactively and explicitly based on SSP-derived scenarios,

Table 1. Covering the uncertainty space with scenarios for sDACCCS deployment. All CDR experiments and the pathway control simulation target SSP1-2.6 [30, 31] and are CO₂ emission-forced.

Uncertainty dimension	Spread covered by simulation experiments	
CDR share in mitigation	<i>min</i> — As implicitly contained in SSP 1-2.6 [30, 31]	<i>max</i> — Pushing the limits of DAC deployment [see 6]
Deployment location	<i>Eql</i> — Delocalized across suitable locations	<i>Prop</i> — Localized according to emission burden [32]
Technological efficiency	<i>hE</i> — Highly efficient, hoped-for technologies [14, 33–35]	<i>IE</i> — Present-day process chain [33–36]
Control experiment	Description	Purpose
Pathway control	Only implicit CDR	Evaluate implications of explicit CDR
Control	Equilibrium simulation starting from 2015 emissions	Estimate internal model variability

and (v) minimize the interference with existing process models to ensure consistency between simulations with and without sDACCCS. Therefore, our main extensions to JSBACH comprise (figure S1):

- a new land cover class and type which represent sDACCCS in JSBACH's surface tiling scheme (supplementary information (SI))
- an implicit handling of sDACCCS on the unvegetated fraction of land when computing grid cell-averaged surface properties (SI)
- a zero-dimensional parametrization of the CO₂ withdrawal through sDACCCS
- a dynamic scheme for deploying sDACCCS on the land surface based on the simulated potential withdrawal and spatiotemporal CDR targets
- amended rules for anthropogenic land cover change, which prioritize agricultural land use transitions over those through sDACCCS (SI) and cover changes in carbon and nitrogen pools.

2.1. Parameterizing CO₂ withdrawal through sDACCCS

The working principle of sDACCCS process chains is to store solar energy in the molecular bonds of liquid or solid carbon-rich products [14]. A solar absorber excites charge carriers through the photoelectric effect. The catalyzed reduction of carbon dioxide molecules subsequently consumes these electrons, either in an integrated device as suggested by May and Rehfeld [14] and covered in our high efficiency (hE) technology scenario or in an industrial-scale electrolysis as assumed in the low efficiency (IE) scenario. Solar energy powers CO₂ capture (hE, IE) and electrolysis (IE).

A zero-dimensional model parameterizes these sDACCCS process chains (figure S4), by deducing the CO₂ withdrawal from the incident irradiation along a sequence of process steps which consecutively reduce the amount of energy available for CO₂ fixation (SI).

From our model's perspective, the IE and hE technology pathways differ by conversion efficiencies along the process chain (all parameters in SI). Thus, by reducing the conversion efficiency, we account for system losses and solar energy harvesting. We choose formate as an exemplary sink product because it has a high, but not optimal solar-to-carbon (STC) efficiency and can form a salt that is easy to store [14, 46] but could be in principle also directly injected [47]. Products like oxalate or elemental carbon would beat the STC efficiency of formate substantially [14, 16]. Thus, we deliberately assume a moderate upper bound for the maximum removal efficiency of sDACCCS. For the radiative balance, we draw on the radiation scheme of the ECHAM6.3 atmosphere model, but include the thermal cooling effect that results from CO₂ fixation in an integrated process chain.

Irradiation is the only environmental variable directly driving CO₂ sequestration and storage in our model. For hE, assuming no effect of temperature on the catalyzed reaction's efficiency is motivated by the large uncertainties of system efficiencies. In the case of IE, we assume electrolysis temperatures can be controlled. Because technological developments are currently uncertain, we neglect the effect of temperature on the CO₂ capturing stage. Further, we assume conversion efficiencies to level off according to a sigmoid curve at low local CO₂ surface concentrations (SI).

2.2. CDR land cover dynamics

Biophysical interactions and feedbacks in the Earth system, such as effects of vegetation composition and land carbon uptake, depend on the CO₂ concentration. Therefore, precisely controlling the effective CO₂ emission forcing is essential for maintaining consistency among sDACCCS simulations and control experiments. However, achieving the same effective forcing, irrespective of individual spatiotemporal CDR targets, is challenging because the explicit CO₂ removal itself responds to climate variability, land availability, and the spatial layout. If only spatially

resolved CDR area changes from theoretical calculations were prescribed, the net emission forcing between experiments and different realizations of the same experiment could drift apart. Therefore, we develop a scheme, which dynamically determines fractional changes in sDACCCS cover based on spatial deployment weights and global SSP-derived CDR targets. The scheme simultaneously accounts for every grid cell's CO₂ withdrawal potential in response to climate variability and land use constraints, corrects previous offsets to the targeted CDR pathway that are due to variability, and determines the necessary land cover change to meet the spatiotemporal CDR targets (SI, figure S2).

Because CO₂ removal through sDACCCS is explicit in our model, we adapt MPI-ESM's spatially-resolved emission forcing such that the net forcing remains in line with the respective SSP. Starting from a forcing baseline, we rescale all grid cells with a positive emission flux according to their relative contribution to the global emissions (figure 2(a), SI). Greenhouse gases besides CO₂ are concentration-forced and always follow SSP3-7.0. In experiments beyond 2100, we extend the modified CO₂ emission forcing and other greenhouse gas forcings as described by Meinshausen *et al* [31]. In all simulations, non-sDACCCS land use forcing [48] follows ScenarioMIP [49] protocols along SSP3-7.0. Different SSP land use forcings could result in incompatible CDR scenarios, because some of them implicitly contain biomass plantations and forestation for CDR purposes. By applying the same forcing baseline in all experiments and not varying land use requirements for any other land cover than sDACCCS, we isolate its effects on the Earth system.

2.3. Scenario design

Our study's simulation experiments cover three uncertainty dimensions. The shared socioeconomic pathways [30] (SSPs) and their extensions to 2500 [31] estimate the need for CDR, the first of these dimensions. These pathways provide self-consistent storylines concerning energy demand, warming target, carbon pricing, land use, and the emission budget [30]. Although the SSPs underestimate alternatives to CDR [51], we let emission forcings effectively follow SSP 1-2.6 (figures 2(a) and (b)). SSP1-2.6 is compatible with limiting global warming below 2 °C at a probability > 67% [3]. Because the SSPs do not define spatially explicit DAC targets, this pathway is a globally evolving control for our experiments. To capture a large spread of CDR reliance under the same emission pathway, we further utilize SSP3-7.0, which is close to the world's current emission pathway. Our low-sDACCCS scenario (min, table 1) corresponds to the amount of carbon capture and storage implicitly

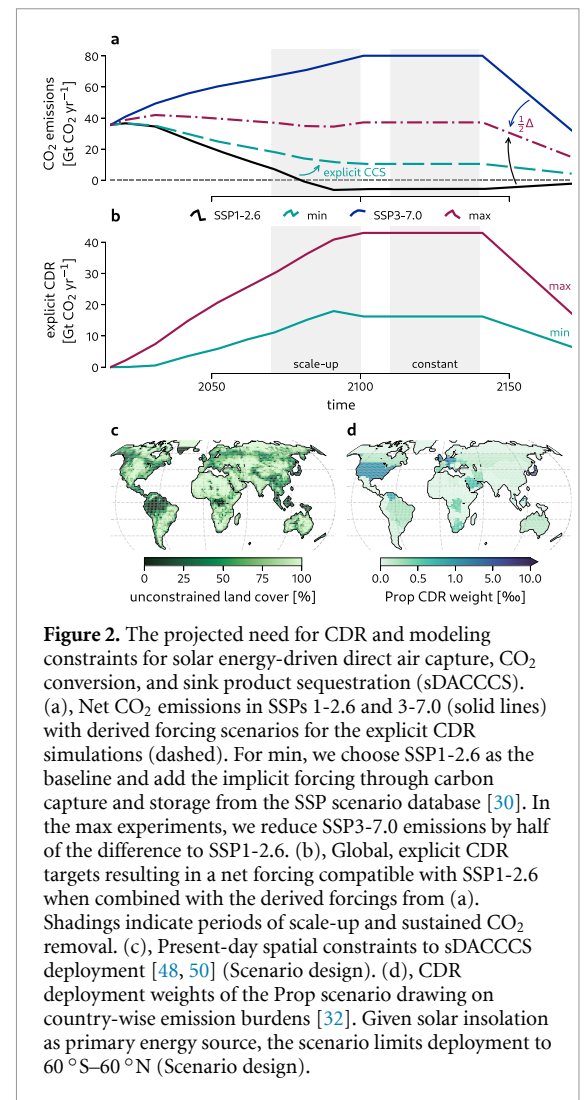


Figure 2. The projected need for CDR and modeling constraints for solar energy-driven direct air capture, CO₂ conversion, and sink product sequestration (sDACCCS). (a), Net CO₂ emissions in SSPs 1-2.6 and 3-7.0 (solid lines) with derived forcing scenarios for the explicit CDR simulations (dashed). For min, we choose SSP1-2.6 as the baseline and add the implicit forcing through carbon capture and storage from the SSP scenario database [30]. In the max experiments, we reduce SSP3-7.0 emissions by half of the difference to SSP1-2.6. (b), Global, explicit CDR targets resulting in a net forcing compatible with SSP1-2.6 when combined with the derived forcings from (a). Shadings indicate periods of scale-up and sustained CO₂ removal. (c), Present-day spatial constraints to sDACCCS deployment [48, 50] (Scenario design). (d), CDR deployment weights of the Prop scenario drawing on country-wise emission burdens [32]. Given solar insolation as primary energy source, the scenario limits deployment to 60 °S–60 °N (Scenario design).

contained within SSP 1-2.6 [30]. In a second scenario (max), we suppose CO₂ emissions to be halfway between the SSP 3-7.0 and SSP 1-2.6 pathways and allocate the excess carbon budget entirely to sDACCCS. While not corresponding to a self-consistent SSP, this scenario allows a test of the Earth system's sensitivity to sDACCCS process chains if the world were locked in on enormous amounts of CDR due to a deferred achievement of net-zero emissions [52]. Reaching ~ 40 Gt CO₂ yearly withdrawal at the end of this century, max is also a potential upper bound for DAC-like CDR [6].

The share of investments, tradeoffs, and gains of large-scale CDR among countries still has to be established [53] while taking appropriate burden sharing [32, 54], technology-specific requirements and land availability (figure 2(c)) into account [6]. Here, two burden-sharing scenarios cover this uncertain spatial CDR layout. The Eql scenario targets equally dispersed deployment of sDACCCS across grid cells, marking the extreme case of minimized

CDR burden per land area (figure S8). On the other hand, in the Prop scenario, we demonstrate the implications of distributing future CDR across countries based on their historical emission burden [32, 54] (figures 2(d) and S8).

All stages of DACCCS process chains contribute to their overall efficiency. For sDACCCS, this includes capturing ambient CO₂, converting it into a safely storable sink product, transporting and storing the product, and energy provisioning [14, 55]. In this study, we assume that photovoltaics provide all necessary external energy and include it in the modeling, as solar energy is the most scalable form of renewable energy [56]. We assume that solar absorbers only provision sDACCCS' energy demand, and do not model solar scale-up for other purposes. This isolates the effects of large-scale sDACCCS deployment, but could overestimate real-world land availability and underestimate synergies in renewable energy provisioning. Present-day DAC facilities combined with industrial-scale electrolytic CO₂ reduction and photovoltaics (IE) would already be available for producing carbon sink products [57]. However, IE has less than optimal conversion efficiencies and is uneconomical. This technology stage still provides a baseline scenario of unrealized technological expectations (3.5% sDACCCS chain efficiency including system losses, SI). In contrast, prospective photoelectrochemical CO₂ reduction which integrates a solar absorber with the catalytic CO₂ reduction [15] (hE) represents a more efficient CO₂ conversion pathway (7.1% chain efficiency, SI). Although derived from specific process chains, one can interpret the uncertainty range spanned by the IE and hE scenarios more widely for any sun-powered DAC chain because the overall chain's efficiency is their single modeling constraint.

2.4. Confidence intervals

To gauge the significance of anomalies among different CDR experiments and between simulations with and without explicit CDR representation, we estimate the range of simulated climate variability. The internal model variability is small compared to this climate variability. We initialize a control simulation with the same 2015 state as all other experiments in our study and run it until 2500. For variability estimates, we report the 95% interquartile range computed from the standard deviation of annual (global carbon stocks, land cover transformations) and three-decadal means (climatic variables, regional anomalies) within the time period from 2260 to 2499 (both years included). Within this period, the control simulation is close to a dynamic equilibrium. We determine confidence ranges after all data processing steps. Thus, we ensure to include non-linear effects of processing operations on uncertainties, for example, when aggregating data over a region.

3. Results

This section presents our results [58] on potential sDACCCS effects on climate, carbon cycle, and land use in topical segments for each aspect.

3.1. Negligible implications for climate of large-scale sDACCCS

A central argument for removing CO₂ through DAC process chains are presumed minor effects on climate, in particular compared to implications of large-scale biomass production [6]. Our experiments confirm that large-scale sDACCCS, which includes solar energy harvest, neither causes additional global climate change (figure 3) nor substantially shifts regional climate (figure 4).

The response of the global mean CO₂ concentration and surface air temperature (figure 3(a), (e)) indicates that none of the three uncertainty dimensions results in a different global climate in the periods of DAC scale-up (anomalies to the pathway control experiment reported for 2069–2099) and constant CDR (2110–2139). Slight differences during CDR scale-down are due to model limitations after 2170 (SI). All experiments fall within the range of the pathway control experiment and meet CDR targets accurately (figures 3(b)–(d)). This suggests that the spatial sDACCCS configuration has a negligible impact on global climate. Thus, it is not per se necessary to represent sDACCCS explicitly in space when considering only the global climate response. However, spatially explicit sDACCCS induces significant changes in surface balances in some IPCC regions (figures 4(a)–(g)). In the extreme case of highly localized CDR cover on the Arabian Peninsula (ARP* region, figure 4(b) within the hE_{maxProp} experiment, sDACCCS increases the excess downwelling radiation at the surface by 32% (43% in lE_{maxProp}) through changes in surface albedo (figures 4(a) and (b)). In hE_{maxProp}, localized sDACCCS also significantly reduces the local CO₂ surface concentration by up to 6.0 ppm in central North America (CNA, 1.4% of the mean), 3.3 ppm in northern and central Europe (NCE, 0.8%), and 1.8 ppm over the Arabian Peninsula (ARP, 0.4%). Except for the Kazakh Steppe and parts of Siberia, impacts on the regional surface energy balance through sDACCCS deployment, as well as interactions with the surface moisture balance (Methods), do not lead to significant local changes in surface air temperature, soil moisture (figures 4(d)–(g) and S17–S18), cloud cover, and precipitation (not shown). Only a few changes stand out against the expected internal variability, such as increased soil moisture in NCE (figure 4(g)). Even when technological efficiencies remain low and the CDR deployment is pushed to the upper limit (lE_{maxProp}), climate implications mostly stay within or close to the range of variability (figures 4(b)–(g), SI).

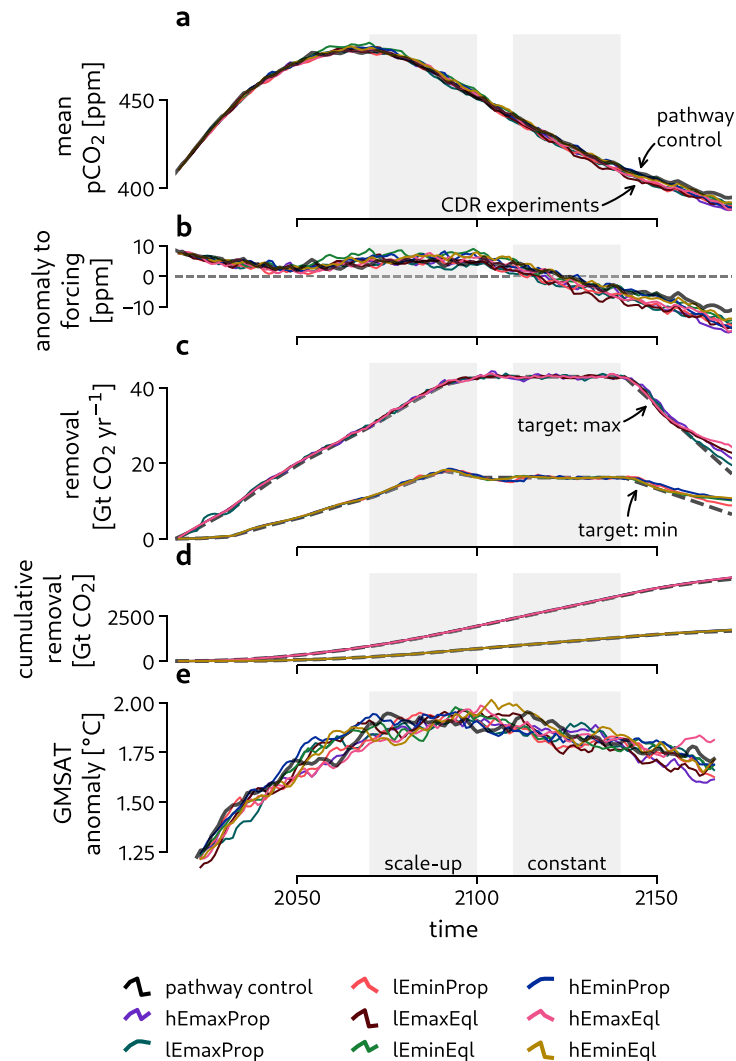
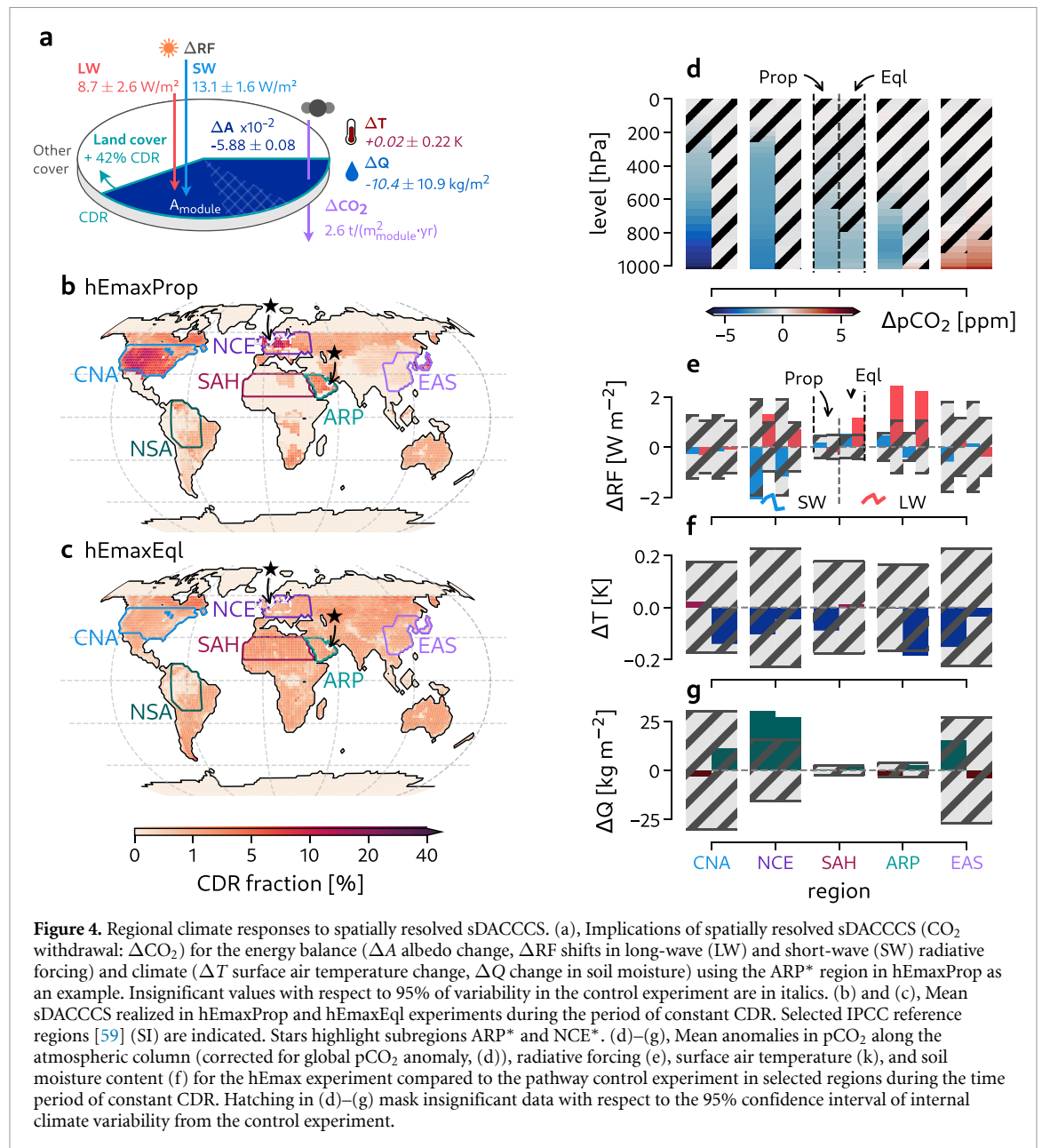


Figure 3. Global climate response to spatially resolved sDACCCS. (a)–(e), Global mean CO_2 concentration (pCO_2 , (a)), anomaly of pCO_2 to SSP-1.26 concentration forcing [30, 31] (b), global CO_2 removal rate (c), cumulative CO_2 removal (d), and global mean surface air temperature anomaly to the pre-industrial (1851–1900, (e)) for pathway control and CDR experiments. Shading highlights periods of final CDR scale-up and constant CDR.

3.2. Small but spatially heterogeneous implications of large-scale sDACCCS for the carbon cycle

Many land regions comprise vast vegetated and agricultural lands. Establishing large-scale sDACCCS could decrease land-stored carbon and biospheric carbon uptake, diminishing the net CO_2 removal potential of sDACCCS. However, our simulation results suggest that while the effects on carbon stocks are globally and regionally significant, they do not substantially reduce the removal potential. sDACCCS causes most land cover degradation in the scale-up period (figure S29), reducing land-stored carbon compared to the baseline experiment (figures 5(a)–(d)). This dynamic is reflected by decreased natural CO_2 uptake during the scale-up phase (figures 5(e) and (f)). During the time of constant CDR, vegetation carbon stocks and associated biomass litter partially recover in the hEmax experiments globally and in

most regions (figures 5(a), (d); SI). In the lEmax experiments, this recovery overcompensates previous losses (figures 5(b) and SI). At the same time, soil carbon stocks diminished through sDACCCS deployment only show little signs of recovery throughout the scenario (figures 5(a) and (b)). Since the baseline and CDR experiments share the same emission pathway (figure 2(a); Methods), overcompensated losses in vegetation-stored carbon during periods of constant CDR and CDR scale-down are not a result of changing climate and vegetation growth. Instead, sDACCCS shifts dominant vegetation types in all phases of CDR deployment, which explains the overcompensation (SI). Total global average losses in land-stored carbon between 4.4 GtC (lEminProp) and 12.9 GtC (lEmaxEql) by 2100 are in the same order of magnitude as sDACCCS' simulated annual removal (17.5 GtCyr^{-1} in lEminProp, 41.1 GtCyr^{-1} in



lEmaxEql), but two orders of magnitude smaller than cumulated removals (705 GtC in lEminProp, 1966 GtC in lEmaxEql; figures 2(c) and (d)).

Regionally, land carbon is not equally distributed on the land surface [60, 61]. Therefore, the implications of sDACCSS for the carbon cycle depend on the spatial scenario. Our simulations show that minimizing its environmental impact is not only a matter of global localization versus delocalization of sDACCSS. For example, the localized Prop scenario results in a higher carbon stock decrease in the CNA and EAS regions than the delocalized Eql scenario, which in turn impairs carbon stocks in the NSA region more substantially (figures 5(c)–(f)). This effect propagates to the global scale, with more pronounced vegetation carbon stock anomalies (in reference to baseline) in Eql experiments during the period of CDR scale-up and more substantial soil carbon decline in

Prop simulations from 2090 onwards (figures 5(a) and (b)).

3.3. Potential for land use conflicts

Land is a pivotal, but limited resource for food production, CO₂ buffering, and biodiversity. Land conversion induced by harvesting energy and processing CO₂ through sDACCSS process chains varies between 0.46% (lEminEql) and 2.82% (lEmaxProp) of global land area (figures 6(a) and S28), with the technological efficiency as a central parameter for these land conversions. For example, CDR covers 3.46 million km² in lEmaxProp, but only 1.69 million km² (1.38% of global land area converted) in hEmaxProp, which is in the range of the global urban land area (1.91 million km² in 2015 [62]). Compared to the strong effect of efficiency parameters, the localization of sDACCSS is less relevant on a

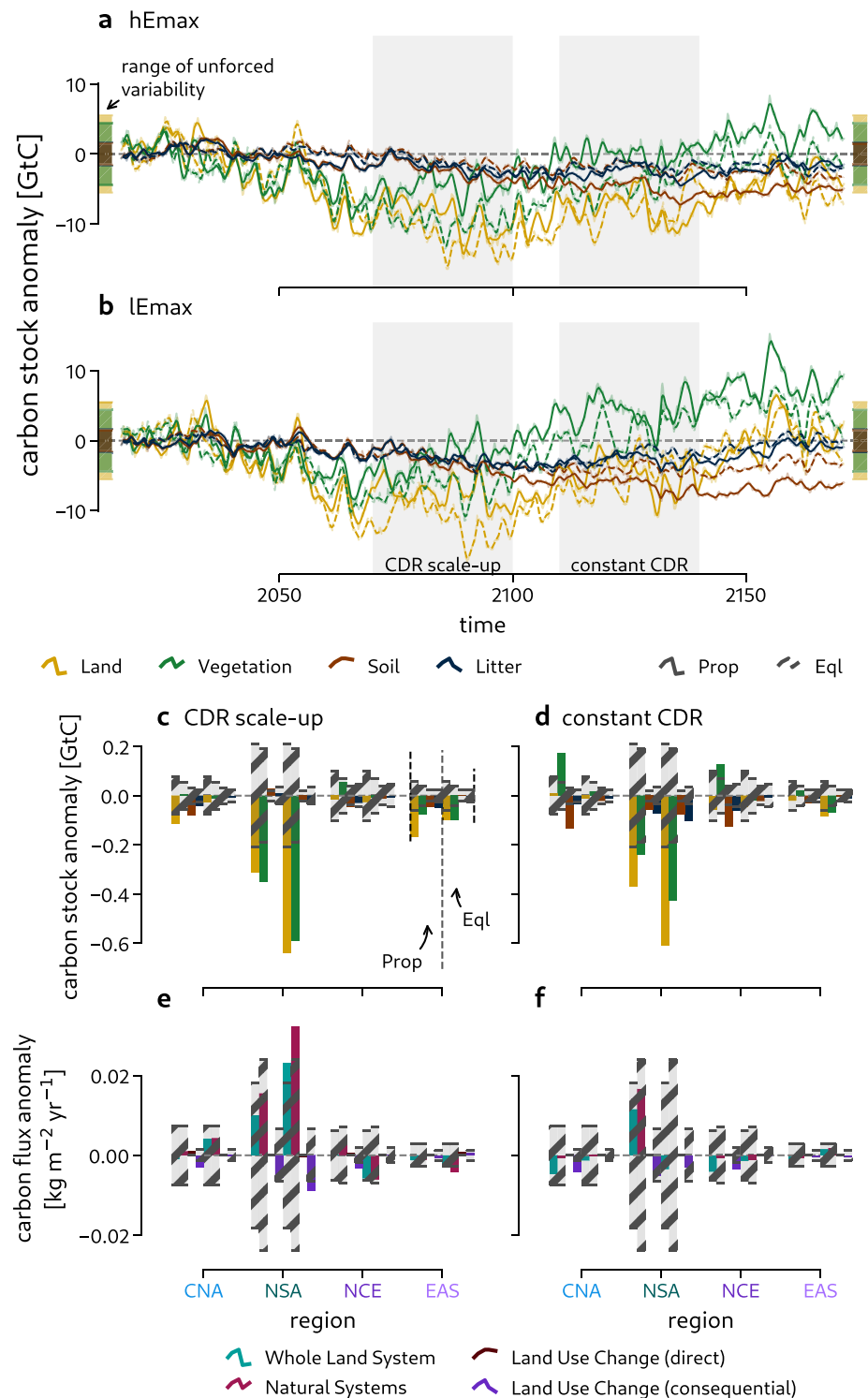


Figure 5. Effects of sDACCCS on global and regional carbon cycle. (a) and (b), Global carbon stock response of hEmax (a) and lEmax (b) experiments. Land carbon stocks comprise carbon stored in live vegetation, soils, litter, and product pools. As product pools are small compared to the other categories, they have been omitted in the figure. (c) and (d), Total carbon stock anomaly of hEmax experiments in selected IPCC regions during periods of CDR scale-up and constant CDR as indicated in (a) and (b). (e) and (f), as (c) and (d) but for average carbon fluxes. Here, negative values indicate an increased carbon sink, while positive anomalies reflect increased emissions. Consequential land use change fluxes reflect decreasing emissions through crop harvest, grazing, and product decomposition as a result of establishing sDACCCS land cover instead. All anomalies are with respect to the pathway control simulation. Hatching indicates the multiannual (a), (b) and three-decadal 95% (c)–(f) interquartile ranges of the control simulation for comparison.

global scale. Increasing the sDACCCS efficiency from lEmaxProp to hEmaxProp causes 44% less grasslands to be replaced (64% less between lEminProp and hEminProp). Conversely, grassland conversion in

simulations with localized CDR (Prop) and delocalized deployment (Eql) under the same global CDR scenario only shifts between 7% (hEmax) and 50% (hEmin). Similarly, the higher efficiency of hE process

chains can prevent up to 43% (maxEql) of agricultural lands from conversion, while the spread between different localizations is 38% at most (lEmax). At the same time, land cover of trees and shrubs increases in simulations with the lower lE efficiency.

While technological efficiency dominates net land conversions globally, the spatial deployment impacts land use regionally. Considering the core of northern and central Europe (NCE*) in the low-efficient lEmax simulations as an example (figures 6(b) and (c)), sDACCCS covers 17.6% of the region in lEmax-Prop during the constant CDR period. As many central European countries have a high historical emission burden, the lEmaxEql experiment only converts 2.4% of land in NCE* for CDR. The implications of the historical burden-sharing scenario become more evident when putting these land cover adjustments into perspective. In the lEmaxEql experiment, NCE* loses grass- and agricultural land only slightly above the Earth system's internal variability. Forests and shrubs dynamically adjust in the same order. In contrast, in lEmaxProp, converted grasslands alone correspond to the equivalent of 37% of the European Union's agricultural area during the constant CDR period. Since agricultural lands make up ~48% of the region's entire area [63], this would constitute a significant intervention into the land system. Converted pastures and croplands add the equivalent of another 13%. Roughly doubling the sDACCCS chain's efficiency (hEmax) would approximately halve the pressure of sDACCCS on regional land resources with the equivalent of 2.4% of the EU's agricultural lands converted to CDR in Eql and 20% for emission burden sharing (figure S30). Because of their historical emission burden, similar regional effects apply to central North America, Japan, South Korea, and parts of the Arabian Peninsula (figures 6(c) and (d)). These solid regional effects of sDACCCS cover on land resources indicate that unmatched technological expectations in a high-CDR world could likely lead to target conflicts between CO₂ removal and land resources, ecosystem services, and food production.

4. Discussion and conclusion

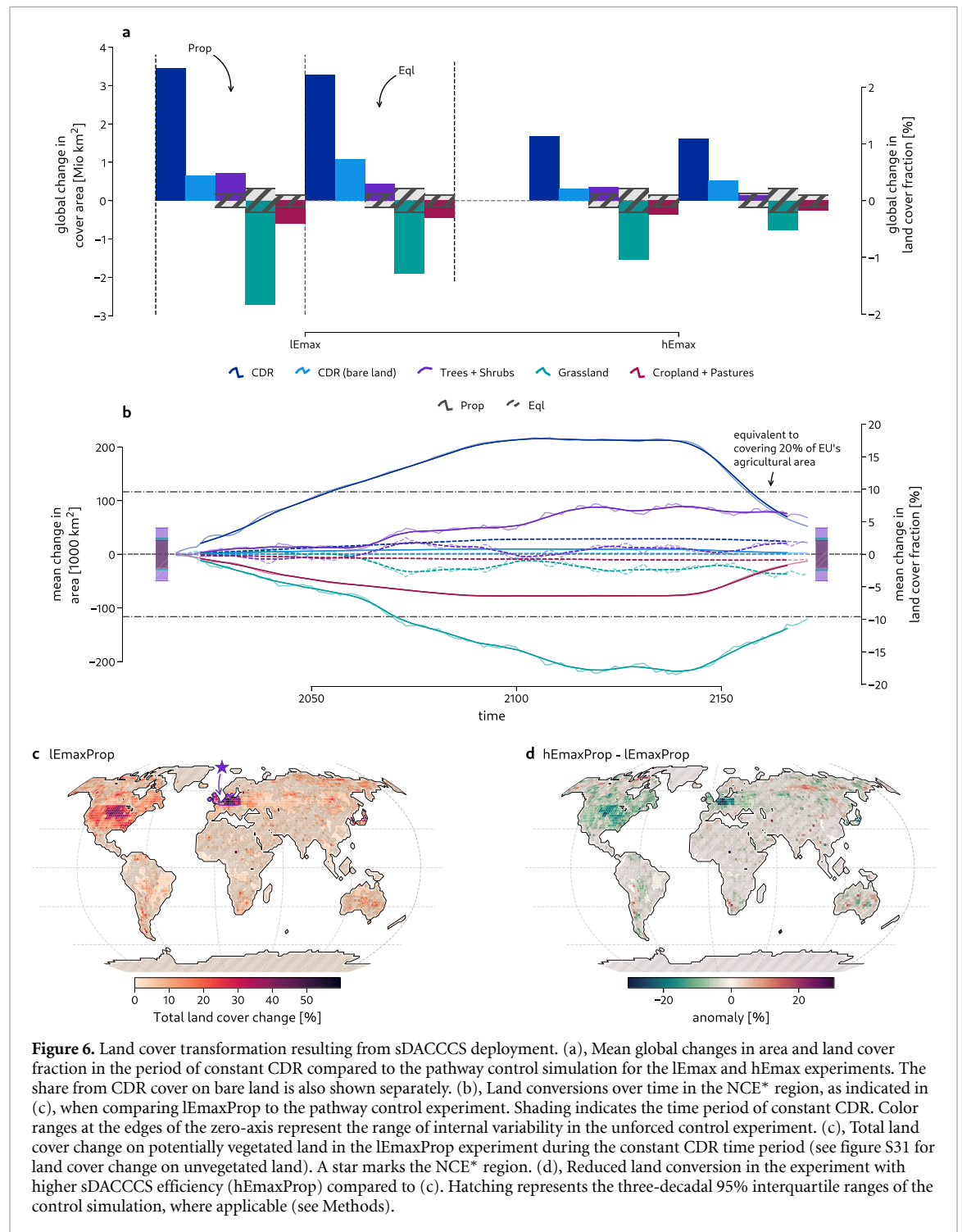
Our study targets unquantified implications of DAC-based process chains on climate, carbon cycle, and land cover identified in IPCC assessments [6, 19]. Leveraging a novel explicit and dynamic representation of land-based CDR in a comprehensive Earth system model, we present simulations of solar energy-powered process chains targeting solid or liquid carbon sink products through direct air capture, CO₂ conversion, and sequestration (sDACCCS). The simulations indicate that large-scale sDACCCS does not substantially offset its climate change mitigation potential by impacting regional surface climate or carbon stocks beyond global-scale effects of CDR on

the Earth system [64]. The Kazakh Steppe and adjacent parts of Siberia are an exception where solar energy harvest for sDACCCS increase surface temperature by ~1K. The minor climatic effects contrast the significant ramifications suggested for some large-scale biomass-based CDR [11, 12]. Further, they are orders of magnitude smaller than studies of exascale solar harvest might suggest [65–67]. These studies find substantial climatic shifts induced by solar farms, but only when pushing photovoltaics beyond demand and localizing facilities predominantly in deserts [65, 66], where albedo effects are most potent. Climate change due to sDACCCS cover does not have to be confined to the deployment location, but could be due to atmospheric teleconnections. However, while our simulations show signs of remote climate variations (figures S17–S18), they barely exhibit significant climate shifts in any region, making offsite consequences unlikely.

Especially if DAC-based technologies cannot meet expectations, there would still be substantial land conversions in a high-CDR world if solar energy harvest is included in the assessment, as previously suggested based on theoretical calculations [20, 68]. These results underline the importance of research efforts into land use-efficient DACCCS process chains. The efficient hE chain, for which we assumed rather conservative efficiencies (Methods) and not the most ideal sink products [14], could constitute such an approach. However, the risks of relying extensively on DAC-type process chains also become evident. For example, land conversions in central Europe which are equivalent to 18% of regional agricultural area (high-CDR world, high efficiency, localized sDACCCS) would constitute a remarkable local intervention into already pressured regions. Underwhelming technological performance could raise this toll to orders of 37%. Hence, reaching a high efficiency both for sDACCCS technology and energy supply can make the difference between an acceptable CDR burden and one exceeding limited land resources [7, 26, 69].

As a consequence of CDR deployment, our simulations reduce agricultural land use and thus emissions through grazing and crop harvest (figures 5(e)–(g)). In some focus regions, these reduced land use emissions offset CO₂ emissions associated with deploying sDACCCS. While the decrease in agricultural land is simply a consequence of the model's land use scheme (Methods, SI), this observation highlights that more efficient food production and plant-based diets would not only decrease land use emissions, but could free up space for CDR deployment [70].

The effect of spatial deployment on global land conversion is almost negligible. However, it co-determines regional land conversions and the potential to lose land-stored carbon. Different distributions of DAC, conversion facilities, and associated energy harvest among countries could shift environmental



impacts between regions. Previous studies already show how the spatial configuration of growing biomass for CDR could affect carbon stocks, land cover, and climate [71]. Thus, burden-sharing should go beyond politico-economical dimensions and climate change impacts and also account for CDR's entire environmental burden.

DAC-like technological progress is uncertain and impossible to extrapolate. Reliable real-world efficiency data is scarce, limiting the accuracy of CDR process models to first-order approximations. In addition, spatial constraints on land availability or

sink product storage are incomplete and future CDR burden sharing is vague. Therefore, our scenario design spreads a range of uncertainty, but whether it covers future technological and political-economic development is unknown. Hence, we interpret our simulations as storyline experiments, not predictions. As hopes for CDR grow, the storylines can provide indications whether DAC and sDACCCS could benefit the climate and environment.

Our CDR submodel exclusively represents DAC-based process chains, including CO₂ conversion to a sink product, and assumes solar energy to drive

the CO₂ reduction. Extending modeling capabilities to assess DAC process chains with several renewable energy sources at a time and alongside natural photosynthesis-based approaches [12] is required to guide the evaluation of CDR portfolios. For instance, our model overestimates the net loss of grasslands in temperate climates because it does not account for the fact that meadows typically fill the space between the absorbers, creating habitats for insect pollinators as a positive side effect [72]. An integrated modeling approach could also help quantifying potential competition and synergies with renewable electricity provisioning. Experiments with interactive land use scenarios could help optimizing adverse and beneficial side effects of CDR approaches in space and time. Finally, generating evidence from a model ensemble could corroborate our results.

We demonstrate that the net CO₂ removal potential of sDACCCS does not suffer substantially from reduced carbon stocks and biospheric carbon uptake due to land conversion. However, the removal potential of sDACCCS is subject to other constraints over its life cycle. Environmental consequences could arise from provisioning resources, constructing and maintaining sDACCCS installations, handling and storing the sink product, and dismantling CDR devices, all of which require life cycle assessment [27, 73]. Other constraints not represented in Earth system models are economic costs, energy and resource demands including post-processing, environmental compatibility, and the geological storage potential and resulting permanence of CO₂ storage, all of which depend on the chosen sink product [14]. Constraining them requires dedicated inventories and modeling. As in general for CDR, permanence, safety and storage potential for sink products merit attention, as they constrain scalability and can contribute to competition for land. We anticipate that storage requirements for solid and liquid products, due to their higher density, are likely less stringent than for storing CO₂ in gaseous form, but it is of crucial importance to evaluate storage potentials, durability, and the environmental compatibility of potential sink products in future work.

Our study provides novel evidence indicating that, within the scope and limitations of our modeling approach, DAC-based process chains targeting liquid or solid products by converting the captured CO₂ cause negligible impacts on climate. Also, these sDACCCS process chains do not induce carbon emissions from the biosphere that would substantially offset their removal potential. At the same time, our results suggest that associated land conversions could lead to substantial target conflicts in a world overly reliant on CDR. In such a world, the risks for target conflicts are particularly high if technological efficiencies fall short of expectations, but persist if highly efficient carbon fixation would be available. Minimizing adverse consequences requires high

technological efficiency, keeping the overall CDR need low through plausible emission reductions, and limiting excessive expectations on CDR. Therefore, reducing the reliance on yet unrealized technological advancements is vital in light of the growing evidence of all lifecycle costs of CO₂ removal.

Data availability statement

The data that support the findings of this study will be openly available following an embargo at the following DOI: [10.5281/zenodo.14795396](https://doi.org/10.5281/zenodo.14795396). Data will be available from 11 July 2025.

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Code availability

MPI-ESM is licensed under the MPI-ESM Software License Agreement, a free, non-commercial, and personalized license and can be obtained at <https://code.mpimet.mpg.de/projects/mpi-esm-license>.

Extensions to represent sDACCCS process chains in MPI-ESM can be made available separately upon request. For code reproducing the figures of the manuscript and the supplementary material, see the Data availability statement.

Author contributions

Conceptualizing the project: MA, KR

Developing the methodology: MA, KR with input from TK and MMM

Developing the software: MA with help from TK

Conducting the simulations, analyzing the data, performing visualization: MA

Acquiring funding: KR, MA, MMM

Administering the project: KR, MMM

Writing the original draft: MA

Contributing to writing and editing the manuscript: all

Conflict of interest

The authors declare no competing interests.

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References

- [1] Matthews H D and Wynes S 2022 Current global efforts are insufficient to limit warming to 1.5 °C *Science* **376** 1404–9
- [2] Pathak M, Slade R, Shukla P, Skea J, Pichs-Madruga R and Ürge-Vorsatz D 2022 Technical summary *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press)
- [3] Riahi K et al 2022 Mitigation pathways compatible with long-term goals *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed P Shukla (Cambridge University Press)
- [4] Babiker M et al 2022 Cross-sectoral Perspectives *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press)
- [5] Nemet G F et al 2018 Negative emissions - Part 3: innovation and upscaling *Environ. Res. Lett.* **13** 063003
- [6] Fuss S et al 2018 Negative emissions - Part 2: Costs, potentials and side effects *Environ. Res. Lett.* **13** 063002
- [7] Lambin E F and Meyfroidt P 2011 Global land use change, economic globalization and the looming land scarcity *Proc. Natl Acad. Sci.* **108** 3465–72
- [8] Smith S M et al 2023 The state of carbon dioxide removal - 1st Edition (<https://doi.org/10.17605/osf.io/w3b4z>)
- [9] Smith P et al 2016 Biophysical and economic limits to negative CO₂ emissions *Nat. Clim. Change* **6** 42–50
- [10] Köhler P, Hartmann J and Wolf-Gladrow D A 2010 Geoengineering potential of artificially enhanced silicate weathering of olivine *Proc. Natl Acad. Sci.* **107** 20228–33
- [11] Heck V, Gerten D, Lucht W and Popp A 2018 Biomass-based negative emissions difficult to reconcile with planetary boundaries *Nat. Clim. Change* **8** 151–5
- [12] Loughran T F et al 2023 Limited mitigation potential of forestation under a high emissions scenario: results from multi model and single model ensembles *J. Geophys. Res.* **128** 12
- [13] Dowell N M, Fennell P S, Shah N and Maitland G C 2017 The role of CO₂ capture and utilization in mitigating climate change *Nat. Clim. Change* **7** 243–9
- [14] May M M and Rehfeld K 2019 ESD ideas: photoelectrochemical carbon removal as negative emission technology *Earth Syst. Dyn.* **10** 1–7
- [15] May M M and Rehfeld K 2022 Negative emissions as the new frontier of photoelectrochemical CO₂ reduction *Adv. Energy Mater.* **12** 2103801
- [16] Lörch D, Mohamed A G A, Euchner H, Timm J, Hiller J, Bogdanoff P and May M M 2024 From CO₂ to solid carbon: reaction mechanism, active species and conditioning the Ce-alloyed GaInSn catalyst *J. Phys. Chem. C* **128** 20827–40
- [17] Fasihi M, Efimova O and Breyer C 2019 Techno-economic assessment of CO₂ direct air capture plants *J. Clean. Prod.* **224** 957–80
- [18] Lackner K S, Brennan S, Matter J M, Park A-H A, Wright A and v. d. Zwaan B 2012 The urgency of the development of CO₂ capture from ambient air *Proc. Natl Acad. Sci.* **109** 13156–62
- [19] Canadell J et al 2021 Global carbon and other biogeochemical cycles and feedbacks *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* ed V Masson-Delmotte (Cambridge University Press) pp 673–816
- [20] Sekera J and Lichtenberger A 2020 Assessing carbon capture: public policy, science and societal need *Biophys. Econ. Sustain.* **5** 14
- [21] Carton W, Asiyani A, Beck S, Buck H J and Lund J F 2020 Negative emissions and the long history of carbon removal *Wiley Interdiscip. Rev.-Clim. Change* **11** 671
- [22] Buck H J 2020 Should carbon removal be treated as waste management? Lessons from the cultural history of waste *Interface Focus* **10** 20200010
- [23] Schreier M, Héroguel F, Steier L, Ahmad S, Luterbacher J S, Mayer M T, Luo J and Grätzel M 2017 Solar conversion of CO₂ to CO using Earth-abundant electrocatalysts prepared by atomic layer modification of CuO *Nat. Energy* **2** 17087
- [24] Goldberg D S, Lackner K S, Han P, Slagle A L and Wang T 2013 Co-Location of Air Capture, Subseafloor CO₂ Sequestration and Energy Production on the Kerguelen Plateau *Environ. Sci. Technol.* **47** 7521–9
- [25] United States National Research Council 2015 *Climate Intervention: Carbon Dioxide Removal and Reliable Sequestration* (2015) (The National Academic)
- [26] Terlouw T, Treyer K, Bauer C and Mazzotti M 2021 Life cycle assessment of direct air carbon capture and storage with low-carbon energy sources *Environ. Sci. Technol.* **55** 11397–411
- [27] Deutz S and Bardow A 2021 Life-cycle assessment of an industrial direct air capture process based on temperature-vacuum swing adsorption *Nat. Energy* **6** 203–13
- [28] Breyer C, Fasihi M, Bajamundi C and Creutzig F 2019 Direct air capture of CO₂: a key technology for ambitious climate change mitigation *Joule* **3** 2053–7
- [29] Zickfeld K et al 2023 Net-zero approaches must consider Earth system impacts to achieve climate goals *Nat. Clim. Change* **13** 1298–305
- [30] Riahi K et al 2017 The shared socioeconomic pathways and their energy, land use and greenhouse gas emissions implications: an overview *Glob. Environ. Change* **42** 153–68
- [31] Meinshausen M et al 2020 The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500 *Geosci. Model Dev.* **13** 3571–605
- [32] Fyson C L, Baur S, Gidden M and Schleussner C-F 2020 Fair-share carbon dioxide removal increases major emitter responsibility *Nat. Clim. Change* **10** 836–41
- [33] Green M A, Dunlop E D, Siefert G, Yoshita M, Kopidakis N, Bothe K and Hao X 2023 Solar cell efficiency tables (Version 61) *Prog. Photovolt., Res. Appl.* **31** 3–16

- [34] Ozkan M, Nayak S P, Ruiz A D and Jiang W 2022 Current status and pillars of direct air capture technologies *iScience* **25** 103990
- [35] Keith D W, Holmes G, Angelo D S and Heidel K 2018 A Process for capturing CO₂ from the atmosphere *Joule* **2** 1573–94
- [36] Schreier M, Curvat L, Giordano F, Steier L, Abate A, Zakeeruddin S M, Luo J, Mayer M T and Grätzel M 2015 Efficient photosynthesis of carbon monoxide from CO₂ using perovskite photovoltaics *Nat. Commun.* **6** 7326
- [37] Melnikova I, Boucher O, Cadule P, Ciais P, Gasser T, Quilcaille Y, Shioyama H, Tachiiri K, Yokohata T and Tanaka K 2021 Carbon cycle response to temperature overshoot beyond 2 °C: an analysis of CMIP6 models *Earth's Future* **9** 1–19
- [38] Mauritsen T *et al* 2019 Developments in the MPI-M earth system model version 1.2 (MPI-ESM1.2) and its response to increasing CO₂ *J. Adv. Modeling Earth Syst.* **11** 998–1038
- [39] Reick C H, Raddatz T, Brovkin V and Gayler V 2013 Representation of natural and anthropogenic land cover change in MPI-ESM *J. Adv. Modeling Earth Syst.* **5** 459–82
- [40] Eyring V, Bony S, Meehl G A, Senior C A, Stevens B, Stouffer R J and Taylor K E 2016 Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization *Geosci. Model Dev.* **9** 1937–58
- [41] Arora V K *et al* 2020 Carbon-concentration and carbon-climate feedbacks in CMIP6 models and their comparison to CMIP5 models *Biogeosciences* **17** 4173–222
- [42] Rast S *et al* 2013 *User Manual for ECHAM6 (Reports on Earth System Science)* (Max Planck Institute for Meteorology)
- [43] Stevens B *et al* 2013 Atmospheric component of the MPI M Earth System Model: ECHAM6 *J. Adv. Modeling Earth Syst.* **5** 146–72
- [44] Jungclaus J H *et al* 2006 Ocean circulation and tropical variability in the coupled model ECHAM5/MPI-OM *J. Clim.* **19** 3952–72
- [45] Paulsen H, Ilyina T, Six K D and Stemmler I 2017 Incorporating a prognostic representation of marine nitrogen fixers into the global ocean biogeochemical model HAMOCC *J. Adv. Modeling Earth Syst.* **9** 438–64
- [46] Xia K *et al* 2018 Heterogeneous reaction of HCOOH on NaCl particles at different relative humidities *J. Phys. Chem. A* **122** 7218–26
- [47] Howard S K 1995 Formate brines for drilling and completion: state of the art *SPE Annual Technical Conf. and Exhibition*
- [48] Hurtt G C *et al* 2020 Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6 *Geosci. Model Dev.* **13** 5425–64
- [49] O'Neill B C *et al* 2016 The scenario model intercomparison project (ScenarioMIP) for CMIP6 *Geosci. Model Dev.* **9** 3461–82
- [50] ESMAP 2020 Global photovoltaic power potential by country (available at: <https://datacatalog.worldbank.org/dataset/global-photovoltaic-power-potential-country>)
- [51] Vuuren D P v *et al* 2018 Alternative pathways to the 1.5 °C target reduce the need for negative emission technologies *Nat. Clim. Change* **8** 391–7
- [52] Realmonte G, Drouet L, Gambhir A, Glynn J, Hawkes A, Köberle A C and Tavoni M 2019 An inter-model assessment of the role of direct air capture in deep mitigation pathways *Nat. Commun.* **10** 1–12
- [53] Peters G P and Geden O 2017 Catalysing a political shift from low to negative carbon *Nat. Clim. Change* **7** 619–21
- [54] Berg N J v d *et al* 2020 Implications of various effort-sharing approaches for national carbon budgets and emission pathways *Clim. Change* **162** 1805–22
- [55] Breyer C, Fasihi M and Aghahosseini A 2020 Carbon dioxide direct air capture for effective climate change mitigation based on renewable electricity: a new type of energy system sector coupling *Mit. Adap. Strat. Glob. Change* **25** 43–65
- [56] Kleidon A, Miller L and Gans F 2016 *Physical Limits of Solar Energy Conversion in the Earth System* (Springer International Publishing) pp 1–22
- [57] Kaur A, Kim B, Dinsdale R, Guwy A, Yu E and Premier G 2021 Challenges in scale up of electrochemical CO₂ reduction to formate integrated with product extraction using electrodialysis *J. Chem. Technol. Biotechnol.* **96** 2461–71
- [58] Adam M, Kleinen T, May M M and Rehfeld K 2025 Data and analysis code in supplement to “Land conversions not climate effects are the dominant indirect consequence of sun-driven CO₂ capture, conversion, and sequestration” *Zenodo* **10.5281/zenodo.14795396**
- [59] Iturbide M *et al* 2020 An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets *Earth Syst. Sci. Data* **12** 2959–70
- [60] Xu L *et al* 2021 Changes in global terrestrial live biomass over the 21st century *Sci. Adv.* **7** eabe9829
- [61] Mo L *et al* 2023 Integrated global assessment of the natural forest carbon potential *Nature* **624** 1–10
- [62] World Bank 2024 World Development Indicators (WDI) (available at: <https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators>)
- [63] Land Use, Food and Agriculture Organization of the United Nations 2023 FAO land use indicators (available at: www.fao.org/faostat/en/#data/RL)
- [64] Zickfeld K, Azevedo D, Mathesius S and Matthews H D 2021 Asymmetry in the climate-carbon cycle response to positive and negative CO₂ emissions *Nat. Clim. Change* **11** 613–7
- [65] Li Y, Kalnay E, Motesharrei S, Rivas J, Kucharski F, Kirk-Davidoff D, Bach E and Zeng N 2018 Climate model shows large-scale wind and solar farms in the Sahara increase rain and vegetation *Science* **361** 1019–22
- [66] Lu Z, Zhang Q, Miller P A, Zhang Q, Bernzell E and Smith B 2021 Impacts of large-scale sahara solar farms on global climate and vegetation cover *Geophys. Res. Lett.* **48** 1–10
- [67] Hu A, Levis S, Meehl G A, Han W, Washington W M, Oleson K W, Ruijven B J v, He M and Strand W G 2016 Impact of solar panels on global climate *Nat. Clim. Change* **6** 290–4
- [68] National Academies of Sciences 2019 *Engineering and Medicine, Negative Emissions Technologies and Reliable Sequestration: A Research Agenda* (The National Academies Press)
- [69] United Nations Convention to Combat Desertification 2022 *The Global Land Outlook* 2nd edn (UNCCD)
- [70] Hayek M N, Harwatt H, Ripple W J and Mueller N D 2021 The carbon opportunity cost of animal-sourced food production on land *Nat. Sustain.* **4** 21–24
- [71] Arora V K and Montenegro A 2011 Small temperature benefits provided by realistic afforestation efforts *Nat. Geosci.* **4** 514–8
- [72] Blaydes H, Gardner E, Whyatt J D, Potts S G and Armstrong A 2022 Solar park management and design to boost bumble bee populations *Environ. Res. Lett.* **17** 044002
- [73] Jacobson M Z 2019 The health and climate impacts of carbon capture and direct air capture *Energy Environ. Sci.* **12** 3567–74

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T. Schürmann	2	5	10	5	5
K. Rehfeld	3	15	-	5	15

Editorial note: Owing to journal requirements, only figure captions are contained within the manuscript, whereas the respective figures are attached to the back of it.

Future volcanic eruptions shift the timing of net-zero emissions

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Abstract

Large explosive volcanic eruptions are inevitable, unpredictable, and impact climate globally. During eruptions, a share of volcanic aerosols may enter the stratosphere, modifying the planetary energy balance. How eruptions affect biosphere carbon uptake is unclear, as including varying volcanic forcing trajectories in climate projections is computationally expensive. Here, we show realistic future volcanic forcing increases projected regional surface air temperature variability for the overshoot scenario SSP5-3.4-OS and adds uncertainty to biosphere carbon sink capacity estimates. We use 300 scenarios of intermittent volcanic forcing to derive estimates of future climate and biosphere productivity from a computationally efficient, regionally explicit simulator. Global mean surface air temperature uncertainty is, on average, 0.32 °C larger with intermittent forcing compared to unforced variability alone (89 % more uncertain). Propagating this uncertainty into net carbon uptake through shared variances between climatic drivers and the biosphere's response increases regional uncertainty by up to 34 % of internal variability. Across low- and mid-latitude land regions, the median of this variability increase corresponds to 35 % of annual net uptake. Regionally, uncertainty in annual temperature is increased by 50 % or more for half of the world's population. Effects aggregate globally and may delay or advance net-zero emissions and stabilization of global mean surface temperature by orders of years to decades, depending on the combination of forcing trajectory and internal variability. Emergent climate variability and forcing uncertainty therefore must also be taken into account when potential deployment of geoengineering is discussed.

Introduction

Intermittent external forcing of the climate system arises from stratospheric aerosol emissions that form after largely unpredictable volcanic eruptions [1]. These varying perturbations significantly increase global temperature variability and future projection uncertainty [2, 3]. Due to computational constraints, regional assessments of this projection uncertainty are not yet widely considered. Climate records, for example, from ice cores, speleothems, and sedimented pollen, indicate that regional climate variability may increase under future volcanic forcing [4]. Higher regional variability in surface air temperature and hydroclimate may increase weather extremes, which challenges biosphere carbon sink resilience and local climate change adaptation and mitigation measures. Volcanic perturbations may amplify modes of variability like ENSO [5] and complicate warming or stabilization trend attribution [3].

When intermittent volcanic forcing leads to changes in surface (hydro-)climate this can impact terrestrial and marine carbon fluxes, because photosynthesis is affected by lowered incoming radiation, plant productivity responds to altered water budgets, and CO₂ solubility is temperature dependent. Considering these effects could yield more representative uncertainty estimates for the efficiency of future carbon sinks and sources. However, the magnitude of future carbon cycle responses to sporadic eruptions remains unquantified. Currently, terrestrial and marine carbon reservoirs are net buffers of anthropogenic CO₂ emissions but re-equilibrate under future climate change [6]. Such re-equilibration dynamics are expected to be particularly strong in likely temperature overshoot scenarios [7], that is emission trajectories resulting in a temporal exceedance of global warming targets set out by the Paris Climate Agreement [8,9]. Whether intermittent volcanic forcing stimulates or reduces natural carbon uptake under future warming, or does both, is unclear. The associated surface cooling and surface radiation reduction could affect various processes across Earth system compartments connected to carbon uptake. Surface cooling enhances the marine CO₂ solubility pump and lowered photosynthetic activity through attenuated solar irradiation could influence the ocean’s biological pump [10]. On land, intermittent volcanic forcing reduces incoming solar radiation and can alter climate, including precipitation patterns and evapotranspiration feedbacks [11,12]. These influence plant water-use efficiency, moisture availability for vegetation, and carbon-positive organic matter decomposition in soils [13–15]. Missing these supplementary uncertainty sources for the carbon sinks impacts future CO₂ emission budget accuracy.

Sporadic volcanic eruptions can be represented in IPCC-class Earth system model (ESM) projections of the recent coupled model intercomparison project phase 6 (CMIP6) and upcoming CMIP7 cycle. Commonly, this is achieved by varying stratospheric aerosol optical depth (AOD), though, a subset of modeling frameworks provides optional, prognostic aerosol chemistry components [16]. However, realistic intermittency is not considered in projections along the shared socioeconomic pathways (SSPs) [17] under CMIP6 or CMIP7 [18,19]. Future eruption timings and magnitudes are unknown, so credible uncertainty estimates require ensemble simulations [2]. This is computationally costly and intractable with ESM simulations for multiple scenarios or model intercomparison. Several statistical approaches have explored emulating future global-mean responses of ESMs to intermittent volcanic forcing [3] or replicating historical temperature evolution [20,21]. This leaves open challenges of using, for example, linear pattern scaling or machine learning for spatially explicit emulation in order to then generate larger ensembles than those possible with ESM simulations [21].

We develop a strategy for resolving regional uncertainties of global mean surface air temperature and net natural carbon uptake along future projection pathways until 2200 using emulation (Data and methods), and apply a large paleo volcanic forcing dataset which covers the last glacial cycle as an analogue for “realistic” future volcanic forcing [22]. The emulation approach balances being physically grounded and tractable, and suitability for broader problems, including low data availability, internal variability and non-linearities [23]. Large volcanic eruptions evoke distinct forced responses of climate modes that contrast from internal variability alone. Therefore, we address the challenge of a sufficiently large simulation ensemble by combining semi-stochastically forced simulations from the comprehensive MPI-ESM [24] with a statistical emulator of the model’s forced response modes (Data and methods). Our Bayesian approach estimates parameters of a stochastic two-box energy balance model (EBM), representing forced and internal variability components. This EBM approach generalizes from Schillinger et al. (2022) [20] to fit two response timescales and two thermodynamic inertias per dominant spatial mode of variability. This enables emulation of spatially resolved, globally consistent temperature time series (Data and methods).

The emulator lets us study spatially resolved Earth system effects of realistic volcanic eruptions under future climate change. We derive an ensemble of 300 forcing realizations along the extended SSP5-3.4-OS temperature overshoot scenario until 2200 [17, 25]. This quantifies supplementary variability in global and regional surface climate from intermittent volcanic forcing (Fig. 3a, b). Based on temperature and moisture variance estimates, we infer supplementary uncertainty in vegetation productivity and carbon uptake into land and ocean sinks regionally and globally, which has the potential to affect the timing of net-zero emissions and temperature stabilization.

Data and methods

We combine Earth system model simulations driven by realistic, intermittent volcanic eruptions with an emulator based on a stochastic EBM, which operates on the dominant spatiotemporal modes of surface air temperature variability. Using the covariance between climatic drivers and biotic response variables, we leverage the emulator to estimate the supplementary uncertainty that volcanic variability induces on surface climate and carbon fluxes. The variability assessment utilizes power spectra and variance ratios.

Earth system model simulations of a temperature overshoot scenario with intermittent, paleo-informed volcanic forcing

Simulations with the Max–Planck–Institute Earth system model (MPI-ESM) version 1.2 [24] provide the basis for our study (Table 1). They serve to quantify the Earth system response to intermittent volcanic forcing (S1 Text), emulate the simulated surface climate’s forced response (next section), and estimate the covariance between climatic and biotic variables. We use the ECHAM6.3 atmosphere model [26] with a T63 spectral truncation (approximately 200 km grid spacing) and the MPIOM ocean model [27] on a GR15 grid (150 km approximate spacing). The model setup features a fully coupled, nitrogen-limited terrestrial and marine carbon cycle, run in an emission-driven mode. Boundary conditions for greenhouse gases and land use follow the CMIP6 and ScenarioMIP protocols [28] and their long-term extensions [25]. ECHAM6.3 parametrizes the radiative impact of external volcanic forcing as modulations of AOD.

Table 1. Overview of simulated and emulated datasets. All datasets contain transient greenhouse gas forcing (SSP1-2.6, 2-4.5, 5-8.5 for MPI-GE and SSP5-3.5-OS for the other datasets).

Ensemble	Size	Volcanic forcing	Purpose
MPI-ESM control	8	PalVolv1 median event within 79–23.5 kyr BP	Baseline
MPI-ESM forced	8	Intermittent, 8 subsets of PalVolv1	ESM reference, calibrate emulator
Emulator forced+internal	300	Intermittent, 300 subsets of PalVolv1	Uncertainty under SSP5-3.4-OS
MPI-GE [29]	50 per SSP	CMIP6-ScenarioMIP [28]	Internal variability for other SSPs

We employ the PalVolv1 dataset of past volcanic eruptions [22] as a paleo-informed boundary condition to model future intermittent volcanic forcing. PalVolv1 is a unique resource that combines the paleo-record of eruptions from the last 140,000 years with stochastic sampling of smaller-sized eruptions. This is to correct for undersampling of small volcanic eruptions in paleo archives by augmenting the paleo-record with stochastically sampled small events and results in a more realistic distribution of occurrences [22]. Sampling effects of intermittent volcanic forcing on climate and carbon cycle demands a sufficiently high number of temporarily contrasting realizations of sporadic volcanic events. Therefore, out of the 100 realizations in the PalVolv1 dataset,

we select the 50th member for our study and derive 55,500 years of consistent, intermittent forcing from it (see below). By contrast, sampling a single time frame across PalVolv1 members would allow studying effects of the member spread within that ensemble on simulated climate and carbon cycle variability, but not of temporal stochasticity. To produce MPI-ESM simulations for emulator calibration, we first subdivide the PalVolv1 realization into five non-overlapping 185-year time segments. These selected segments are spaced apart by at least 1000 years. Subsequently, three of the segments are shifted forward in time by 61 years, increasing the ensemble size to eight members. This approach reduces biases in the distribution of events over time, albeit not eliminating them entirely (Fig. 2). This yields more reliable mean climatologies (S1 Text) and has no impact on the emulator’s parameter estimates (next section, S4 Fig). In contrast to the volcanic forcing of varying intensity, each member of the climatological control ensemble experiences the median event of one of the stochastically forced simulations. This yields an ensemble of background climatologies without the timely varying volcanic influence on climate variability but the same median background as the stochastically forced ensemble.

Our goal with the emulator is to derive a time-stable and more realistic uncertainty envelope from intermittent volcanic forcing for SSP scenarios. We therefore divide the selected PalVolv1 realization into time series segments of 185 years. We cut 300 members out of the time frame 79,000–23,500 before present, which is characterized by the absence of substantial trends in volcanic activity [22]. Each of the members are then fed into the Easy Volcanic Aerosol version 1.2 (EVA) forcing generator [30], as are the eight forcing realizations of the MPI-ESM simulations. EVA employs a three-box parametrization of aerosol transport in the stratosphere and a simple scaling relationship between aerosol mass and AOD to convert aerosol load, timing, and location of volcanic eruptions into aerosol optical properties by latitude and radiative band [30]. In contrast to EVA_H [31], the recent generator iteration that will be used within CMIP7, EVA does not account for aerosol injection height, which leads to higher stratospheric AOD estimates [31]. However, MPI-ESM is a model from the CMIP6 cycle and Paleoclimate Modelling Intercomparison Project (PMIP) phase 4. Therefore, using EVA provides consistency with previous studies [e.g., 32–34] employing this model along the lines of the PMIP4 protocol [35]. Moreover, the characterization of PalVolv1 by Schindlbeck-Belo et al. (2023) [22] is directly compatible with our forcings, since it also applies the original version of EVA. Despite the different forcing generators, the ensemble median of time-averaged stratospheric AOD at 550 nm of our intermittent forcing dataset (0.014, S1 Fig) closely matches the constant AOD value assumed for 2015–2100 in CMIP7 [18] and the median of the time-averaged stochastic forcing ensemble used by Chim et al. (2025) [3] to drive their global impulse–response function approach. Accounting for the differences between EVA and EVA_H described above, our forcing reflects a lower mass of sulfurous oxide injected than in CMIP7 but effectively yields a similar median stratospheric AOD forcing, maintaining forward compatibility.

Separating internal climate variability and forced response of the simulated surface air temperature

We expand the two-box emulator approach of Schillinger et al. (2022) [20] to spatiotemporal data. For this purpose, we decompose the simulated temperature data into empirical orthogonal functions (EOFs, S2 Fig) and fit a stochastic EBM to the resulting principal components of variability. EOFs are a standard approach for reducing the dimensionality of spatiotemporal data [36]. Essentially, the EOF method uses spatiotemporal covariance in the data to perform a base decomposition into dominant and orthogonal spatial modes. Each mode is associated with a time series

(“principal component”) representing the variations of that mode. For our study, we perform a decomposition into ten spatial modes and principal components using the entire annually averaged surface air temperature dataset from MPI-ESM simulations with intermittent volcanic forcing from 2015 to 2200 (Fig. 1). These ten orthogonal modes capture 69 % of the variability contained in the data. The first seven modes already account for 66 % of the overall variance. This truncation results in a root mean square error (RMSE) of 0.3 K averaged over space and time. After the spatial decomposition, we linearly regress principal component time series containing a CO₂ trend onto the CO₂-forcing and subtract that trend from the time series (Fig. 1). The trend is still included for visualizing climate change over time, but not counted into the internal variability component for relative comparisons with internal+forced variability from volcanic intermittency.

Fig 1. Forward (a) and inverse application (b) of the spatiotemporal emulation approach. Solid lines represent data inputs and dashed lines depict outputs.

Finally, we fit the two-box EBM on each principal component to separate the forced response to external volcanic forcing from internal variability (Fig. 1, S3 Fig). For this step, we employ the ClimBayes package [20], with prior ranges and parameters of the fitting algorithm as documented in S1 Table and the original publication. The stochastic model resolves space implicitly through the upstream EOF decomposition. Therefore, as input for the EBM, we globally average the latitudinally resolved ESM forcing and limit it to the 550 nm band (441.5–625 nm). We conduct the Bayesian inference step [20] separately for each forcing realization, yielding an ensemble of EBM parameters for each principal component (S4 Fig). These parameters describe the dynamics of the principal components and are consequently dimensionless. However, they still provide insights into the characteristic physical timescales and (thermo-)dynamic inertia of the spatial modes (S4 Fig). In addition, comparing the parameters between different realizations confirms that the EBM fitting is stable across them (S4 Fig), justifying using the median value of each EBM parameter for projections.

We exploit the fitted EBM in two ways. The first separates the internal and volcanically forced components of surface air temperature fields by recombining the EOFs with either the forced or internal contributions to the principal components. Core to the stochastic EBM, this assumes additivity of the forced and internal variability components. The second turns the fitted EBM into an emulator of the MPI-ESM forced response to intermittent volcanic forcing (Table 1) by inverting it with new forcing realizations, adding the internal variability component and CO₂ trend, and recombining the spatiotemporal decomposition (Fig. 1b). In this process, we reuse the internal variability inferred during the fitting stage. While creating synthetic variability samples would be an alternative [20], this approach conserves the internal spatiotemporal covariance structure of the ESM. The average RMSE is 0.019 K between the inverted EBM and the recombined EOF truncation, and 0.027 K when comparing the ten-year mean response after the 30 % strongest volcanic events between the fit and the ESM simulations.

We define the uncertainty $q(t)$ of regional and global future projections as the 95 % inter-quartile range of a simulation ensemble at time t with inter-quartile range q_j

$$q_j = q_{u-l}(t) = q_u(t) - q_l(t) \quad (1)$$

and the specific case

$$q(t) := q_{97.5-2.5}(t) = q_{97.5}(t) - q_{2.5}(t) \quad (2)$$

where the lower and upper linear empirical sample quantiles q_l and q_u are set to the 2.5th and 97.5th quantile, respectively. In our convention, this uncertainty envelope encompasses both the volcanically forced and internal variability components. We denote the uncertainty envelope q^{int} if the forced response to volcanic intermittency has been excluded.

Estimating the additional uncertainty of regional and global carbon fluxes and their climatic drivers due to volcanic forcing

We provide a first-order estimate of the supplementary uncertainty that intermittent volcanic forcing adds to natural carbon fluxes at regional and global levels. To achieve this, we propagate the uncertainty increase relative to internal variability – which was determined explicitly for surface air temperature – by weighting it according to the shared variance between carbon fluxes and climatic drivers. Here, we assume surface air temperature (T) and the hydrological cycle are the predominant drivers of (terrestrial) vegetation productivity (f_{GPP}) and (terrestrial+marine) net CO₂ uptake into natural sinks (f_{nat}). We consider either precipitation (P) or soil moisture (M) as proxies for hydrological conditions. The shared variance between observables i, j is defined by the Pearson correlation ρ .

$$r_{ij} = \rho(x_i, x_j)^2 \quad (3)$$

For the regional analysis, we determine shared variances r_{ij} for each region using annually averaged data. On the global scale, a variable windowing takes place when necessary (next section).

Based on the ratio between volcanically forced+internal and internal temperature uncertainty, and assuming the shared variance does not change substantially over the time interval of interest, the relative change $\Delta^r q_i = q_i/q_i^{int} - 1$ in precipitation uncertainty is

$$\Delta^r q_P = \Delta^r q_T \cdot r_{T \times P} \quad (4)$$

The computation for soil moisture as the hydrological proxy is analogous. For the carbon fluxes, illustrated for f_{GPP} below, we assume that temperature and hydroclimate contribute additively without overlapping.

$$\Delta^r q_{f_{GPP}} = \Delta^r q_T \cdot r_{T \times f_{GPP}} + \Delta^r q_P \cdot r_{P \times f_{GPP}} \quad (5)$$

$$= \Delta^r q_T \cdot \left(r_{T \times f_{GPP}} + r_{T \times P} \cdot r_{P \times f_{GPP}} \right) \quad (6)$$

This simplification is adequate for a first-order estimate since typically either temperature or moisture exerts dominant control over regional vegetation productivity, but not both simultaneously. The correlation between precipitation and the ocean-atmosphere carbon flux is negligible in the first place. We compare uncertainty changes to the total annual carbon fluxes $[f_{GPP}]$, $[f_{nat}]$ by rescaling the relative uncertainty change with respect to internal variability using the ratio between internal variability and total fluxes.

$$\Delta^r q_{f_{GPP}} \cdot \frac{q_{f_{GPP}}^{int}}{[f_{GPP}]} = \frac{q_{f_{GPP}} - q_{f_{GPP}}^{int}}{[f_{GPP}]} \quad (7)$$

Estimates of increased SSP uncertainty

Deriving global uncertainty cones along SSP pathways relies on the same reasoning. However, instead of scaling only uncertainties defined by inter-quartile ranges, we perform an empirical quartile transformation of the uncertainty distributions of the MPI-ESM grand ensemble's SSP projections [29] produced under the

CMIP6-ScenarioMIP protocol [28]. Each of these SSP ensembles comprises 50 members and is not forced by intermittent volcanic eruptions (Table 1. This extension accounts for asymmetries in the distributions when propagating increased uncertainty through additional variability components. As a first step, we diagnose the relative difference in each inter-quartile range q between T in our emulated ensemble with intermittent volcanic forcing and T in our control ensemble. As before, the propagated uncertainty increase δq_i for the first- and second-order response variables ($i \in \{P, M, f_{GPP}, f_{nat}\}$) results from their shared variances (index i subsequently dropped).

$$\delta q = \Delta^r q \cdot q^{int} \quad (8)$$

Next, for each of those variables, we calibrate the quartile transformation based on simulations with intermittent forcing and the control ensemble using a weighting factor

$$a_u = \frac{q_u^v - m^v}{m^v - q_l^v} \cdot \frac{m^c - q_l^c}{q_u^c - m^c} \quad (9)$$

where m^v , m^c are the medians of the volcano-forced and the control case, respectively. a_u captures the contributions of a shifting upper quartile q_u and lower quartile q_l to the change in inter-quartile range δq . The contribution of q_u is given by

$$\tilde{a}_u = \frac{a_u}{1 + a_u} \quad (10)$$

and of q_l by

$$\tilde{a}_l = \frac{1}{1 + a_u} \quad (11)$$

Then, the transformed quartiles are given by

$$q_u = q_u^c + \delta q \cdot \tilde{a}_u \quad (12)$$

$$q_l = q_l^c - \delta q \cdot \tilde{a}_l \quad (13)$$

S12 Fig displays the resulting distributions for different timescales. These uncertainty estimates are rather conservative, since we calibrate the quartile transformation on the relationship between simulations with intermittent volcanic forcing and median event forcing (control), but apply it to the MPI-ESM grand ensemble [29], which does not include varying volcanic forcing (also no median event). While sub-decadal variability dominates the overall uncertainty distributions, varying volcanic forcing stimulates multi-annual to multi-decadal climate in particular, which is reflected in overproportionally high relative uncertainty increase on these time scales (S12 Fig).

Computing power spectra and variance ratios

Power spectra provide insight into the relative importance of variations on specific timescales for the overall variability of a variable. Mathematically, the power spectral density (PSD) is the Fourier transform of a time series' autocovariance function. To minimize artefacts when computing power spectra, the multitaper approach has proven reliable and superior to non-parametric approaches. Here, we employ it in the same way as Ellerhoff et al. (2021) [37] to compute the PSD with corresponding uncertainties. Similar to Schillinger et al. (2022) [20], the PSD is smoothed logarithmically with a Gaussian kernel of 0.04 dB. To obtain timescale dependent variance ratios, we divide the PSD estimate of interest by that of the baseline experiment and propagate the uncertainties based on the PSD's degrees of freedom following Ellerhoff et al. (2021) [37].

Computation of the relative global variance increase $\hat{\sigma}^2$ differs by variable. For the global mean surface air temperature, we infer it directly from the variance ratio of forced realizations to the model’s internal variability

$$\hat{\sigma}^2(\tau) = \frac{\sigma_{\text{forced}}^2}{\sigma_{\text{internal}}^2}(\tau) - 1 \quad (14)$$

Increases in variance of the remaining variables build on propagating this temperature uncertainty on logarithmically spaced time intervals with the shared variance approach. For this purpose, we first apply a Gaussian bandpass filter to the global time series for each time interval and compute the shared variance. We use these time-scale-dependent values to compute the scaling factors described in the previous section.

Results

Increased multi-annual to -decadal climate and biosphere variability along the temperature overshoot

We investigate the potential of intermittent volcanic forcing to shift the timing of net-zero emissions along an overshoot pathway (Fig. 2a, 3a). Our simulations show volcanic aerosol forcing reduces energy input over most land and many ocean regions (Fig. 2c). This causes surface cooling almost universally, particularly over land and in mid- to high-latitudes (Fig. 2, S1 Text). A belt from the Sahara to India is an exception, showing an increasing top-of-atmosphere radiative forcing from shifting circulation and cloud patterns (Fig. 2c, e; S7 Figa). Hydroclimate responses to eruptions are spatially heterogeneous, with weakened equatorial precipitation systems and strengthening over the southern Indian Ocean and North Atlantic, suggesting dynamic and thermodynamic adjustments (S1 Text).

Fig 2. Global and regional effects of intermittent volcanic forcing on the radiation budget, surface climate, and natural carbon sinks under a 2°C-overshoot scenario. (a) Ensemble median and spread of the top-of-atmosphere radiative imbalance, global mean surface air temperature (GMSAT) anomaly to the pre-industrial era, global annual GPP flux through vegetation (f_{GPP}), and natural carbon uptake (f_{nat} , positive for uptake, negative for net release) for 35-year time slices (grey shading) over the course of the SSP5-3.4-OS scenario and for the simulation ensemble forced with intermittent volcanic forcing (IVF) and the control ensemble with constant volcanic forcing (CVF). Dots indicate the individual ensemble members which are bandpass-filtered for time scales from three to 40 years to remove the long-term trend in the variability calculation and shifted by the ensemble median. Thin lines represent the CO₂ concentration evolution for each of the IVF members. Depiction is building upon Bethke et al. (2017) [2]. (b) Global mean power spectral density (PSD) on multi-annual to multi-decadal time scales τ for the two simulation ensembles. Shading represents the 95 % uncertainty range. Units U^* are analogous to panel (a). (c-h) Mean responses of IVF simulations to the strongest 30 % of volcanic events (≥ 5 TgS peak stratospheric aerosol load) in the ten years after an eruption displayed as anomalies to the CVF baseline. Panels show (c) the TOA radiation imbalance, (d) surface air temperature, (e) annual precipitation, and (f) soil moisture content. Stippling marks insignificant values based on a 95 % confidence t-test against the CVF control ensemble. Coastlines reflect land-sea mask and grid resolution of MPI-ESM.

Vegetation productivity anomalies and net carbon uptake relate to soil-moisture anomalies and are spatially confined (S7 Figb, c; Fig. 2f). Following eruptions,

Fig 3. Volcanic-induced surface air temperature variability relative to internal variability. (a) Median values (lines) and 95 %-confidence intervals (shading) for ensembles of ESM-modeled (pink) and emulated (red) global mean annual surface temperature (GMSAT) compared to the unforced variability component (blue). The emulated ensemble yields temporarily stable uncertainty estimates. (b) Share of world population exposed to additional SAT variability relative to internal variability. South, Eastern and South-Eastern Asia as defined by IPCC reference regions [38] are specifically highlighted. (c) Regional inter-quartile ranges (IQR) of unforced surface air temperature variability (left bars) and relative increase of temperature variability through sporadic volcanic events (*, right bars) for all IPCC reference regions and the forced simulation and emulation ensembles. Coastlines reflect land-sea mask and grid resolution of MPI-ESM.

equatorial Africa’s vegetation productivity decreases due to changes in radiative and climatic drivers, but net carbon uptake into natural sinks increases locally. This is due to simulated slowing of soil organic matter decomposition under cooler, less humid conditions. In mid-latitudes (southern Africa, North America, parts of Eurasia) intermittent volcanic forcing reduces natural carbon uptake. Here, precipitation surplus stimulates organic matter decomposition, which is not outweighed by increasing vegetation productivity (S7 Figc).

Climatological variables such as surface air temperature exhibit strongly increasing multi-annual to decadal variability under intermittent volcanic forcing (average ensemble spread increases by 4.4 times compared to the control; Fig. 2a). The variability increase of gross primary productivity (GPP) fluxes and net carbon uptake is lower than that of the climatological variables but still substantial (ensemble spread +49 % for GPP, +35 % for net carbon uptake). This effect scales with the aerosol load emitted within the averaging period. Differences in power spectral density are smaller for carbon flux than abiotic variables (Fig. 2b, S8 Fig). On multi-annual timescales, net carbon uptake into natural sinks is slightly lower and, over 15–20 years, more variable in the forced ensemble. Significant spectral density differences persist for 11–18- and 23–28-year timescales in the global GPP flux.

Increasingly uncertain regional temperature pathways

Volcanic forcing increases multi-annual to multi-decadal surface air temperature variability in future environmental and climatological projections. Consequently, uncertainty in the temperature pathway, which depends on the forcing’s realization, increases. Across our 300-member emulation ensemble, aerosol forcing increases the global mean temperature pathway’s uncertainty envelope by a time-average of 0.32 K versus internal variability, corresponding to an 89 % uncertainty growth in the global temperature pathway (Fig. 3a). The eight-member ESM simulation ensemble shows an 0.20 K increase in average uncertainty, indicating a 56 % higher uncertainty (Fig. 3c, legend). Simulated and emulated results suggest consistent regional heterogeneity in surface air temperature variability increases (Fig. 3). Many regions, particularly in low-to mid-latitudes where inter-quartile ranges (IQR) of unforced surface air temperature variability are comparably low, experience a high relative increase of temperature variability through sporadic volcanic events (Fig. 3c). Consequently, additional SAT variability affects much of the world population (Fig. 3b). Under realistic volcanic forcing, around half the world population faces a 50 %+ increase in expected regional mean annual surface air temperature variability (Fig. 3b), mainly due to increased variability in eastern, southeastern, and central Asia.

Subtropical regions and mid-latitudes witness the highest relative increases over land

and oceans (Fig. 3c). However, absolute uncertainties are about an order of magnitude smaller over oceans than on continents because the land-sea contrast in thermodynamic inertia causes lower unforced variability over waters. Intermittent volcanic forcing most strongly impacts regional temperature uncertainty relative to the unforced variability in a region spanning from northern Africa and the Mediterranean through central Eurasia to eastern Asia (Fig. 3c). In these regions, relative uncertainty increases by 68 % to 99 %, matching the near doubling globally. This trend is also evident in northern-central America (95 % relative increase), southeastern South America (78 %), and over the oceans (42 % – 119 %), excluding the Equatorial Pacific and Polar Oceans. In polar regions, South America and much of the Northern Hemisphere, internal variability is high, with volcanic forcing adding further minor uncertainty (e.g., 16 % in northwestern South America, 20 % in eastern Europe, and 15 % in northwestern North America). Where internal variability is lower but substantial (e.g., in northern central North America, South Africa, northern Australia), volcanic-induced forced variability almost doubles it.

Heightened uncertainty in regional and global carbon fluxes with consequences for climate stabilization and net-zero pathways

We propagate the additional variability due to expected intermittent volcanic forcing using high correlations between climatic drivers and carbon flux responses (Fig. 4a-c, e) in a conservative, shared variance approach, which combines regional correlations with two levels of driver and response variables (Data and methods). Volcanic impacts start out with radiative imbalance as external forcing. This correlates mostly positively with surface air temperature (Fig. 4a). By first order, surface air temperature, emulated as the forced response to the radiative forcing from volcanic events, drives precipitation (Fig. 4b) and natural carbon fluxes (Fig. 4c, S9 Fig). Outside high-latitudes and eastern Asia, regional temperature–precipitation correlations are negative over land due to evapotranspiration feedbacks [39,40]. Over oceans, volcanic-induced temperature and precipitation changes correlate positively, since temperature controls evaporation [40]. Equatorial Atlantic is an exception, showing a negative correlation due to its ties to neighboring landmasses. Surface air temperature inversely correlates with GPP in virtually the same regions (Fig. 4c), whereas precipitation correlates positively with GPP, coinciding with a dominant moisture control on vegetation (Fig. 4e). Strong temperature control accompanies positive temperature–GPP correlations (e.g., in the Northern Hemisphere’s mid- to high-latitudes, eastern Asia, North America’s eastern coast, southwestern and southern South America, New Zealand), so precipitation weakly or inversely correlates with GPP here. Generally, GPP responses depend more directly on soil moisture than precipitation. Considering soil moisture as a climatic driver strengthens the anti-correlation with GPP in high-latitudes, but yields similar shared variances elsewhere (S10 Fig).

Fig 4. Shared variances between climatic drivers and GPP, and the resulting supplementary GPP uncertainty from intermittent volcanic forcing in all IPCC regions. (a–d) Driver–response correlations of regional mean time series averaged over the simulation ensemble with long-term trends removed. To propagate supplementary uncertainty of intermittent volcanic forcing up to GPP, the first-order temperature response to external radiative forcing is explicitly emulated. Second- and third-order responses are estimated with the shared variance approach (Data and methods). (e) Resulting increase in the 2.5–to–97.5 % inter-quartile range of regional GPP fluxes relative to spread from internal variability. All maps report continuous data despite the regions being categorical.

By propagating the additional variability of the regional temperature pathway through pair-wise regional correlations (Data and methods), we obtain increased uncertainties of regional GPP fluxes (Fig. 4d) and net uptake (S9 Fig). Substantial GPP uncertainty increases are comparably localized, particularly in subtropical and some temperate regions, most notably in eastern Asia (25 % relative to internal), northern Central America (26 %), and northern and central Australia (22 % to 40 %). Relative uncertainty rises by 15 % in northern South America, 15 % in southern Asia, 18 %–21 % in southern Africa, and 13 % in the Mediterranean. While the shared variance approach suggests GPP flux uncertainty increases substantially, it remains small compared to total regional GPP turnover (S11 Fig).

The propagated uncertainty increase of net carbon uptake is substantial when compared to the total annual uptake particularly over land (S11 Fig). Across low and mid-latitude regions, it reaches a 35 % median, due to high variability in regional carbon sinks relative to net carbon uptake. We also obtain uncertainty estimates for oceans. Since CO₂ water-solubility is temperature-dependent, the pattern and magnitude of the oceanic impacts follow regional temperature uncertainty (S9 Fig, +2–17 % over some non-polar oceans). Despite their varying influence on total annual flux rates, the spatial patterns and magnitude of propagated uncertainty relative to the internal component align closely with the GPP flux (median of land regions 5.7 %, maximum 34 %; Fig. 4, S9 Fig).

The additional variability impact from climatic drivers on the carbon cycle response is timescale dependent (Fig. 5). Concerning climatic drivers, the variance increases prominently by up to 114 % in global mean surface air temperature on multi-annual to multi-decadal timescales, with a large ensemble spread of 69 %–165 % (95 % range). The propagated variance increase for global precipitation is similar but muted, peaking at an 87 % variability increase (50 %–128 %). This muting is expected given the share of precipitation variability not temperature correlated. Notably, muting is more pronounced on multi-annual to decadal timescales than for multi-decadal variability modes. Differing covariance characteristics between vegetation productivity, net carbon uptake, and the two climatic driver variables considered here (Fig. 4, S9 Fig) lead to differences between vegetation productivity and net carbon uptake. The maximum variance increase for net carbon uptake is +42 % (25–60 %) at 10–20 year timescales, while vegetation productivity shows +47 % (20 %–78 %) across 20–30 years (Fig. 5).

Fig 5. Time-scale dependence of global variance increase from intermittent volcanic forcing for mean surface air temperature (GMSAT), mean annual precipitation (GMP), GPP flux (f_{GPP}), and net natural carbon uptake (f_{nat}). Values are relative to internal variability and computed from annual values. Temperature variance increase is directly emulated, while precipitation, GPP and natural carbon flux are inferred indirectly (Data and methods). Time scale is reported on a logarithmic axis. Thick lines mark the mean; shading and thin dashed lines indicate the 95 %-confidence range.

Variability in the Earth system from intermittent volcanic forcing increases SSP scenario uncertainty (Fig. 6). Notably, stabilizing global climate and achieving net-zero emissions can be delayed or accelerated (Fig. 6a, d). This delay/acceleration is pathway dependent and reaches an order of several years to a decade. A wider uncertainty envelope implies a higher probability that a single realization will deviate farther from the ensemble mean pathway. Global mean surface air temperature and global precipitation show predominantly negative excursions arising from the cooling effect of stratospheric aerosols and the Clausius–Clapeyron relationship. This makes it more likely to exceed global warming targets later when volcanic eruptions occur (Fig. 6a). Equally, a realization is more likely to temporarily reach or undercut a global warming

target early in stabilization or after overshooting it (Fig. 6). However, volcanic events are sporadic, so realizations do not necessarily follow a persistently cool pathway even if they reach comparably cool temperatures or high natural carbon uptake at some point in time. As an example for the impact of volcanic intermittency, our results suggest surpassing 1.5 °C warming in 2046 under SSP2-4.5 could be shifted by up to 19 years into the future, provided major volcanic eruptions take place (Fig. 6a).

Fig 6. Increased variability along future global climate and carbon cycle pathways from intermittent volcanic forcing. (a) Mean surface air temperature anomaly to the pre-industrial era, (b) mean precipitation, (c) annual GPP flux, (d) net annual carbon uptake into terrestrial and marine sinks for 50-member MPI-ESM ensembles of the SSPs 1-2.6, 2-4.5, and 5-8.5 [29] as indicated. Solid lines represent the ensemble mean. Shading indicates the 95 % ensemble spread without intermittent volcanic forcing (no IVF, colored) and with intermittent volcanic forcing (IVF, gray). Estimates of increased uncertainty employ the shared variance approach (Data and methods) corrected for slight differences between the internal variability of the 50-member ensembles and that diagnosed by the emulator for the explicitly forced IVF ensemble. Markers in (a) indicate the raised likelihood for a delayed surpassing of a global warming target. In (d), they illustrate the increased likelihood of more effective (5-8.5) and less effective natural carbon sinks (1-2.6). A 10-year running average is applied to the ensemble statistics to improve readability. S13 Fig reports the unsmoothed data.

Owing to spatially varied responses of the hydrological cycle to global cooling, additional variability in the global GPP pathway and net uptake is not unidirectional (Fig. 6c). Considering intermittent volcanic forcing increases the likelihood that natural carbon sinks, which buffer anthropogenic CO₂ emissions, will vary more strongly in effectiveness (Fig. 6d). Therefore, intermittent volcanic forcing can both delay and advance achieving global net-zero emissions by modulating natural carbon sink efficacy. As an example under SSP1-2.6, natural carbon sinks could turn into temporary sources earlier and reach net emission rates of 2091 already ten years prior (Fig. 6d), which would delay reaching net-zero emissions.

Discussion

Marine and terrestrial carbon sinks buffer a substantial share of CO₂ emissions in future climate pathways. In this context, evolution and disequilibrium dynamics of long-term average global carbon sinks in our simulations are consistent with multi-model ensembles of SSP5-3.4-OS [7]. In addition, for many mid- and low-latitude regions, our results suggest intermittent volcanic forcing increases net carbon uptake uncertainty on land by 35 % or more relative to net annual uptake averaged over the time frames with highest uptake rates, which correspond to times of rising and peaking CO₂ forcing (Fig. 2). Globally, we find a 34 % increase in the uncertainty envelope using a conservative estimation technique that aggregates only the uncertainty increase explained linearly through covariance. Thus, volcanic eruptions could both advance and delay reaching net-zero carbon emissions by altering natural carbon sink efficacy, depending on the forcing trajectory and Earth system feedbacks. This is in line with previous work on natural and deliberate stratospheric aerosol injections suggesting sporadic aerosol forcing propagates into vegetation productivity [41,42], although there is substantial model spread regarding sign and localization of net effects. However, these studies take a contrasting view of single eruptions and do not focus on effects of forcing stochasticity. It is unclear how pathway-dependent responses to inevitable

forcing from volcanic eruptions may interact with deliberately timed aerosol injections. Therefore, future work should combine the views of single events which may serve as analogs for geoengineering and of naturally occurring stochasticity. Natural carbon sinks are pivotal in climate stabilization scenarios, with increased uncertainty impacting net-zero or net-negative emissions planning and limiting planetary temperature rise. Accounting for and communicating net-zero's lower temporal certainty in state-of-the-art climate projections is crucial for avoiding misconceptions about knowns and unknowns regarding CO₂-driven climate change and geoengineering.

Carbon flux uncertainty originates from increased temperature and hydroclimate variability. Our time-averaged estimate of uncertainty increase in global annual mean surface temperature (0.32 K, 89 % of the internal component) is comparable to estimates by Chim et al. (2025) [3] (~ 0.3 K absolute increase, ~ 100 % of internal variability, referring to Fig. 1a in their publication) but exceeds estimates by Bethke et al. (2017) [2] for uncertainty increases in global mean surface temperature (0.2 K absolute increase, ~ 66 % of internal variability, referring to Fig. 2a and its discussion in their publication). The differences likely stem from MPI-ESM's higher climate sensitivity than of the NorESM model [43] employed by Bethke et al. (2017) [2]. Our study accounts for under sampling of smaller volcanic events in ice-core records (Data and methods). The smaller 60-member ensemble in Bethke et al. (2017) [2] could cause a negative bias of 0.02 to 0.05 K (S6 Fig). Our results suggest that ensemble sizes of 150+ members ensure convergence and time-stable uncertainty estimates (S2 Text, Fig. S6 Fig).

Our results reveal substantial spatial heterogeneity. Annual mean surface air temperature uncertainty increases of at least 50 % affect half the global population [44], particularly across Asia, Central America, Africa, and Australia. Contributing factors likely include the many active volcanoes near the equator, modulating circulation patterns, and land-sea contrasts after outbreaks. Given the links between mean temperature, hydroclimate variability, and weather extremes, future research should explore how increased regional uncertainty affects the probability of severe extremes and how societies should adapt. Uncertainty increases at or well above 35 % of net (terrestrial) carbon uptake, especially in subtropical regions, suggest hydroclimate shifts after volcanic events increase carbon flux uncertainty. The subtropics substantially contribute to the land carbon sinks and play a key role in shaping its variability [45].

Our ESM emulator can reproduce internal and forced variability consistent with MPI-ESM's response to varying aerosol forcing, presenting an optimized complexity design between large, comprehensive simulation ensembles with intermittent volcanic forcing, and standard ScenarioMIP projections with constant mean aerosol forcing envisaged in CMIP7 [18]. Fitting and inverting the emulator requires fewer computational resources than running the full-scale model repeatedly and reliably reproduces key spatial and temporal characteristics. We utilized eight 185-year explicit ESM simulations to estimate the emulator's parameters, which vary only slightly (S4 Fig). Meanwhile, the underlying inference algorithm performs well even for a single, sufficiently long, realization [20] and the overall emulation approach could be applied to other ESMs and updated intermittent forcing products like the one provided by EVA_H (Data and methods). We expect this will enable the inferring of statistically stable multi-model uncertainty envelopes from a single to few stochastically forced, multi-event runs per model, not limited to, but ideally with interactive stratospheric aerosols [16].

We propagate regional uncertainties from climatic drivers via shared variances into carbon fluxes. Emulating spatiotemporal carbon fluxes directly requires adjusting our emulator since Schillinger et al. (2022) [20]'s algorithm assumes Gaussian-distributed variables. Our emulator uses truncated Empirical Orthogonal Functions (Data and methods), which omit some polar-region variability. This could be reduced by increasing the traceable orthogonal modes or exploring other dimensionality reduction approaches.

Our approach adapts seamlessly to model improvements and various model setups, scenarios, or forcing datasets. This makes it ideal for augmenting diverse, multi-source datasets with an uncertainty envelope from sporadic volcanic forcing with low effort.

We assume future eruptions occur with similar frequency as in the past. Magnitudes and timings of past eruptions as analogues for future events can only be approximate. Eruption frequency and their climate impact could change under warming due to isostatic adjustments from ice sheet melt [46–48], more frequent heavy precipitation [49,50], sea level rise [51,52], and circulation changes [46]. This study used paleo forcing of the last glacial period without considerable trend in volcanic activity. However, testing other forcing time frames such as the deglaciation, evaluating uncertainty within paleo-derived forcing ensembles like PalVolv1, and expanding the paleo record for improving ESM accuracy [50] could advance the model representation of state- and pathway-dependent dynamics. The PalVolv1 forcing employed here corrects for underreporting of small-magnitude eruptions in the paleo record, but there are still signs of undersampling for stratospheric sulfur injections below approximately 0.5 teragrams (S1 Figa). Further reducing biases from undersampling small events, both in paleo and satellite records, would increase forcing realism. Our approach can adapt to ESM improvements that alter climate sensitivity by adjusting the box model’s response parameters (Data and methods). It could also identify state-dependent sensitivities of (paleo-)data and models [4], and differentiate between consequences for internal climate variability and forced response.

Our estimates of supplementary future natural carbon uptake variability could be influenced by inaccurately represented carbon flux dynamics and biosphere–climate interactions in our methodological approach and the underlying MPI-ESM. Over the historical period, global variability of net uptake and GPP flux in MPI-ESM corresponds with the global carbon budget [53]. Yet over the last few thousand years, MPI-ESM, like most ESMs, displays less regional variability than reconstructions [54]. Our sensitivity experiments explored whether (negative) vapor and (positive) sensible heat feedback could increase multi-annual and multi-decadal internal surface air temperature variability components without changing the forced response to volcanic events (S3 Text, S16 Fig). Too low internal variability of surface temperature and terrestrial carbon fluxes could shift the increased uncertainty envelope’s relative importance. The vegetation model tends to underestimate the compounding multi-annual to decadal effects of consecutive volcanic events on the moisture budget (S2 Text), possibly leading to a low bias in vegetation productivity and soil respiration responses. These effects are unlikely to qualitatively alter the Earth system’s response to intermittent volcanic forcing but highlight limitations of ESMs in capturing variability. Future research could therefore explore how varying parametrizations of surface–atmosphere interactions affects climate stability and the Earth system’s forced response to sporadic volcanic aerosol emissions.

In conclusion, we determined the supplementary uncertainty in global and regional surface climate and carbon fluxes resulting from realistically varying volcanic aerosol concentrations during a temperature overshoot. In our ensemble, intermittent forcing increased global mean annual temperature uncertainty on average by 89 % relative to internal variability, and we inferred a time-averaged 34 % uncertainty rise in global annual carbon uptake into natural sinks. This implies achieving net-zero CO₂ emissions and the 2 °C target can be delayed or accelerated through stratospheric aerosol forcing, underscoring its necessary inclusion in climate stabilization pathway estimates. This includes assessments of potential geoengineering, because naturally occurring volcanic eruptions cannot be prevented, advanced or delayed and forcing uncertainty must therefore be taken into account. Our scaling factors provide a first-order estimate of supplementary uncertainty due to intermittent volcanic forcing for any projection

pathway or model configuration. Based on our proof-of-concept, it appears straightforward to obtain such factors for other Earth system models and model ensembles, too. Therefore, we suggest operationalizing emulators to enhance future climate assessments encompassing forced responses to volcanic eruptions, or for exploring geoengineering pathways relying on stratospheric aerosol injections.

Supporting information

S1 Text Climatic responses to volcanic forcing.

S2 Text Probing the sensitivity of uncertainty estimates on ensemble size and forcing characteristics.

S3 Text Destabilizing land–atmosphere feedbacks enhance internal surface air temperature variability without affecting the forced response.

S1 Table ClimBayes prior ranges for EBM fitting.

S1 Fig. Statistics of the volcanic forcing ensemble.

S2 Fig. Spatial modes obtained from EOFs.

S3 Fig. Exemplary fits of the EBM to principal components.

S4 Fig. Exemplary EBM parameters obtained for the principal components.

S5 Fig. Sensitivity testing of the predicted temperature uncertainty.

S6 Fig. Convergence of temperature uncertainty estimates.

S7 Fig. Additional regional climatologies.

S8 Fig. Global mean power spectral density for all simulations.

S9 Fig. Shared variances between climatic drivers and f_{nat} , with resulting supplementary regional uncertainty.

S10 Fig. Shared variances between temperature and soil moisture as climatic drivers and f_{GPP} in response, with resulting supplementary regional uncertainty.

S11 Fig. Absolute and relative regional f_{GPP} and f_{nat} uncertainty increase.

S12 Fig. Widened uncertainty distributions due to varying volcanic forcing.

S13 Fig. Increased variability along future climate and carbon cycle pathways for the raw signal.

S14 Fig. Climatological anomalies of the sensitivity experiments with lowered C4 albedo.

S15 Fig. Climatological anomalies of the sensitivity experiments with disabled climate change feedback on vegetation.

S16 Fig. Effect of vegetation feedbacks on climate’s internal variability and forced response.

S17 Fig. Effect of vegetation feedbacks on the internal variability of global mean surface air temperature, f_{GPP} , and f_{nat} .

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References

1. Kremser S, Thomason LW, Hobe Mv, Hermann M, Deshler T, Timmreck C, et al. Stratospheric aerosol—Observations, processes, and impact on climate. *Reviews of Geophysics*. 2016;54(2):278-335. doi:10.1002/2015rg000511.
2. Bethke I, Outten S, Otterå OH, Hawkins E, Wagner S, Sigl M, et al. Potential volcanic impacts on future climate variability. *Nature Climate Change*. 2017;7(11):799-805. doi:10.1038/nclimate3394.
3. Chim MM, Aubry TJ, Smith C, Schmidt A. Neglecting future sporadic volcanic eruptions underestimates climate uncertainty. *Communications Earth & Environment*. 2025;6(1):236. doi:10.1038/s43247-025-02208-1.
4. Ellerhoff B, Kirschner MJ, Ziegler E, Holloway MD, Sime L, Rehfeld K. Contrasting State-Dependent Effects of Natural Forcing on Global and Local Climate Variability. *Geophysical Research Letters*. 2022;49(10). doi:10.1029/2022gl098335.
5. Pausata FSR, Chafik L, Caballero R, Battisti DS. Impacts of high-latitude volcanic eruptions on ENSO and AMOC. *Proceedings of the National Academy of Sciences*. 2015;112(45):13784-8. doi:10.1073/pnas.1509153112.
6. Koven CD, Arora VK, Cadule P, Fisher RA, Jones CD, Lawrence DM, et al. Multi-century dynamics of the climate and carbon cycle under both high and net negative emissions scenarios. *Earth System Dynamics*. 2022;13(2):885-909. See notes for preprint. doi:10.5194/esd-13-885-2022.
7. Melnikova I, Boucher O, Cadule P, Ciais P, Gasser T, Quilcaille Y, et al. Carbon Cycle Response to Temperature Overshoot Beyond 2°C: An Analysis of CMIP6 Models. *Earth’s Future*. 2021;9(5):1-19. Overshoot scenario response of CMIP6 subset. doi:10.1029/2020ef001967.

8. Tavoni M, Bauer N, Drouet L, Fujimori S, Paltsev S, Pirani A, et al. Implications of overshoot for climate mitigation strategies. *Nature Climate Change*. 2026;16(3):261-72. doi:10.1038/s41558-026-02563-7.
9. Johansson DJA. Temperature stabilization, ocean heat uptake and radiative forcing overshoot profiles. *Climatic Change*. 2011;108(1-2):107-34. doi:10.1007/s10584-010-9969-4.
10. DeVries T. The Ocean Carbon Cycle. *Annual Review of Environment and Resources*. 2022;47(1):317-41. doi:10.1146/annurev-environ-120920-111307.
11. D'Agostino R, Timmreck C. Sensitivity of regional monsoons to idealised equatorial volcanic eruption of different sulfur emission strengths. *Environmental Research Letters*. 2022;17(5):054001. doi:10.1088/1748-9326/ac62af.
12. Catalano F, Alessandri A, Felice MD, Zhu Z, Myneni RB. Observationally based analysis of land-atmosphere coupling. *Earth System Dynamics*. 2016;7(1):251-66. doi:10.5194/esd-7-251-2016.
13. Gentine P, Green JK, Guérin M, Humphrey V, Seneviratne SI, Zhang Y, et al. Coupling between the terrestrial carbon and water cycles—a review. *Environmental Research Letters*. 2019;14(8):083003. doi:10.1088/1748-9326/ab22d6.
14. Prescott CE. Litter decomposition: what controls it and how can we alter it to sequester more carbon in forest soils? *Biogeochemistry*. 2010;101(1-3):133-49. doi:10.1007/s10533-010-9439-0.
15. Green JK, Seneviratne SI, Berg AM, Findell KL, Hagemann S, Lawrence DM, et al. Large influence of soil moisture on long-term terrestrial carbon uptake. *Nature*. 2019;565(7740):476-9. doi:10.1038/s41586-018-0848-x.
16. Timmreck C, Mann GW, Aquila V, Hommel R, Lee LA, Schmidt A, et al. The Interactive Stratospheric Aerosol Model Intercomparison Project (ISA-MIP): motivation and experimental design. *Geoscientific Model Development*. 2018;11(7):2581-608. doi:10.5194/gmd-11-2581-2018.
17. Riahi K, Vuuren DPv, Kriegler E, Edmonds J, O'Neill BC, Fujimori S, et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*. 2017;42:153-68. SSP baselines reference. doi:10.1016/j.gloenvcha.2016.05.009.
18. Aubry TJ, Toohey M, Khanal S, Chim MM, Verkerk M, Johnson B, et al. Stratospheric aerosol forcing for CMIP7 (part 1): Optical properties for pre-industrial, historical, and scenario simulations (version 2.2.1). *EGUsphere*. 2025;2025:1-53. doi:10.5194/egusphere-2025-4990.
19. van Vuuren DP, O'Neill BC, Tebaldi C, Sanderson BM, Chini LP, Friedlingstein P, et al. The Scenario Model Intercomparison Project for CMIP7 (ScenarioMIP-CMIP7). *Geoscientific Model Development*. 2026;19(7):2627-56. doi:10.5194/gmd-19-2627-2026.
20. Schillinger M, Ellerhoff B, Scheichl R, Rehfeld K. Separating internal and externally forced contributions to global temperature variability using a Bayesian stochastic energy balance framework. *Chaos: An Interdisciplinary Journal of Nonlinear Science*. 2022;32(11):113146. arXiv:2206.14573. doi:10.1063/5.0106123.

21. Verkerk M, Aubry TJ, Smith C, Hopcroft PO, Sigl M, Tierney JE, et al. Using reduced-complexity volcanic aerosol and climate models to produce large ensemble simulations of Holocene temperature. *Climate of the Past*. 2025;21(10):1755-78. doi:10.5194/cp-21-1755-2025.
22. Schindlbeck-Belo JC, Toohey M, Jegen M, Kutterolf S, Rehfeld K. PalVol v1: a proxy-based semi-stochastic ensemble reconstruction of volcanic stratospheric sulfur injection for the last glacial cycle (140 000–50 BP). *Earth System Science Data*. 2023;16(2):1063-81. doi:10.5194/essd-16-1063-2024.
23. Lütjens B, Ferrari R, Watson-Parris D, Selin NE. The Impact of Internal Variability on Benchmarking Deep Learning Climate Emulators. *Journal of Advances in Modeling Earth Systems*. 2025;17(8). doi:10.1029/2024ms004619.
24. Mauritsen T, Bader J, Becker T, Behrens J, Bittner M, Brokopf R, et al. Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and Its Response to Increasing CO₂. *Journal of Advances in Modeling Earth Systems*. 2019;11(4):998-1038. MPI-ESM1.2 + CO₂ response Most important: 5. Revisions to HAMOCC6 6. Revisions to JSBACH. doi:10.1029/2018ms001400.
25. Meinshausen M, Nicholls ZRJ, Lewis J, Gidden MJ, Vogel E, Freund M, et al. The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geoscientific Model Development*. 2020;13(8):3571-605. - long term GHG conc extensions - discusses underlying assumptions on emission (and CDR) pathway extensions. doi:10.5194/gmd-13-3571-2020.
26. Stevens B, Giorgetta M, Esch M, Mauritsen T, Crueger T, Rast S, et al. Atmospheric component of the MPI-M Earth System Model: ECHAM6. *Journal of Advances in Modeling Earth Systems*. 2013;5(2):146-72. doi:10.1002/jame.20015.
27. Jungclaus JH, Keenlyside N, Botzet M, Haak H, Luo JJ, Latif M, et al. Ocean Circulation and Tropical Variability in the Coupled Model ECHAM5/MPI-OM. *Journal of Climate*. 2006;19(16):3952-72. doi:10.1175/jcli3827.1.
28. O'Neill BC, Tebaldi C, Vuuren DPv, Eyring V, Friedlingstein P, Hurtt G, et al. The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*. 2016;9(9):3461-82. Reference for ScenarioMIP (concentration-driven). doi:10.5194/gmd-9-3461-2016.
29. Olonscheck D, Suarez-Gutierrez L, Milinski S, Beobide-Arsuaga G, Baehr J, Fröb F, et al. The New Max Planck Institute Grand Ensemble With CMIP6 Forcing and High-Frequency Model Output. *Journal of Advances in Modeling Earth Systems*. 2023;15(10). doi:10.1029/2023ms003790.
30. Toohey M, Stevens B, Schmidt H, Timmreck C. Easy Volcanic Aerosol (EVA v1.0): an idealized forcing generator for climate simulations. *Geoscientific Model Development*. 2016;9(11):4049-70. doi:10.5194/gmd-9-4049-2016.
31. Aubry TJ, Toohey M, Marshall L, Schmidt A, Jellinek AM. A New Volcanic Stratospheric Sulfate Aerosol Forcing Emulator (EVA_H): Comparison With Interactive Stratospheric Aerosol Models. *Journal of Geophysical Research: Atmospheres*. 2020;125(3). doi:10.1029/2019jd031303.
32. Ziegler E, Weitzel N, Baudouin JP, Kapsch ML, Mikolajewicz U, Gregoire L, et al. Patterns of changing surface climate variability from the Last Glacial Maximum to present in transient model simulations. *Climate of the Past*. 2025;21(3):627-59. doi:10.5194/cp-21-627-2025.

33. Kapsch ML, Mikolajewicz U, Ziemann FA, Rodehacke CB, Schannwell C. Analysis of the surface mass balance for deglacial climate simulations. *The Cryosphere*. 2021;15(2):1131-56. doi:10.5194/tc-15-1131-2021.
34. Dallmeyer A, Claussen M, Lorenz SJ, Sigl M, Toohey M, Herzschuh U. Holocene vegetation transitions and their climatic drivers in MPI-ESM1.2. *Climate of the Past*. 2021;17(6):2481-513. doi:10.5194/cp-17-2481-2021.
35. Jungclaus JH, Bard E, Baroni M, Braconnot P, Cao J, Chini LP, et al. The PMIP4 contribution to CMIP6 – Part 3: The last millennium, scientific objective, and experimental design for the PMIP4 past1000 simulations. *Geoscientific Model Development*. 2017;10(11):4005-33. doi:10.5194/gmd-10-4005-2017.
36. Storch HV, Navarra A. Analysis of climate variability: applications of statistical techniques. Springer Science & Business Media;.
37. Ellerhoff B, Rehfeld K. Probing the timescale dependency of local and global variations in surface air temperature from climate simulations and reconstructions of the last millennia. *Physical Review E*. 2021;104(6):064136. arXiv:2102.00458. doi:10.1103/physreve.104.064136.
38. Iturbide M, Gutiérrez JM, Alves LM, Bedia J, Cerezo-Mota R, Gimadevilla E, et al. An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets. *Earth System Science Data*. 2020;12(4):2959-70. doi:10.5194/essd-12-2959-2020.
39. Berg A, Lintner BR, Findell K, Seneviratne SI, Hurk Bvd, Ducharme A, et al. Interannual Coupling between Summertime Surface Temperature and Precipitation over Land: Processes and Implications for Climate Change. *Journal of Climate*. 2015;28(3):1308-28. doi:10.1175/jcli-d-14-00324.1.
40. Adler RF, Gu G, Wang J, Huffman GJ, Curtis S, Bolvin D. Relationships between global precipitation and surface temperature on interannual and longer timescales (1979–2006). *Journal of Geophysical Research: Atmospheres*. 2008;113(D22). doi:10.1029/2008jd010536.
41. Zhang X, Peng S, Ciais P, Wang Y, Silver JD, Piao S, et al. Greenhouse Gas Concentration and Volcanic Eruptions Controlled the Variability of Terrestrial Carbon Uptake Over the Last Millennium. *Journal of Advances in Modeling Earth Systems*. 2019;11(6):1715-34. doi:10.1029/2018ms001566.
42. Parry IM, Ritchie PDL, Boucher O, Cox PM, Haywood JM, Niemeier U, et al. Stratospheric aerosol injection geoengineering has the potential to increase land carbon storage and to protect the Amazon rainforest. *Earth System Dynamics*. 2026;17(2):387-414. doi:10.5194/esd-17-387-2026.
43. Bock L, Lauer A. Cloud properties and their projected changes in CMIP models with low to high climate sensitivity. *Atmospheric Chemistry and Physics*. 2023;24(3):1587-605. doi:10.5194/acp-24-1587-2024.
44. Tatem AJ. WorldPop, open data for spatial demography. *Scientific Data*. 2017;4(1):170004. doi:10.1038/sdata.2017.4.
45. Ahlström A, Raupach MR, Schurgers G, Smith B, Arneth A, Jung M, et al. The dominant role of semi-arid ecosystems in the trend and variability of the land CO₂ sink. *Science*. 2015;348(6237):895-9. doi:10.1126/science.aaa1668.

46. Huybers P, Langmuir C. Feedback between deglaciation, volcanism, and atmospheric CO₂. *Earth and Planetary Science Letters*. 2009;286(3-4):479-91. doi:10.1016/j.epsl.2009.07.014.
47. Watt SFL, Pyle DM, Mather TA. The volcanic response to deglaciation: Evidence from glaciated arcs and a reassessment of global eruption records. *Earth-Science Reviews*. 2013;122:77-102. doi:10.1016/j.earscirev.2013.03.007.
48. Sigmundsson F, Albino F, Schmidt P, Lund B, Pinel V, Hooper A, et al. Multiple effects of ice load changes and associated stress change on magmatic systems. *Climate Forcing of Geological and Geomorphological Hazards*. 2013:108-23.
49. Kerle N, Vries BvWd, Oppenheimer C. New insight into the factors leading to the 1998 flank collapse and lahar disaster at Casita volcano, Nicaragua. *Bulletin of Volcanology*. 2003;65(5):331-45. doi:10.1007/s00445-002-0263-9.
50. Aubry TJ, Farquharson JJ, Rowell CR, Watt SFL, Pinel V, Beckett F, et al. Impact of climate change on volcanic processes: current understanding and future challenges. *Bulletin of Volcanology*. 2022;84(6):58. doi:10.1007/s00445-022-01562-8.
51. Coussens M, Wall-Palmer D, Talling PJ, Watt SFL, Cassidy M, Jutzeler M, et al. The relationship between eruptive activity, flank collapse, and sea level at volcanic islands: A long-term (1 Ma) record offshore Montserrat, Lesser Antilles. *Geochemistry, Geophysics, Geosystems*. 2016;17(7):2591-611. doi:10.1002/2015gc006053.
52. Crowley JW, Katz RF, Huybers P, Langmuir CH, Park SH. Glacial cycles drive variations in the production of oceanic crust. *Science*. 2015;347(6227):1237-40. arXiv:1408.4976. doi:10.1126/science.1261508.
53. Friedlingstein P, O'Sullivan M, Jones MW, Andrew RM, Hauck J, Landschützer P, et al. Global Carbon Budget 2024. *Earth System Science Data*. 2025;17(3):965-1039. doi:10.5194/essd-17-965-2025.
54. Laepple T, Ziegler E, Weitzel N, Hébert R, Ellerohoff B, Schoch P, et al. Regional but not global temperature variability underestimated by climate models at supradecadal timescales. *Nature Geoscience*. 2023;16(11):958-66. doi:10.1038/s41561-023-01299-9.

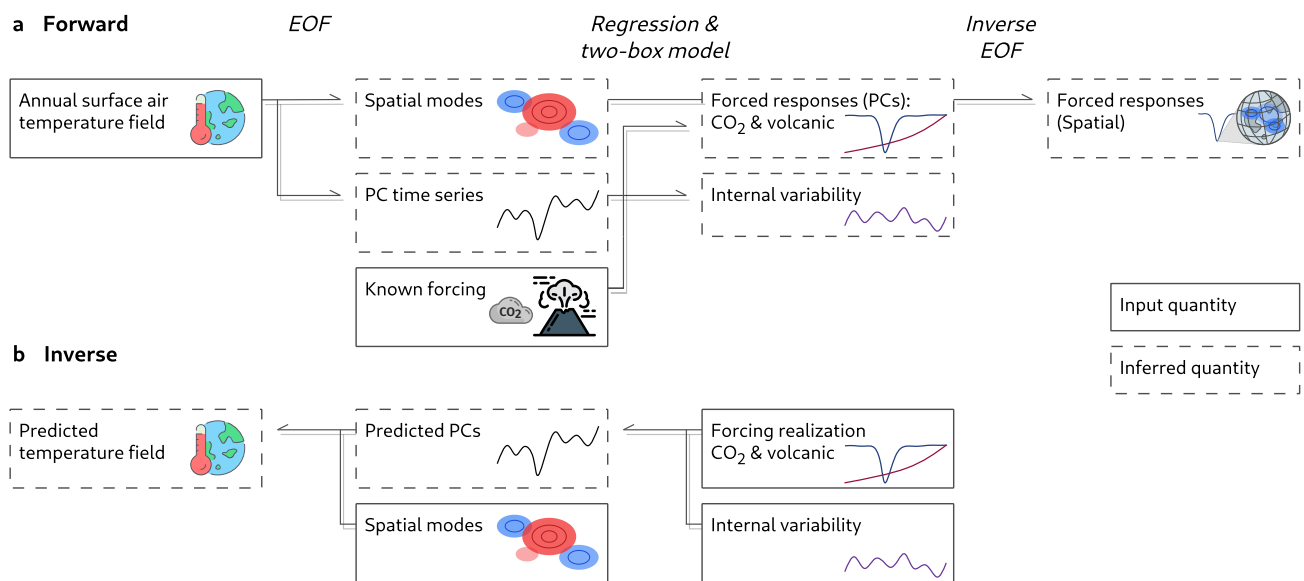


Figure 1

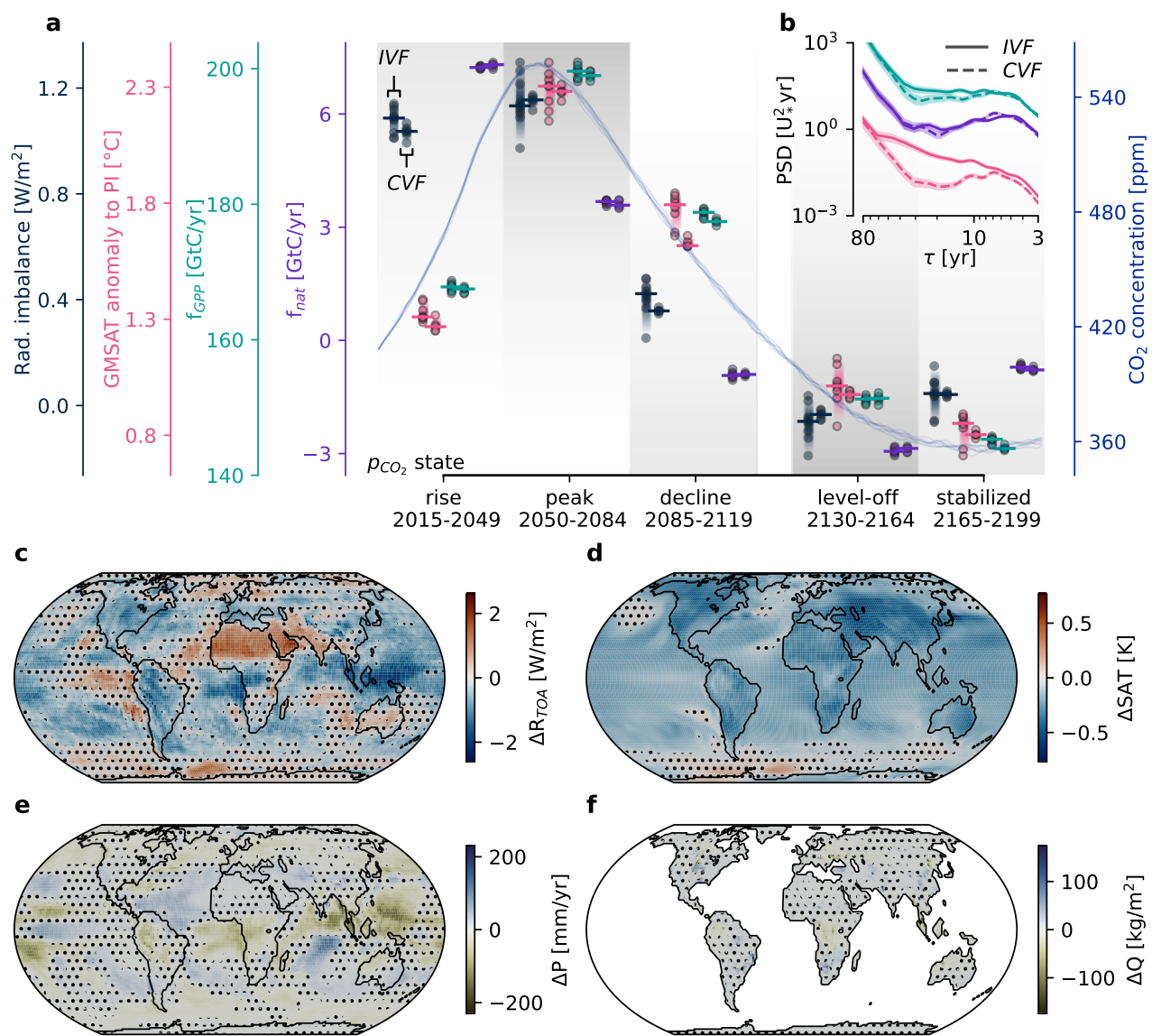


Figure 2

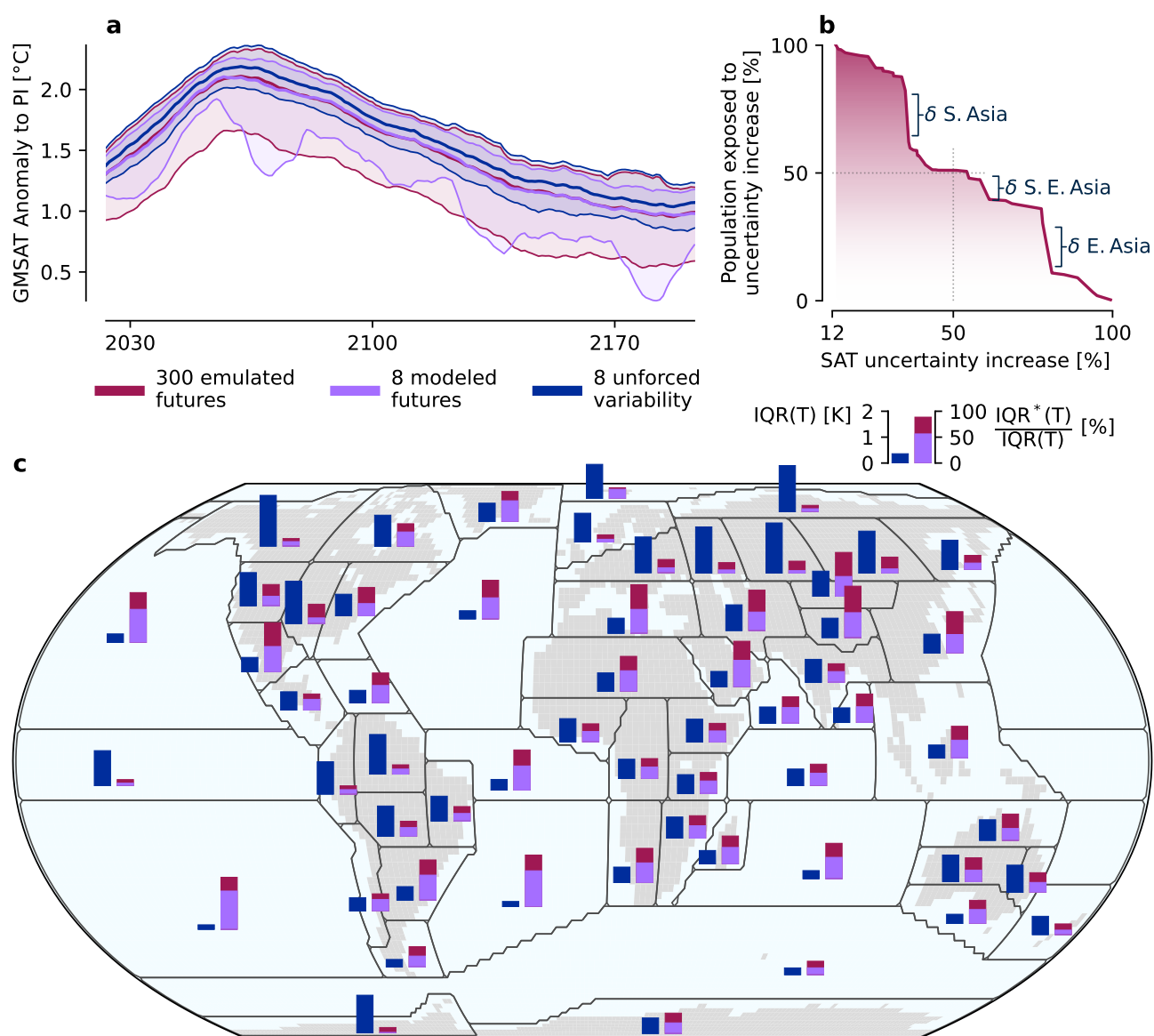


Figure 3

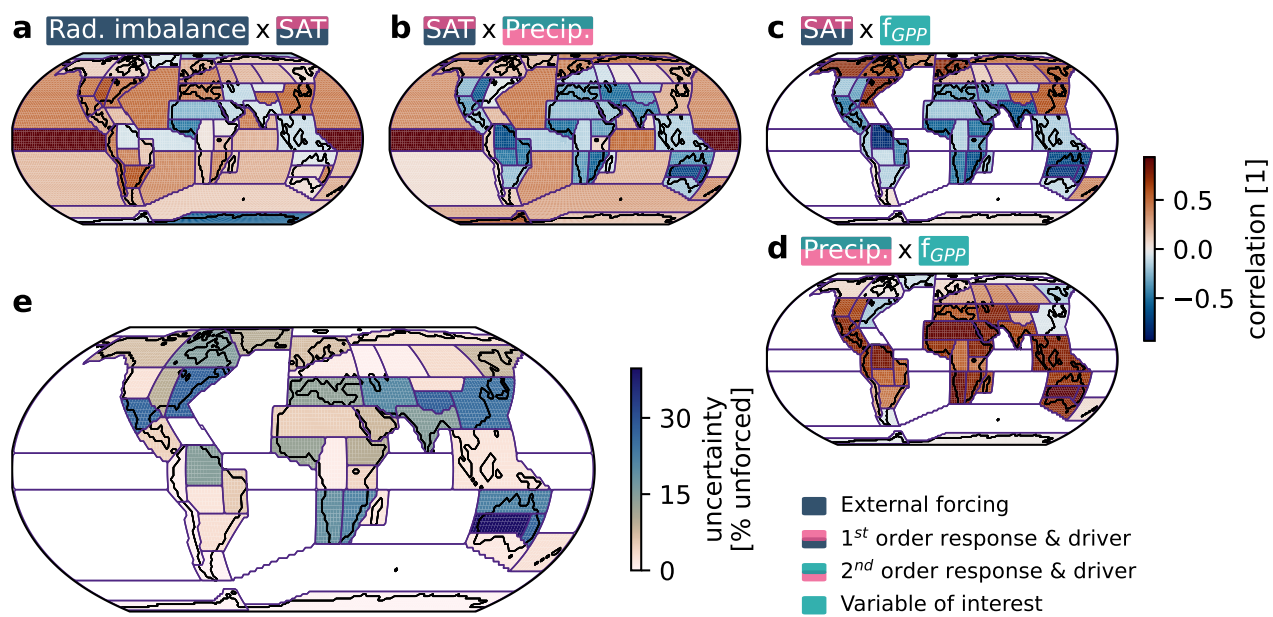


Figure 4

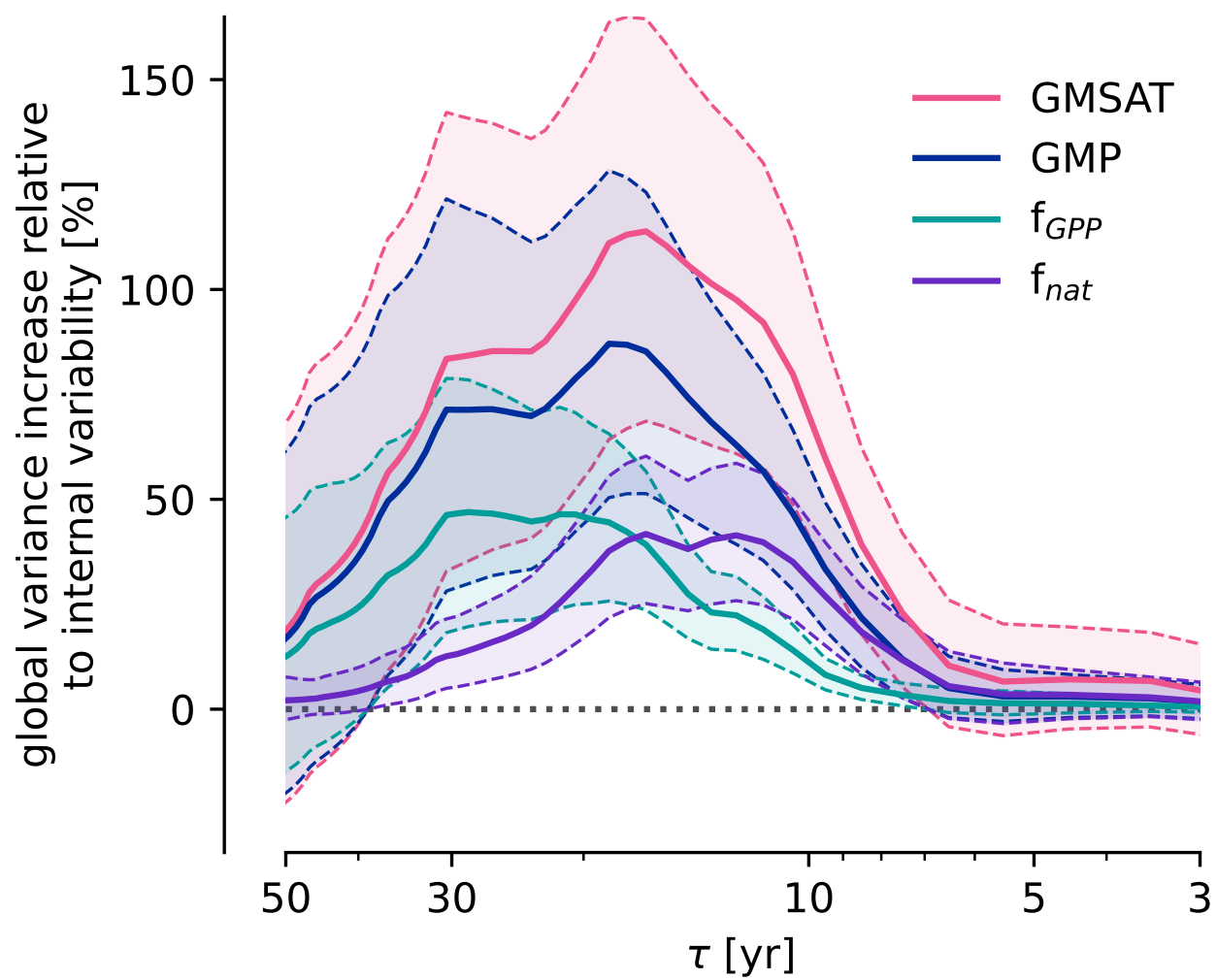


Figure 5

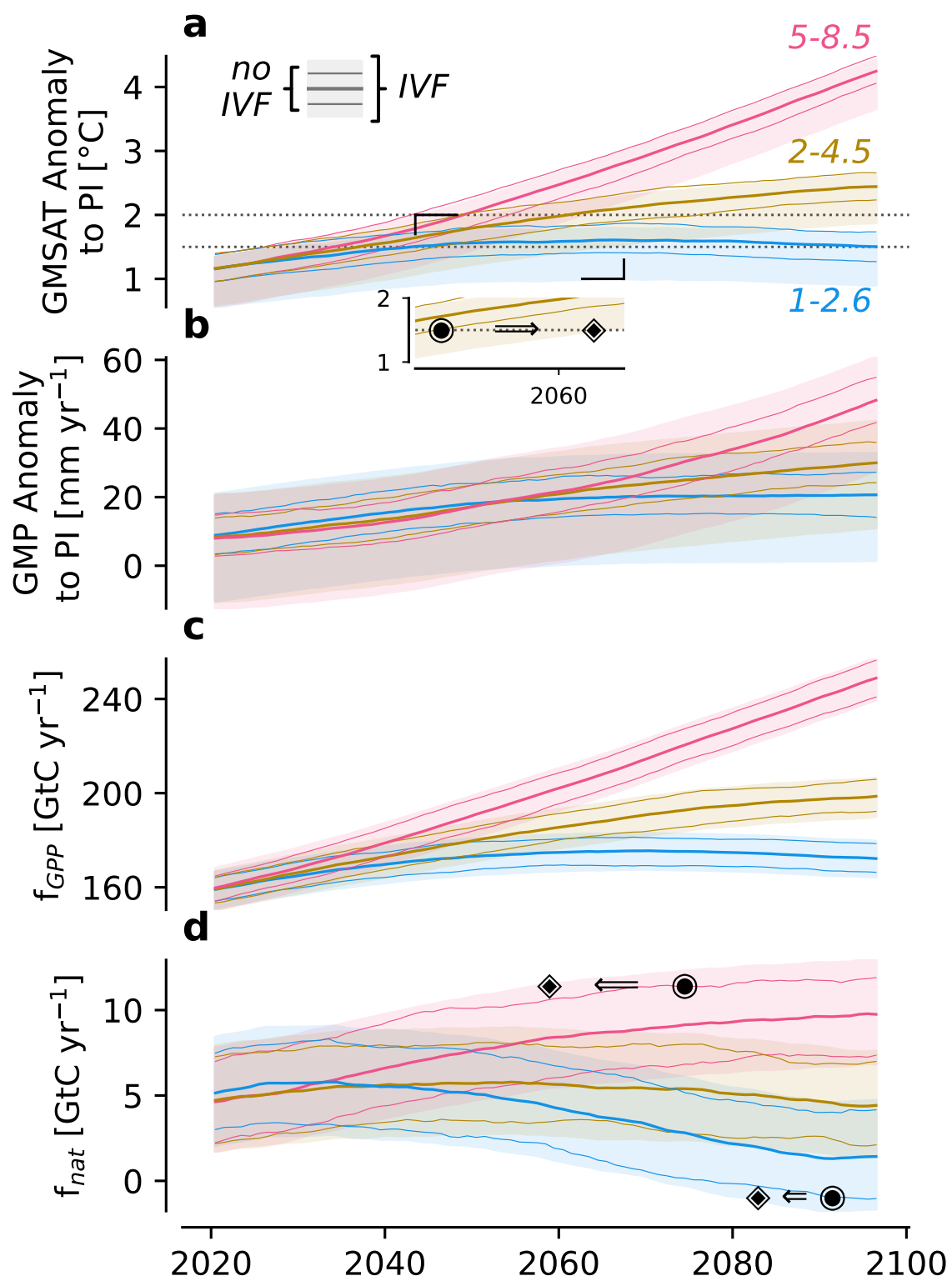


Figure 6

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Author	Author position	Scientific ideas (%)	Data generation / programming (%)	Analysis, interpretation, technical work (%)	Paper writing (%)
M. Adam	1	50	50	55	60
E. Ziegler	2	25	10	20	15
B. Gonzalez	3	10	40	20	5
N. Weitzel	4	10	-	5	15
K. Rehfeld	5	5	-	-	5



Earth system models might overestimate the local plant productivity response to temperature–moisture extremes

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Abstract. Compound temperature–moisture extremes, such as droughts or hot–wet extremes, have a pronounced and sometimes long-lasting impact on vegetation productivity. Accurate simulation of the involved processes by emission-driven Earth system models (ESMs) is crucial for inferring future terrestrial carbon uptake. However, ESMs often exhibit biases in the frequency and intensity of climate and weather extremes. Their ability to reproduce observed impacts of extreme atmospheric conditions on gross primary productivity (GPP) is therefore unclear. Comprehensive assessments of the statistical link between compound events and vegetation productivity beyond individual regions or event types are rare. Here, we scrutinize the relationship between temperature–moisture extremes and exceptionally low or high vegetation productivity in two state-of-the-art ESMs, CESM2 and MPI-ESM1.2, and gauge their performance relative to observation-constrained data. We find that temperature-moisture extremes modulate vegetation productivity in observations and models. The global-scale strength and timing of the statistical relationship agree well between observation-based data and model output. However, this agreement deteriorates towards smaller spatial scales, especially in the low latitudes. Here, an overestimated coupling strength by both models, likely related to biased rates of soil moisture change, suggests potentially unrealistic evaporative feedbacks, exaggerated drainage, or inadequate effective water-holding capacity in ESMs. Nevertheless, all data sources identify coherent significant relationships for all combinations of temperature–moisture and GPP extremes. This result highlights both beneficial and detrimental influences of temperature–moisture compound events on vegetation productivity and the importance of comprehensive assessments beyond single event types for capturing the net effect of climatic extremes on the biosphere. Further research should examine whether overestimated plant productivity responses to extreme conditions are a recurring phenomenon across all Earth system models. It could also investigate non-stationarity and nonlinearity of the relationships between climatic and vegetation extremes under climate change.



20 1 Introduction

Climate change goes far beyond shifting the Earth's mean state. Rising CO₂ levels increase the likelihood of temperature and hydroclimate extremes, threatening the planet's ecosystems and human livelihoods (Mahecha et al., 2024). Temperature and moisture anomalies can, individually, affect the biosphere. However, they tend to be particularly impactful when they co-occur as compound extreme events (Zscheischler et al., 2014b), which is increasingly likely (Ridder et al., 2022; Li et al., 2024).
 25 Examples of past compound events that severely damaged vegetation productivity include European heat–droughts diminishing carbon uptake by forests in 2018 and 2022 (Van Der Woude et al., 2023; Gharun et al., 2024; Zscheischler and Fischer, 2020), spring- and summertime cold–dry spells reducing gross primary production (GPP) in the mid- to high latitudes over the past decades (Li et al., 2022), and diminishing tropical GPP in response to droughts caused by El Niño in 2015/2016 (Bastos et al., 2018). At the same time, heat–drought events followed by high GPP anomalies in Siberia in the 2010s (Flach
 30 et al., 2021) and stronger tree growth in response to larger rainfall amounts from heavy precipitation days in semi-arid Australia (O'Donnell et al., 2021) are examples of climatic extremes that promoted vegetation growth. Disentangling these diverse, damaging, and beneficial impacts of temperature–moisture extremes on vegetation, as well as being able to model and project them under future climate change scenarios, is crucial (Zhou et al., 2019; Wu et al., 2021; Li et al., 2024), given the pivotal role of GPP for the land carbon sink (Sharma et al., 2023) and other ecosystem services provided by vegetation (Mahecha et al., 2024).

35 Earth system models (ESMs), i.e., comprehensive models of ocean, atmosphere, land surface, and the carbon cycle, struggle to capture the real-world frequency and intensity of temperature and moisture extremes both individually and in combination (Lorenz et al., 2016; Haren et al., 2015; Norris et al., 2021; Simpson et al., 2025; Reichstein et al., 2013). It is unclear how well ESMs capture the relationship between climatic (compound) events and vegetation productivity extremes. Both increased like-
 40 lihoods of compound events and changes in their mechanistic link to vegetation extremes under climate change influence the land carbon sink and ecosystem functioning (Li et al., 2024; Tschumi et al., 2023). Abilities of ESMs to simulate the relation of moisture availability and vegetation extremes have been studied for specific extreme event combinations such as heat–droughts or heavy rainfall events (Harris et al., 2024; Flach et al., 2021; Li et al., 2022), but there are no comprehensive assessments across event types and regions for the co-occurrence of temperature–moisture and vegetation. Most often, bias assessments
 45 have focused on the drivers of vegetation extremes or their impacts, and were limited to specific areas (e.g., Villalobos-Herrera et al., 2021; Vogel et al., 2021). Assessing both on a global scale is crucial for model improvement and for developing statistical bias corrections, if necessary, to feed into climate change impact assessments. ESMs may continue to underestimate the likelihoods of temperature–moisture events and productivity extremes individually. However, if they accurately represented the statistical relationships between compound and GPP extremes, relative changes in these relationships could still provide
 50 valuable indications of shifting likelihoods of vegetation extremes under (hydro-)climate change.

ESMs draw on land surface models (LSMs) to simulate impacts of weather extremes on vegetation. LSMs simplify or disregard fine-grained, localized representation of plant species diversity, demographics, and ecosystem heterogeneities. Parametriza-



tions aggregate effects of vegetation–climate interactions on the carbon cycle at sub-grid-scales. This includes processes that
55 affect a plant’s ability to assimilate carbon, plant physiology, plant-soil interactions, nutrient availability, surface and sub-
surface water budgets, and climatic constraints (Blyth et al., 2021). The parameterizations employed in models from the sixth
climate model intercomparison project (CMIP6; Eyring et al., 2016) and the imminent CMIP7 cycle typically generalize
vegetation categories into functional types and average across heterogeneities, such as soil properties and root-zone nutrient
dynamics (Blyth et al., 2021).

60 Land and vegetation models within ESMs operate at a high level of abstraction compared to real-world complexity. Calibra-
tion of the remaining free parameters allows ESMs to represent average land carbon stocks and dynamics well (Arora et al.,
2020), at least in a transient mean state under present-day or recent-past climates. This suggests some predictive capabilities
for regional-to-global mean changes in terrestrial carbon stocks under near-future climate change. However, models tend to ex-
65 aggerate CO₂ fertilization trends (Kou-Giesbrecht et al., 2025). It is also challenging to model the highly variable land carbon
sink since (hydro-)climate variability affects moisture availability and, therefore, carbon uptake through vegetation (Gentine
et al., 2019). ESMs can represent the well-understood mechanisms by which moisture availability drives GPP, but results differ
across models, and they often miss the precise timing, intensity, and location of compound event impacts (Harris et al., 2024).
They also underestimate legacy effects on vegetation productivity compared to observations and paleovegetation reconstruc-
70 tions (Kolus et al., 2019; Dallmeyer et al., 2022). Whether these simplifications and model biases in occurrence and intensity
of climate and biosphere extremes affect possible statistical links between the two types of extremes is unclear.

Here, we quantify model performance across combinations of compound and GPP extremes, for different regions, and spa-
tial scales. As a step towards quantifying the net effects of compound events on GPP extremes, we study whether compound
75 events increase the likelihood of subsequent GPP extremes, as well as potentially mitigating effects from the occurrence of
compound events. For example, a prolonged cold-wet extreme in spring could increase soil moisture storage enough to reduce
the likelihood of low GPP extremes in summer.

We explore the statistical relation between temperature–moisture compound events and GPP extremes in two CMIP6 models
80 and assess them relative to gridded, observation-based products (Sect. 2). Employing a generalizable measure and statistical
null model for this relationship (Sect. 3), we find reasonable agreement between models and observations (Sect. 4). However,
this agreement depends on spatial aggregation and is subject to model-specific biases. In particular, both ESMs tend to overes-
timate the local strength of the coupling between climatic and vegetation extremes. We suggest that this overestimation might
arise from an inaccurate soil moisture representation in the ESMs (Sect. 5.1). We find mechanistically comparable results
85 across both data sources despite the biases (Sect. 4.3, Sect. 5.2), providing opportunities to study climate change impacts on
vegetation productivity beyond the mean state in comprehensive model intercomparisons (Sect. 5.3).



2 Data

We scrutinize the capabilities of two frequently used, state-of-the-art ESMs from the CMIP6 cycle to capture statistical couplings between temperature–moisture compound events and extremes in GPP within simulations of the recent past (1979–2014 CE). We explore historical simulations with global coverage from the Max Planck Institute ESM version 1.2 (MPI-ESM) (Mauritsen et al., 2019; Wieners et al., 2019) and the Community ESM version 2 (CESM2) (Danabasoglu et al., 2020; Danabasoglu, 2019). Both fall into typical ranges of CMIP6 models and commonly perform well in different types of model evaluations (Tokarska et al., 2020; Kim et al., 2020; Arora et al., 2020; Wang et al., 2021). The models combine interacting submodels of the atmosphere, ocean, land surface (including vegetation), and marine and terrestrial biogeochemistry at atmospheric resolutions of 1.875° by 1.875° (MPI-ESM) and 1.25° by 0.9° (CESM2), respectively. MPI-ESM contains JSBACH version 3.2 as a land and dynamic global vegetation model (Reick et al., 2013). The community land model (CLM) version 5 (Lawrence et al., 2019) is the land and vegetation component of CESM2. Both land models are state-of-the-art for the CMIP6 cycle (Blyth et al., 2021) and represent the (sub-)surface energy and moisture budgets, vegetation composition through plant functional types (PFTs), nitrogen-limited photosynthesis with autotrophic respiration, and above- and below-ground heterotrophic respiration. They both use LUH2 (Hurtt et al., 2020) as a historical land-use constraint, but differ in their ability to resolve land use management practices as granular PFTs, for example, regarding irrigation.

By selecting MPI-ESM and CESM2 for our case study, we bracket different characteristics of simulated extreme events. Heavy precipitation extremes in CESM2 are more intense and closer to observations than in many other models, whereas they are weaker in MPI-ESM than in most ESMs (Norris et al., 2021). This is reflected in surface and soil water budgets of JSBACH3.2, which show a low bias relative to observations and several other land models, including CLM5.0 (Seiler et al., 2022). These differences between the ESMs are attractive for assessing the link between temperature-moisture and GPP extremes, because they can provide mechanistic insights into potential biases and commonalities. In contrast to the differences in hydroclimate variability, the global carbon budget is close to the CMIP6 multi-model mean in both models, with a relatively larger importance of land carbon sinks and more pronounced land carbon sink feedbacks in CESM2 compared to MPI-ESM (Arora et al., 2020). Against observational benchmarks of annual GPP, net biosphere productivity, carbon stocks, and latent heat flux, CLM5.0 and JSBACH3.2 also show similar performance (Seiler et al., 2022). While JSBACH slightly outperforms CLM5.0 for GPP and carbon stock benchmarks, CLM5.0 in turn outperforms JSBACH on evaporative feedbacks reflected in the surface latent heat flux (Seiler et al., 2022).

For assessing the statistical coupling between climate and vegetation productivity extremes, we leverage gridded FLUXCOM GPP data as an observation-based benchmark (Tramontana et al., 2016; Jung et al., 2020). FLUXCOM, specifically the FLUXCOM+RS+METEO product, combines machine learning techniques, satellite observations, and meteorological data from reanalyses to propagate localized FluxNet eddy covariance measurements into a spatially resolved product (0.5° by 0.5°) (Jung et al., 2020). FLUXCOM is available with different reanalysis datasets used to upscale point measurements. We employ



the ERA5 version of FLUXCOM (Hersbach et al., 2020; Muñoz Sabater, 2019), because, unlike the other reanalyses, ERA5 provides volumetric soil water content in addition to surface temperature and precipitation. Temperature, precipitation, and soil moisture in ERA5 have been constrained by in-situ and remote sensing observations (Hersbach et al., 2020). We choose soil moisture as the primary indicator for moisture, as it directly reflects the water available to the plants (McColl et al., 2022).

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FLUXCOM's mean GPP estimate was extensively tested against satellite observations, atmospheric inversions, and model datasets (Jung et al., 2020). Seasonal GPP fluxes in FLUXCOM agree well with observational constraints on water stress, despite deficiencies of soil moisture remote sensing data and FLUXCOM's tendency to underestimate interannual variability (Jung et al., 2020). Because FLUXCOM does not explicitly account for CO₂ fertilization effects on GPP, long-term CO₂ trends are not consistently realistic, especially in the late 1970s to early 1990s (Jung et al., 2020). However, since we are focusing on the statistical link between climatic compound events and GPP extremes in general and not on its state-dependency, this shortcoming is not limiting our assessment.

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Our analysis covers the years 1979 to 2014, constrained by the ERA5 data used to produce the FLUXCOM dataset (starting in 1979) and the termination of MPI-ESM historical simulations (at the end of 2014). We draw on daily climate data (surface air temperature, soil moisture, precipitation), but GPP is available only at monthly resolution. During preprocessing, all data sources and variables are trimmed to this time interval and remapped to the spatial resolution of MPI-ESM1.2-LR.

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3 Methods

We aim to quantify statistical relations between temperature–moisture extremes and extremes in vegetation productivity in FLUXCOM, CESM2, and MPI-ESM data. The analysis workflow comprises four steps: 1. Pre-processing (Sect. 2), 2. computation of temperature–moisture compound and vegetation productivity extremes (Sect. 3.1), 3. computation of co-occurrence rates for the extremes (COR, Sect. 3.2), 4. significance testing (Sect. 3.3). Significant CORs reflect the strength of the statistical coupling between temperature–moisture and vegetation productivity extremes and indicate characteristic response times to plant-physiologically demanding and beneficial conditions (Sect. 3.4).

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3.1 Definition of climatic compound and GPP extremes

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After removing the seasonal trend, we define extreme events based on monthly thresholds and local extreme conditions. We deliberately keep the anthropogenic CO₂ trend in the data, because we are mainly interested in the mechanistic link between temperature–moisture and GPP extremes and not on potential state dependencies of this link. Preliminary tests indicated that artifacts from detrending outweigh the benefits of reducing non-stationarity.

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We determine extreme conditions based on the univariate monthly event distributions of daily-resolved temperature and soil moisture, and monthly-resolved GPP (Fig. 1a). For each variable, we define the 90th and 10th percentiles as thresholds for

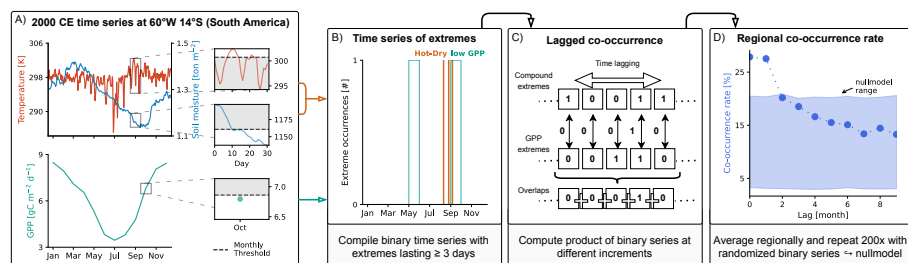


Figure 1. Definition and link of compound temperature–moisture events with GPP extremes for the example of hot–dry compound events followed by low GPP extremes at 60 °W 14 °S, which is part of the South-American monsoon reference region (SAM; Iturbide et al., 2020). Extreme conditions in grid cell surface air temperature, soil moisture, and GPP are defined separately for each variable with respect to local monthly quantile thresholds and the period from 1979 to 2014 (a). Threshold values and whether exceedance or undercutting is evaluated depend on the type of compound extreme. For a temperature–soil moisture compound event, extreme conditions must occur in both variables and persist for at least three consecutive days. The outcome of this event detection is two binary time series of GPP and compound extreme occurrences (b). If a compound and a GPP extreme occur with lag τ ($\tau \in [0, 12]$ months), they are said to overlap (c). Using this (lagged) co-occurrence, dividing by the number of compound extremes, and averaging across regions yields the regional (lagged) co-occurrence rate (COR), here, for the SAM region (d). Because of the difference in resolution, a single GPP extreme can overlap with multiple daily temperature–precipitation compound events. After normalization by climate–extreme occurrences, the COR ranges from 0 to 1. The COR computation is repeated with 200 randomized extreme occurrence time series to compute the central 95% of the null model’s probability distribution (see Sect. 3.3).

hot/cold, wet/dry, and high GPP/low GPP extremes, respectively. Those percentile thresholds allow the identification of locally extreme conditions relevant for local vegetation. Unique percentile thresholds for each location and dataset ensure we correctly interpret different interannual variability structures in the datasets (Jung et al., 2020). Vegetation productivity is modulated by combined and integrated temperature–moisture conditions. Therefore, we combine the univariate temperature and soil moisture extreme conditions and identify compound extreme conditions if the respective thresholds are crossed simultaneously (Fig. 1a). This definition of compound extremes is independent of the data sources and simple to calculate, even for distributions with multi-modality, zero inflation, and heavy tails, making it a robust measure of compound extremes (Hao et al., 2022). Short-lived compound extreme conditions, lasting for some hours to a couple of days, have minimal physiological impact on vegetation productivity. Therefore, we require temperature–moisture compound events to last for a minimum of three consecutive days.

The analysis primarily relies on soil moisture to identify moisture extremes. However, we repeat the entire analysis using precipitation to test robustness and mechanistic implications. Precipitation is indirectly linked to plant-available moisture, but directly indicates extreme atmospheric conditions. It also reduces the effective integration timescale of extreme hydrological conditions. For precipitation, we restrict the event population to non-zero values before determining the threshold for low-precipitation extremes, yet retain all time points in the analysis. This restriction is necessary to address regions with few precipitation events.



3.2 Co-occurrence rate (COR): measure of statistical coupling between temperature–moisture and GPP extremes

We compute the co-occurrence of both types of extremes with varying lag from 0 to 12 months to quantify the statistical relation between compound temperature–moisture events and GPP extremes. The occurrence of compound and GPP extremes yields two binary event time series, which contain 1 if conditions are extreme at a given time step, and 0 otherwise (Fig. 1b, c). Then, the co-occurrence of compound climate and GPP extremes at the same time is given by the product of both time series (Fig. 1c). To compare the daily temperature and soil moisture data with the monthly GPP fluxes, we sum all compound extreme occurrences within a month and compare the time series at monthly resolution. Therefore, several compound events can overlap with one vegetation productivity extreme, such that the values in the co-occurrence time series may exceed 1 at an individual time step.

Since vegetation productivity can react to changing climatological conditions with a delay, we extend the computation to cover non-zero time lags to include GPP extremes happening in the 12 months after extreme temperature–moisture conditions (Fig. 1c). For the resulting co-occurrences, a value of 1 indicates that a GPP extreme follows a compound climate extreme with lag τ . We sum the co-occurrences at lag τ for the whole time series and normalize the sum by the total count of compound extremes, yielding the *co-occurrence rate* $COR(\tau)$ (Fig. 1d). The normalization ensures a COR between 0 and 1. The higher the COR, the higher the share of GPP extremes that follow after a compound climate extreme at a specific lag. For $COR(\tau) = 1$ a GPP extreme would follow after every compound extreme with a lag τ , while for $COR(\tau) = 0$ there would be no extreme GPP response.

3.3 Significance testing

We implement a two-sided randomization test to extract significant links between climatic precursors and GPP extremes. We construct a null model for the null hypothesis that the observed COR occurs by chance by shuffling monthly time blocks, effectively randomizing each event time series. With a block size of one month, we assume no persistent memory in the null model. Increasing the block size to several months has a negligible impact on the results (not shown). 200 null model realizations proved sufficient for the resulting distribution and significance thresholds to converge approximately (Fig. S1, Supplementary Information). We compute the CORs for each randomized time series in the ensemble, for each grid cell, and for each positive time lag between a compound event and a GPP extreme.

If the COR for the original data falls outside the central 90% of the null model probability distribution, we reject the null hypothesis (two-sided test) and consider the statistical link of GPP extremes and compound extremes to be significant. If the COR lies in the upper 5%, the occurrence of a compound event appears to significantly increase the likelihood of a subsequent GPP extreme. In turn, if the COR is below the null model's 5th percentile, the occurrence of a compound event significantly reduces the likelihood of a subsequent GPP extreme.



3.4 Interpreting the co-occurrence rate through its peak height and timing

We use the maximum offset of the COR to the null model (“*peak height*”) to quantify the coupling strength between compound and GPP extremes in the observation-based and model data. The corresponding time lag (“*peak timing*”) then describes the characteristic time for GPP fluxes to reach extreme values in response to temperature–moisture extremes. This response time does not necessarily imply that a GPP extreme will always or exclusively occur within that period, but that it is most likely for a GPP extreme to occur at that time. Grid cell-level pattern correlations of peak height and timing provide a measure of spatial agreement between modeled and observed responses.

In summary, co-occurrence rates quantify the strength and timing of the statistical relationship between GPP extremes in the succession of temperature–moisture extremes. A significant COR implies that this relation is stronger than expected by chance. Depending on the context, significant statistical links either indicate an increase or a decrease in the likelihood of a GPP extreme following a climatic extreme event. To comprehensively analyze the relationships between compound events and GPP extremes, we separately analyze the coupling strength and timing for all combinations of hot/cold, dry/wet, and low/high GPP extremes.

4 Results

We investigate the relationships between temperature-precipitation compound extremes and GPP flux extremes in CESM2, MPI-ESM1.2, and FLUXCOM observations. Based on the co-occurrence rate of compound events and GPP extremes, we quantify regional variations in the mechanistic response and the agreement between simulation and observation data. We first discuss the characteristics of the statistical relationship between cold–wet compound events and high GPP extremes as an example (Sect. 4.1). Subsequently, we aggregate the results at regional and global scale to systematically evaluate model biases across all event combinations (Sect. 4.2). Finally, we explore mechanistic regimes that could explain the similarities and differences between the data sources (Sect. 4.3). Note that we use shorthand expressions: “hot–dry–low” would, for example, indicate co-occurrences of hot–dry climatic compound events followed by low GPP extremes.

4.1 Significant local links between cold–wet compound events and high GPP extremes

To provide an intuitive understanding of the COR as a measure of statistical coupling, we first explore how often cold–wet events are followed by very high vegetation productivity (cold–wet–high). The peak height of the co-occurrence rate (Fig. 2, left column) reflects the maximum coupling strength between GPP extremes and compound events. The corresponding peak timing (Fig. 2, right column) provides a characteristic response time of GPP to compound extreme conditions in temperature and soil moisture (Sect. 3). For cold–wet–high, all datasets exhibit distinct regional and latitudinal patterns in peak height and timing (Fig. 2). Mid- and low-latitude semi-arid to arid regions exhibit the strongest and spatially most extensive link between cold–wet events and high GPP extremes, reflecting the positive impact of additional moisture and lower evaporative pressure

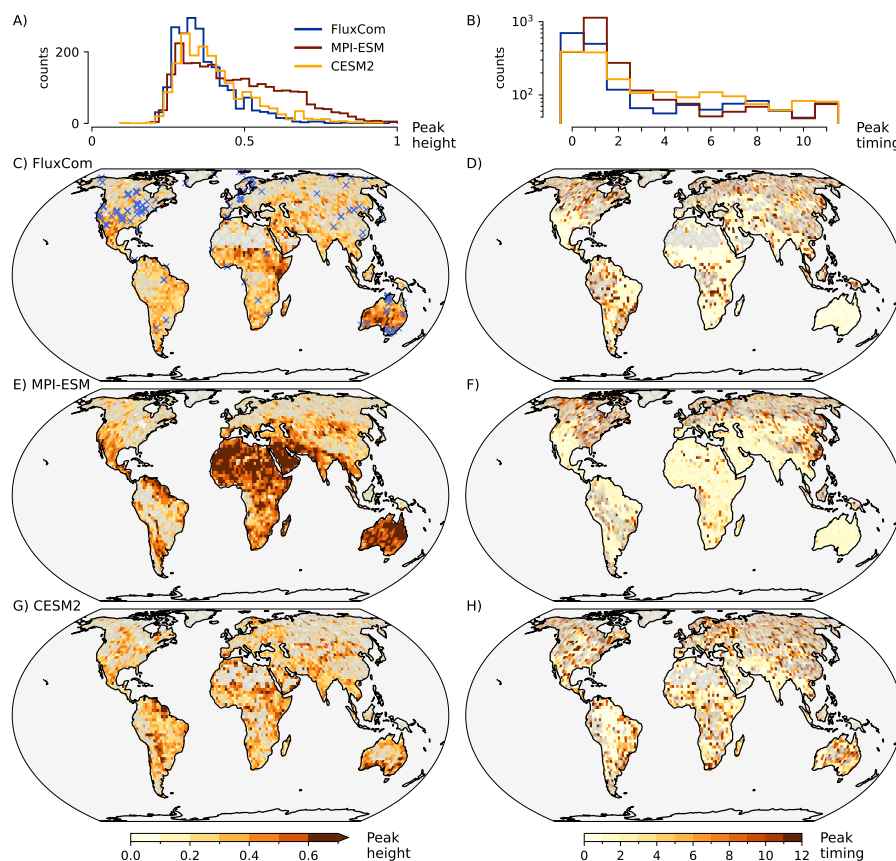


Figure 2. Highest share of co-occurrences (peak height) between cold–wet compound events and high GPP extremes (left column) and the corresponding timing (right column) in FLUXCOM and simulations. Histograms in (a), (b) show all significant grid cells with respect to the null model. Note that counts of peak timing are given on a logarithmic scale in (b). Gray shading in (c)–(h) masks these insignificant data points. Crosses in (c) mark the FluxNet observation sites contributing to the FLUXCOM dataset. The 52 Central European FluxNet sites are depicted as a single thick cross.

in moisture-limited environments. In contrast, there are almost no significant statistical links at high latitudes. The significant coupling is particularly pronounced in MPI-ESM (Fig. 2a, e). Although the spatial patterns are often more pronounced in the simulations, they are largely similar to those in FLUXCOM. This can be seen in pattern correlation coefficients between the datasets: 0.48 (FLUXCOM with MPI-ESM), 0.39 (FLUXCOM and CESM), and 0.44 (CESM and MPI-ESM). These correlations give an indication of the average local agreement of spatial patterns between our datasets, regardless of systematic biases (Fig. 3). For peak height, pattern correlations are medium to high for all combinations of compound events and GPP extremes, ranging from 0.39 to 0.76, with hot–wet and cold–dry ranking higher than hot–dry and cold–wet events (Fig. 3a). Both ESMs largely agree with FluxCom, more so than with each other.

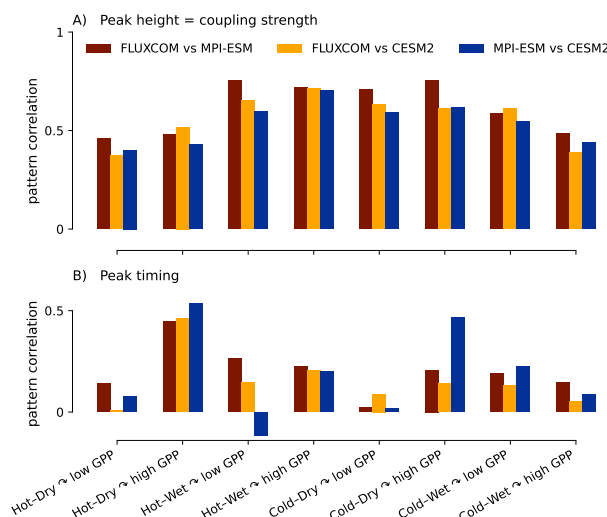


Figure 3. Global spatial pattern correlation coefficients of COR peak heights (a) and peak timings (b) for all combinations of extremes and datasets. Note that pattern correlations were only computed for grid cells that are significant in both datasets. The share of overlapping patterns is generally high, but varies by extreme type and dataset (Fig. S2).

Where the statistical link between cold–wet events and high GPP extremes is strong, the peak timing is typically small, ranging from zero to two months. Notable exceptions are scattered across South America and Africa in FLUXCOM and CESM2, and Australia in CESM2, where peak timings lie between 4 and 12 months. There are some local model-specific discrepancies. For example, MPI-ESM simulations show lead times of 6 to 12 months in northern North America, whereas CESM2 tends to produce occasionally higher lead times across all regions (Fig. 2b, h). Additionally, the spatial patterns for peak timing tend to be more noisy than for peak height. This is also reflected in low pattern correlations of the peak timing (Fig. 3b). Across event types, average local agreement is mostly low for peak timing (Fig. 3b), unlike for peak height. As an exception, across all dataset combinations we consistently find that hot–dry–high extremes behave similarly, with pattern correlations between 0.45 and 0.54.

4.2 Regional variations in coupling strength and timing between types of extremes

To systematically assess global and regional biases between the datasets, we aggregate the spatially resolved results for peak heights and timings across all combinations of extremes. We use the IPCC AR6 land reference regions, which decompose the global land area into 46 regions with coherent climatic conditions (Iturbide et al., 2020).

As an example, Northeastern South America (NES) shows a rapidly increasing co-occurrence rate of hot–dry or cold–wet compound extremes (Fig. 4a, b). In this region, which is characterized by a tropical non-seasonal climate, low moisture-high-temperature conditions appear to have an up to eight-month legacy impact on vegetation productivity in MPI-ESM and CESM.

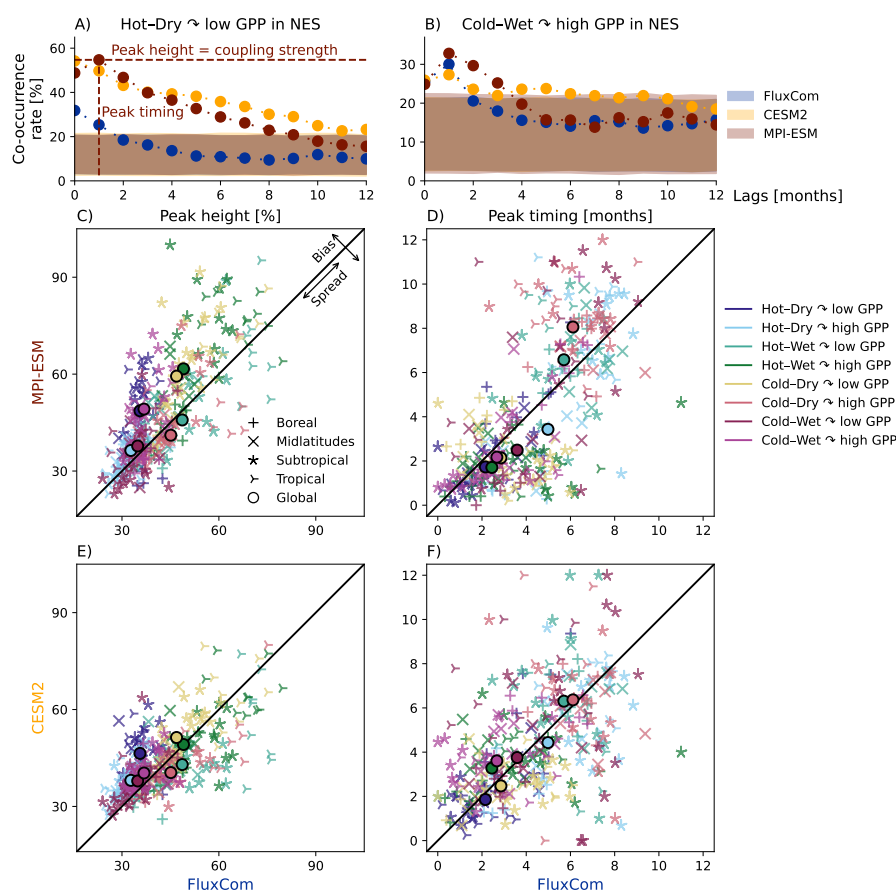


Figure 4. Agreement in regionally averaged co-occurrence rate and timing between FLUXCOM and the MPI-ESM and CESM model simulations. Average co-occurrence rates in North Eastern South America (NES) for hot–dry compounds followed by low GPP extremes (a) and cold–wet events followed by high GPP extremes (b). Horizontal bands represent the 95% range of the null model realizations. Peak height (c,e) and timing (d, f), as illustrated in (a), compared between FLUXCOM data and the MPI-ESM (c, d) and CESM simulations (e, f) for all combinations of compound climate events and GPP extremes (color-coded). Only significant co-occurrences are shown. Marker styles categorize IPCC AR6 land reference regions (Figure S5). Diagonal lines indicate perfect agreement between datasets. Global mean agreement for any extreme type combinations (marked by different colors) is marked by circles.

In FLUXCOM, the strength of this effect is lower, and it declines more rapidly (Fig. 4a). By contrast, cold conditions associated with excess moisture appear to support vegetation productivity more immediately, and consistently between observations and simulations (Fig. 4b). While the peak height and timing vary between regions, datasets and variables, the share of co-occurrences gradually declines in regions where a notable initial peak above the significance threshold was found. In NES for example, both models show a peak height of around 55% for hot–dry–low, whereas the FLUXCOM data peaks around 31% (Figure 4a). In contrast, all data sources agree on a lower peak height at around 30% for cold–wet–high (Figure 4b).



4.2.1 Coupling strength

Overall, regional and especially globally averaged couplings between climate and vegetation extremes appear to be similar in observation-based and model data (Fig. 4c, e). All data sources consistently suggest the highest statistical association of hot–wet–high and cold–dry–low extremes. However, these combinations, along with hot–wet–low extremes, also exhibit the greatest regional spread in coupling strength. In FLUXCOM, globally averaged hot–wet–low and cold–dry–low extremes exhibit coupling strengths similar to those of their high GPP counterparts. In contrast, in MPI-ESM, all combinations of dry events followed by low GPP extremes and wet events followed by high GPP extremes are biased high compared to FLUXCOM. Therefore, unlike for FLUXCOM, all of these combinations rank higher than hot–wet–high and cold–dry–high. Global mean statistical coupling strengths in CESM2 do not differ as much between event types as in MPI-ESM. However, this model also exhibits a positive mean bias for hot–dry–low extremes.

Biases observed on the global scale are more pronounced regionally, where both models tend to overestimate statistical coupling strength between temperature–moisture and GPP extremes compared to FLUXCOM. This regional bias is particularly evident in MPI-ESM for hot–dry–low, cold–wet–high, cold–dry–low, and hot–wet–high extremes. In CESM2 simulations, the direction of biases is similar to MPI-ESM, but their amplitude tends to be smaller.

Cold–dry and hot–wet temperature–moisture extremes appear to have a larger regional spread than hot–dry and cold–wet extremes. The pronounced latitudinal structure likely contributes to this as hot–wet extremes exhibit the highest coupling strength in the tropics and subtropics (e.g., hot–wet–high mean (standard deviation): 56 (19)% in MPI-ESM, 47 (12)% in CESM2, and 48 (13)% in FLUXCOM) compared to the higher latitudes (41 (8)% in MPI-ESM, 41 (6)% in CESM2, and 40 (5)% in FLUXCOM). To a slightly lesser extent, this pattern holds for cold–dry extremes (e.g., for cold–dry–low in FLUXCOM, 44 (12)% in the subtropics and tropics and 38 (4)% in high latitudes).

4.2.2 Timing

The capacity of vegetation and soils to buffer extreme conditions, and the type of growth-limiting regime (energy, moisture, nutrients) influence the duration over which vegetation can sustain extremes and the time it takes for the GPP flux to respond to them. This is reflected in the COR's peak timing. Global model-observation biases are small, between -1.6 months (model leading FLUXCOM data) and +1.9 months (model lagging FLUXCOM) for MPI-ESM simulations and between -0.6 and +0.9 for CESM2 (Fig. 4d, f). Timing is short for immediate responses when buffering capacity is low, and supplies are limited. MPI-ESM tends towards faster response times than FLUXCOM for all but the two slowest cases (hot–wet–low and cold–dry–high events), highlighting how an immediate response can occur both for extreme events that damage and benefit vegetation productivity. Hot–dry compound events followed by low GPP extremes exhibit the shortest response time across the datasets at 1.7 to 2.2 months. Hot–wet–high, cold–dry–low, and cold–wet with low or high GPP events have similarly short response times, ranging from 1.7 to 3.8 months. The event combinations with the slowest response in all datasets are hot–wet–low (MPI-ESM:



6.6, CESM2: 6.3, FLUXCOM: 5.7) and cold–dry–high extremes (MPI-ESM: 8.1, CESM2: 6.4, FLUXCOM: 6.1). Such long response times can occur when extremes expose supply limitations after prolonged buffering or due to seasonality, or when they stimulate supplies for a future growing season.

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Regionally, there are notable differences in model–observation biases and a substantial spread across the regions. Some combinations of events exhibit latitudinal patterns in these biases. For example, for cold–dry–high extremes, biases are mostly positive in the tropics and subtropics, indicating that the model response there is slower than that shown by FLUXCOM. In the mid-latitudes and boreal regions, on the other hand, the models tend to respond faster for this event combination. When cold–dry events are followed by low GPP extremes, the opposite latitudinal pattern tends to appear.

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4.3 Regionally opposing patterns of vegetation productivity as a consequence of changing extreme moisture-temperature relationships

To comprehensively differentiate the spatial response of vegetation productivity to temperature–moisture extremes, we classify the effects of these extremes into three classes according to their GPP response: (i) damaging to vegetation productivity due to an increase (reduction) of the likelihood of low (high) GPP extremes, (ii) beneficial to vegetation productivity due to an increase (reduction) of the likelihood of high (low) GPP extremes, or (iii) damaging and beneficial at different lags after the compound extreme. The latter is included only for completeness, as it occurs rarely. Fig. 5 shows the spatial patterns of the classified effects of compound extremes on vegetation productivity for the FLUXCOM dataset across all combinations of temperature, soil moisture, and GPP extremes. The patterns are generally similar for the model data (Fig. S14, S15).

315

Under extraordinarily wet conditions, temperature and moisture limitations materialize differently in the productivity response. Exceptionally high temperatures stimulate productivity in the boreal and some temperate regions (Fig. 5a), whereas low temperature extremes damage productivity in the same regions (Fig. 5f). However, under exceptionally wet conditions, other than in arid regions, the moisture supply and latent heat transport remain sufficient to outweigh the damaging potential of enhanced evaporation during hot extremes (Fig. 5a, h). Likewise, contrasting their influence under extremely dry conditions, low temperature extremes contribute to beneficial growth environments by attenuating evaporation in moisture-limited, low-latitude regions (Fig. 5c, e). This shift in evaporative balance is also why vegetation is less likely to experience low GPP extremes under cold–wet conditions in some (sub-)tropical regions (Fig. 5f).

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In cold–dry extreme conditions, reduced evaporation in transition zones that outweighs the moisture shortage could explain beneficial effects on high GPP extremes in some subtropical and midlatitude regions (Fig. 5d). Dry conditions have adverse effects elsewhere, both by reducing the likelihood of exceptionally high productivity and increasing the likelihood of extraordinarily low productivity for short lags (Fig. 5b, e, g). Here, a lack of moisture supply dominates the response in mid- to low-latitude regions under hot–dry conditions (Fig. 5e, g). In contrast, a shortened growing season or unfavorable growth con-

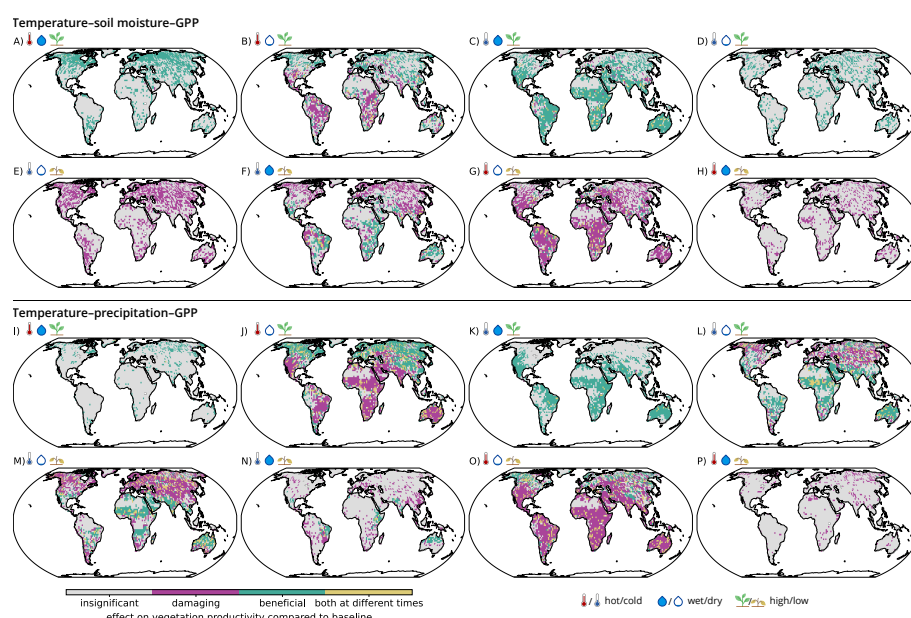


Figure 5. Categorization of enhanced and muted co-occurrence rates between temperature–soil moisture and GPP extremes (a-h) and between temperature–precipitation and GPP extremes (i-p) in the FLUXCOM dataset. Panels display the categorization for the different types of compound events from hot–wet–high (a, i) through hot–wet–low (h, p) as indicated by icons and aggregated for all time lags. Co-occurrence rates are diagnosed as “damaging”/“beneficial” when they exceed/undercut the null model’s 95% range for low GPP extremes and undercut/exceed the range for high GPP extremes. This categorization presumes that an increased/decreased statistical coupling between temperature–moisture extremes and low/high GPP extremes corresponds to less favorable conditions for plant growth and carbon uptake. Vice versa, a decreased/increased coupling with low/high GPP extremes reflects more favorable conditions for vegetation productivity. In rare cases, co-occurrence rates both exceed and undercut the null model range at different lags. This behavior is categorized as “both at different times.”

330 ditions caused by low temperatures explain the high-latitude response (Fig. 5e).

We find consistent and sometimes mirrored patterns between regions and types of extremes (Fig. 5). This mirroring can be found for all combinations of extremes, when contrasting hot and cold, dry and wet, and high and low GPP extremes. For example, hot–dry extremes significantly increase the likelihood of high GPP events in the Northern Hemisphere’s high and mid latitudes (Fig. 5b), indicating beneficial conditions for plant growth with increased warmth. At the same time, hot–dry events reduce the likelihood of high GPP extremes in the subtropics and tropics, where a lack of moisture supply damages vegetation productivity. Vice versa, cold–wet events create less favorable growth conditions in mid- and high latitudes, indicated by an increased likelihood of low GPP extremes (Fig. 5f). In low latitudes, cold–wet extremes reduce the likelihood of extremely low plant productivity, particularly in rainforest regions, thereby having a positive effect on plant growth. Combining the two (nearly) complementary patterns illustrates how vegetation productivity benefits from one type of temperature–moisture event,



but gets damaged by an opposing type of event.

Juxtaposing cold–wet–high extremes (Fig. 5c) and hot–dry–low extremes (Fig. 5g) shows that cold–wet events increase the chance for high GPP extremes in the same regions, effectively associated with benefiting plant growth. In contrast, hot–dry events increase the likelihood of low GPP extremes, reducing vegetation productivity, particularly in mid- and low latitudes. Similar patterns exist for cold–dry–low extremes (Fig. 5e) with damaging effects east in the Andes and throughout Eurasia and North America, in contrast to the beneficial effects of hot–wet–high extremes in similar regions (Fig. 5a).

Following from the regional agreement in peak height and timing, the response patterns of vegetation productivity are similar in the three datasets, albeit with regionally different biases and extent in the models compared to FLUXCOM (Fig. S14, S15). In CESM2, productivity benefits are more pronounced for hot–dry–high extremes in the high latitudes compared to FLUXCOM (Fig. S14). CESM2 also overemphasizes damages in the mid- and low latitudes when low GPP extremes follow hot–dry and cold–dry events, reducing the latitudinal gradient for cold–dry–low extremes. MPI-ESM responds analogously for hot–dry–high extremes, but overestimates spatial extent and coherence compared to FLUXCOM (Fig. S15). It matches FLUXCOM patterns in the high latitudes somewhat better than CESM2, particularly in Eastern Siberia. Similar observations hold for cold–wet–low. Here, MPI-ESM matches FLUXCOM’s response patterns reasonably well, but again overestimates spatial extent and coherence. CESM2, by contrast, tends to underestimate the spatial extent of response patterns for this event combination (Fig. S14). Notably, compared with FLUXCOM and CESM2, MPI-ESM also predicts a much stronger response in and around the Sahara region for low GPP extremes following dry events and for high GPP extremes following wet events.

Overall, at an aggregated level, a lack of moisture is predominantly detrimental to vegetation productivity. In this case, modulating effects of temperature extremes outweigh moisture shortages only at a few locations in the high latitudes for hot–dry–high extremes and in the transition zones for cold–dry–high extremes. On the other hand, high temperature extremes mostly benefit plant growth when moisture is abundant, particularly in the high and mid-latitudes. In turn, (extreme) moisture abundance will generally support vegetation productivity, unless temperature limits access to water in boreal zones or confines the evaporative water budget in some subtropical and temperate climatological transition zones.

4.4 Evaporative effects and the moisture integrating time modulate the vegetation response to climatic extremes

Almost all plants take up necessary moisture from the soil, most of which comes from rainwater. Precipitation, as an alternative indicator of moisture availability, reduces the effective integration time of the climatic compound events compared to soil moisture. It comes with lower latent temperature control on wet/dry extreme conditions through evaporative effects, as these affect soil moisture but not (directly) precipitation. As a result, responses to hot–wet–low, cold–dry–high, cold–dry–low, and hot–dry–low extreme conditions qualitatively differ for precipitation across all datasets (Fig. 5).

Patterns of advantageous and adverse conditions for vegetation productivity are often opposed for contrasting temperature–soil moisture extreme conditions. For example, plant growth benefits from hot–wet–high extremes, but suffers from cold–dry–low extremes (Fig. 5a, e). The mirrored patterns disappear with temperature–precipitation extremes because soil moisture and



375 precipitation emphasize different mechanistic aspects. With precipitation, typically only one of the complementary extreme conditions exhibits a coherent spatial pattern, as is the case for cold-dry-low (Fig.5m), whereas hot-wet extremes do not increase the likelihood of high GPP extremes (Fig.5i).

Response maps for temperature-precipitation extremes also no longer show the globally uniform response of high and low
 380 GPP extremes to cold-dry extremes (Fig. 5l, m). Instead, they exhibit strong dipoles. While vegetation productivity in the tropics benefits from cold-dry temperature-precipitation extremes, these events have damaging effects in the mid- and high latitudes. Similarly, the almost uniform damaging effect of hot-dry conditions shifts toward a dipole pattern (Fig. 5j, o). In this case, hot-dry temperature-precipitation events support growth conditions in the high latitudes. On the other hand, there is barely any significant link between compound hot-wet temperature-precipitation events and high/low GPP extremes (Fig. 5i,
 385 p), unlike for soil moisture with a substantially increased likelihood of high GPP extremes in the mid- and high latitudes (Fig. 5a). More subtle differences between the two moisture indicators occur for hot-dry and cold-wet events. While statistical coupling with precipitation as an indicator is lower for hot-dry-low and higher for cold-wet-low extremes compared to soil moisture (Fig. S13), response patterns are more extensive and coherent in space, particularly for hot-dry extremes that benefit productivity in the high latitudes (Fig. 5j, o).

390

Despite the mirrored patterns occurring only for temperature-soil moisture extremes, significant beneficial and detrimental patterns for vegetation productivity often concur well between temperature-soil moisture and temperature-precipitation extremes (Fig.5). It is also notable that precipitation-based CORs are substantially higher under wet than dry conditions in all datasets, and biases between observations and simulations are reduced (Fig. S13c, d). However, global-scale model response
 395 times tend to be biased high with precipitation, i.e., the peak heights are reached later in the models than in FLUXCOM (Fig. S13e, f). This bias is most pronounced for event combinations with short characteristic response times. Biases for peak times are also larger when using precipitation and the regional spread increases for all datasets. By contrast, for peak heights model biases are reduced when using precipitation instead of soil moisture.

In contrast to temperature-soil moisture extremes, patterns including temperature-precipitation extremes are inherently consistent, i.e., the same type of temperature-precipitation extreme creates damaging (beneficial) effects through changes in both,
 400 low and high GPP extremes, or affects only one of the extreme types. In contrast, there are several occasions where the same type of temperature-soil moisture extreme is both damaging by lowering (increasing) the likelihood of high (low) GPP extremes and beneficial by reducing (increasing) the likelihood of low (high) GPP at the same location.

5 Discussion

405 5.1 Similarity between observations and model data

Both models appear capable of capturing essential dependencies that influence vegetation productivity a few months into the future. Spatial aggregation impacts the degree of consistency of the statistical link between extremes in temperature-moisture and



vegetation productivity between MPI-ESM, CESM2, and the observation-based data from FLUXCOM. Models and FLUXCOM agree most at the global and regional scale, despite some model-specific biases (Sect. 4.2). The agreement decreases at the grid-cell level. Aggregating localized statistical links leads to more reliable estimates from the ESMs. This highlights the complexity of developing and calibrating state-of-the-art ESMs that represent local climate–biosphere interactions beyond the mean state well (Reichstein et al., 2013; Villalobos-Herrera et al., 2021).

Contrasting the qualitative agreement, there is a substantial spread in regional performance, with model-specific biases. Raw, not bias-corrected ESM data can be considered reliable only in some regions. For example, there is a clear latitudinal gradient in local model performance. Both MPI-ESM and CESM2 tend to perform better in the mid-latitudes and boreal regions compared to the (sub-)tropics (Fig. 3, S9). Much of this regional spread stems from both ESMs systematically overestimating the strength and spatial coherence of the statistical coupling between climate and vegetation extremes on the local level. This partly carries over to regional aggregations (Sect. 4.2). Spatially variable climate variability could influence the regional spread, but is unlikely to cause substantial biases over a 36-year analysis period.

ESMs mostly underestimate the intensity of daily precipitation extremes and underestimate the dry day frequency in comparison to observations (Seneviratne et al., 2021; Norris et al., 2021). It may appear counterintuitive that climate extremes pre-condition vegetation towards productivity extremes more strongly in the ESMs than in the observational data. However, the two phenomena are not directly linked to overestimated vegetation–climate coupling, which may well be due to deficiencies in the land models, particularly the soil. Biases in both models occur under extremely dry conditions. This points to oversensitive evaporative feedbacks, exaggerated drainage, or too low soil water holding capacity, leading to accelerated evaporation of soil moisture. Higher soil moisture decay rates in both ESMs compared to ERA5 support this interpretation of exaggerated dry-out (Figure 6). MPI-ESM shows additional biases under extremely wet conditions, which could arise from an overly simplified representation of precipitation input to soil water pools, missing moisture routing above and below the surface, or misaligned soil water-holding capacity, which is compatible with other model benchmarking results (Seiler et al., 2022). The overestimated rates of soil moisture change in MPI-ESM are not just connected to biases in the coupling between climatic and vegetation extremes, but also translate into mean GPP biases (Fig. S16). This could indicate an influence of the biased extreme representation on the mean state biases, given the strong influence of productivity extreme events on terrestrial carbon stocks (Zhou et al., 2019).

Intriguingly, the ESMs do not overestimate coupling strengths when considering temperature–precipitation rather than temperature–soil moisture compound extremes. This could indicate that biases in the soil moisture–vegetation relationship may be compensated by biases in precipitation–soil moisture relationships. Alternatively, temperature–precipitation extremes could drive GPP extremes through different mechanistic links than temperature–soil moisture extremes. This interpretation would be supported by the differing orders of global mean peak heights and timings between extreme types when using pre-



precipitation rather than soil moisture (Figure 3).

5.2 Potential biases of observations and models

445 The observation-constrained FLUXCOM data aggregates uncertainties from the upscaling process and underlying FluxNet site data (Jung et al., 2020). FLUXCOM also underestimates interannual GPP variability and exhibits partly unrealistic GPP growth rates (Jung et al., 2020). Both of these shortcomings could lead to FLUXCOM biases being mistaken for model biases in our comparison, if they alter the GPP event distribution. However, the comparison between precipitation-based and soil moisture-based estimates indicates a mechanistic explanation for the largest part of the model–observation differences. Deficiencies in
 450 the HTESSEL soil model used to produce ERA5 soil moisture estimates (Balsamo et al., 2015) could also enhance perceived ESM biases. However, HTESSEL performs well with respect to observations (Balsamo et al., 2015), and assimilation of soil moisture observations from in-situ and satellite observations in ERA5 should further reduce soil moisture biases (Hersbach et al., 2020). Given that the observed biases have model-specific characteristics, the mechanistic shortcomings are likely located on the side of the ESMs.

455

Both CESM2 and MPI-ESM show substantial regional spread in the statistical relationships between hot-wet and high GPP extremes. MPI-ESM overestimates the strength and underestimates the lag between climatic driver and vegetation response, whereas CESM2 underestimates the strength and overestimates the lag. At the same time, both models tend to exaggerate the spatial extent of significant coupling, particularly within (sub-)tropical regions (Fig. S6). Both suggest that GPP extremes are
 460 significantly affected by hot–wet compound events in around half of the (sub-)tropics (Fig. S3), which is more than twice the area based on FLUXCOM/ERA5 (Fig. S3). The MPI-ESM land component JSBACH was tuned for a high moisture sensitivity of vegetation in the Sahel to study the phenomenon of the African humid period in the late Pleistocene and early Holocene (Groner et al., 2018). Sensitive, perhaps oversensitive, vegetation productivity in the (sub-)tropics is most likely also the reason for the large regional spread observed in both ESMs for cold–dry compound events that lead to low GPP extremes and for high
 465 GPP extremes following cold–wet events in MPI-ESM (Fig. S3, S7, S8). However, FLUXCOM tends to overestimate tropical mean GPP and net ecosystem exchange, partly due to weaknesses in FluxNet site data (Jung et al., 2020). Although this bias does not necessarily affect the GPP event distribution in a way that propagates into the COR, it is crucial to better constrain observations and models in this pivotal region for the global carbon budget.

470 Our analysis builds on CORs to quantify how well ESMs relate climatic and productivity extremes. The COR imposes no constraints on causality and latent variables. This is advantageous for our impact-oriented analysis. However, it will not necessarily identify if a model performs well for the wrong reasons. To assess causality, rather than correlation, the COR would need to be applied incrementally to driver and response variables. This would result in large data requirements for intermediate state variables that are rarely available, especially on the observation side.

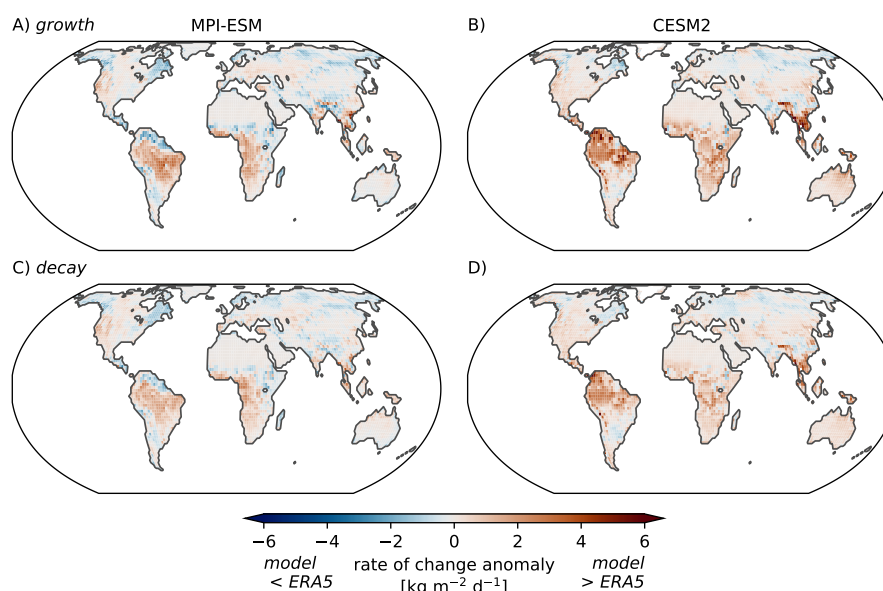


Figure 6. Divergent change rates in soil moisture between ERA5 and the ESMs. Panels depict smoothed annual maximum rates of change averaged over 1979–2014 as anomalies to ERA5 for increasing (a, b) and decreasing soil moisture (c, d).

475 5.3 Mechanisms

We find that both beneficial and detrimental preconditioning effects of temperature–moisture extremes for vegetation growth conditions manifest as coherent spatial patterns in the observation-based and model data (Fig. 5). The spatial response patterns provide mechanistic insights into the repercussions of temperature–moisture extremes on vegetation growth around the globe. On the one hand, it is evident that temperature–soil moisture extremes can benefit vegetation productivity through an increased likelihood of high GPP extremes in many regions. An exception are hot–dry events where extreme climatic conditions have damaging effects in the tropics and subtropics. On the other hand, climatic extremes almost always increase the likelihood of low GPP extremes, with harmful consequences for vegetation productivity. In this case, cold–wet extremes are the exception, as they reduce the likelihood of low GPP extremes in the (sub-)tropics, thereby benefiting plant growth conditions. These opposing responses suggest differing mechanistic links for high compared to low GPP extremes.

Our results suggest that process-based links have to be contextualized on an event-type and region-specific basis. In addition, seasonality is an important factor to consider, particularly in explaining varying peak timings across events and regions (Zscheischler et al., 2014a; Guan et al., 2015). Overall, the spatial patterns mostly reflect the dominant temperature limitation for growth in the high latitudes and moisture limitations in the mid- and low latitudes. For example, in the context of extremely dry but hot conditions, these limitations lead to increased likelihoods for beneficial high GPP extremes in boreal latitudes (Fig. 5b), either because they free up frozen water early in the growing season, or because of the growth promoting effect of



high temperature outweighing the relatively reduced moisture (Flach et al., 2021) (Fig. 3, 5). In contrast, hot–dry events are significantly linked to damaging effects, as they increase the likelihood of low and reduce the likelihood of high GPP extremes in moisture-limited regions (Fig. 5b,g). If insufficient moisture supply persists, it can severely degrade growing conditions
495 (Green et al., 2019).

Compounding temperature–soil moisture extremes require soil moisture to integrate sustained atmospheric drought (high precipitation) and high (low) evaporation facilitated by high (low) temperature. At the same time, to promote extreme conditions, temperatures must remain relatively high (low) for an extended period, which is less likely than shorter temperature
500 extremes. This is different for temperature–precipitation extremes, which only require temporal coincidence, but no build-up time. Soil moisture also has a prolonged memory, potentially causing legacy effects, although these are typically under-resolved in ESMs (Kolus et al., 2019; Anderegg et al., 2015). In contrast, atmospheric dynamics that drive precipitation extremes exhibit low temporal autocorrelation. These differences may partly explain why we observe more extensive and coherent spatial patterns with precipitation. Additionally, precipitation as an indicator of atmospheric drought and soil moisture content as a
505 measure of soil drought partly represent different mechanisms of how plants experience drought (Harris et al., 2022; Wu et al., 2022), which could contribute to the different spatial patterns.

It would be worthwhile to expand our approach to additional moisture indicators and latent variables in the future, such as vapor pressure deficit or soil conditions. Our first-order approach can only implicitly account for the potential of compound
510 extremes to cause persistent physical damage to vegetation from floods, fires, or other natural disturbances (Jain et al., 2022). In addition, changes in anthropogenic land use and land management practices, such as irrigation, can significantly alter physical surface properties and the moisture budget, affecting the likelihood of extremes (Findell et al., 2017). Future work could therefore also explore how both natural and anthropogenic disturbances shape the preconditioning of GPP extremes under climate change.

515 **6 Conclusions**

The interplay between temperature–moisture extremes and vegetation productivity will co-determine resilience and vulnerability of the land carbon sink and terrestrial ecosystems to future climate change. ESMs are essential tools for projecting this link between climatic and biosphere extremes and the resulting impacts on carbon stocks. While research efforts often focus either on extreme drivers, impacts, or on specific event types, we comprehensively benchmarked the statistical link between
520 temperature–moisture and GPP extremes across all event combinations in two state-of-the-art ESMs against an observation-constrained dataset. We introduced a generalizable metric that can be translated to more complex networks of extreme event interactions. Expanding our analysis to comprehensive model-data and inter-model comparisons in the context of CMIP6 and CMIP7 would add confidence in the generalizability of our results.



525 While there is substantial regional variation in models and data, with spurious deviations in the lag between climatic drivers
 and GPP responses, there is reasonable agreement on the strength of the statistical relationship for regionally and especially
 globally aggregated results. We found that MPI-ESM and CESM2 locally overestimate the association between temperature–
 moisture and GPP extremes. We hypothesize that this discrepancy arises due to overestimated rates of change in soil moisture
 in the ESMs. This may perhaps be due to unrealistic evaporative feedbacks, exaggerated drainage, or inadequate effective
 530 water-holding capacity in the model soils. Assessments of legacy- and state-dependencies of this statistical coupling under
 climate change can build on general agreement found regionally and globally and the quantified local biases. However, as GPP
 integrates short-lived disturbances, biases in the statistical link can propagate into the annual mean GPP, as appears to be the
 case for MPI-ESM. The link between climatic and GPP extremes could potentially be exploited further as a proxy to test mean
 GPP biases beyond the immediate effects of atmospheric extremes.

535 Model and observation-based data indicated both adverse and advantageous effects of temperature–moisture extremes on
 vegetation productivity in different regions. There is justified and wide interest in extreme events that damage vegetation and
 ecosystems. However, as our results showed, beneficial impacts on vegetation can occur across all latitudes and cover a similar
 share of land as detrimental effects. This situation could change, either due to shifts in the frequency of different types of
 540 climate extremes or changes in the link between climate extremes and GPP extremes. Whether the beneficial impacts will
 persist under future climate change or evolve asymmetrically to an increasing likelihood of GPP decline should be further
 quantified and could be highly relevant for the strongly variable and interconnected net land carbon uptake.

Code and data availability. ERA5 data is available through the Copernicus Climate Change Service (C3S) Climate Data Store (CDS)
 (Copernicus Climate Change Service (C3S), 2019, 2023). Monthly data from the FLUXCOM initiative are available via the Max Planck
 545 Institute for Biogeochemistry data portal (Boenisch, 2020) upon free registration (Jung et al., 2020; Tramontana et al., 2016). CESM2 out-
 put (Version 20190312; Danabasoglu, 2019) and MPI-ESM1.2-LR output (Version 20210921; Wieners et al., 2019) are publicly available
 through the Earth System Grid Federation (ESGF), for example, on their server at DKRZ: [https://esgf-metagrid.cloud.dkrz.de/search/cmip6-](https://esgf-metagrid.cloud.dkrz.de/search/cmip6-dkrz/)
[dkrz/](https://esgf-metagrid.cloud.dkrz.de/search/cmip6-dkrz/). Analysis code, along with intermediate data, will be made available on Zenodo upon acceptance.

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565 References

- Anderegg, W. R. L., Schwalm, C., Biondi, F., Camarero, J. J., Koch, G., Litvak, M., Ogle, K., Shaw, J. D., Shevliakova, E., Williams, A. P., Wolf, A., Ziaco, E., and Pacala, S.: Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models, *Science*, 349, 528–532, <https://doi.org/10.1126/science.aab1833>, 2015.
- Arora, V. K., Katavouta, A., Williams, R. G., Jones, C. D., Brovkin, V., Friedlingstein, P., Schwinger, J., Bopp, L., Boucher, O., Cadule, P.,
 570 Chamberlain, M. A., Christian, J. R., Delire, C., Fisher, R. A., Hajima, T., Ilyina, T., Joetzjer, E., Kawamiya, M., Koven, C. D., Krasting, J. P., Law, R. M., Lawrence, D. M., Lenton, A., Lindsay, K., Pongratz, J., Raddatz, T., Séférian, R., Tachiiri, K., Tjiputra, J. F., Wiltshire, A., Wu, T., and Ziehn, T.: Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models, *Biogeosciences*, 17, 4173–4222, <https://doi.org/10.5194/bg-17-4173-2020>, 2020.
- Balsamo, G., Albergel, C., Beljaars, A., Boussetta, S., Brun, E., Cloke, H., Dee, D., Dutra, E., Muñoz-Sabater, J., Pappenberger, F., de Rosnay,
 575 P., Stockdale, T., and Vitart, F.: ERA-Interim/Land: a global land surface reanalysis data set, *Hydrology and Earth System Sciences*, 19, 389–407, <https://doi.org/10.5194/hess-19-389-2015>, 2015.
- Bastos, A., Friedlingstein, P., Sitch, S., Chen, C., Mialon, A., Wigneron, J.-P., Arora, V. K., Briggs, P. R., Canadell, J. G., Ciais, P., Chevallier, F., Cheng, L., Delire, C., Haverd, V., Jain, A. K., Joos, F., Kato, E., Lienert, S., Lombardozzi, D., Melton, J. R., Myneni, R., Nabel, J. E. M. S., Pongratz, J., Poulter, B., Rödenbeck, C., Séférian, R., Tian, H., Van Eck, C., Viovy, N., Vuichard, N., Walker,
 580 A. P., Wiltshire, A., Yang, J., Zaehle, S., Zeng, N., and Zhu, D.: Impact of the 2015/2016 El Niño on the terrestrial carbon cycle constrained by bottom-up and top-down approaches, *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373, 20170304, <https://doi.org/10.1098/rstb.2017.0304>, 2018.
- Blyth, E. M., Arora, V. K., Clark, D. B., Dadson, S. J., De Kauwe, M. G., Lawrence, D. M., Melton, J. R., Pongratz, J., Turton, R. H., Yoshimura, K., and Yuan, H.: Advances in Land Surface Modelling, *Current Climate Change Reports*, 7, 45–71,
 585 <https://doi.org/10.1007/s40641-021-00171-5>, 2021.
- Boenisch, G.: Max Planck Institute for Biogeochemistry, Data Portal, <https://www.bgc-jena.mpg.de/geodb/projects/Home.php>, 2020.
- Copernicus Climate Change Service (C3S): ERA5-Land hourly data from 1950 to present, <https://doi.org/10.24381/cds.e2161bac>, 2019.
- Copernicus Climate Change Service (C3S): ERA5 monthly averaged data on single levels from 1940 to present, <https://doi.org/10.24381/cds.f17050d7>, 2023.
- 590 Dallmeyer, A., Kleinen, T., Claussen, M., Weitzel, N., Cao, X., and Herzschuh, U.: The deglacial forest conundrum, *Nature Communications*, 13, 6035, <https://doi.org/10.1038/s41467-022-33646-6>, 2022.
- Danabasoglu, G.: IPCC DDC: NCAR CESM2 model output prepared for CMIP6 CMIP historical, <https://doi.org/10.26050/WDCC/AR6.C6CMNRCES2hi>, 2019.
- Danabasoglu, G., Lamarque, J., Bacmeister, J., Bailey, D. A., DuVivier, A. K., Edwards, J., Emmons, L. K., Fasullo, J., Garcia, R., Gettelman,
 595 A., Hannay, C., Holland, M. M., Large, W. G., Lauritzen, P. H., Lawrence, D. M., Lenaerts, J. T. M., Lindsay, K., Lipscomb, W. H., Mills, M. J., Neale, R., Oleson, K. W., Otto-Bliesner, B., Phillips, A. S., Sacks, W., Tilmes, S., Kampenhout, L. v., Vertenstein, M., Bertini, A., Dennis, J., Deser, C., Fischer, C., Fox-Kemper, B., Kay, J. E., Kinnison, D., Kushner, P. J., Larson, V. E., Long, M. C., Mickelson, S., Moore, J. K., Nienhouse, E., Polvani, L., Rasch, P. J., and Strand, W. G.: The Community Earth System Model Version 2 (CESM2), *Journal of Advances in Modeling Earth Systems*, 12, <https://doi.org/10.1029/2019ms001916>, 2020.



- 600 Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E.: Overview of the Coupled Model
 Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geoscientific Model Development*, 9, 1937–1958,
<https://doi.org/10.5194/gmd-9-1937-2016>, 2016.
- Findell, K. L., Berg, A., Gentine, P., Krasting, J. P., Lintner, B. R., Malyshev, S., Santanello, J. A., and Shevliakova, E.: The impact of anthro-
 pogenic land use and land cover change on regional climate extremes, *Nature Communications*, 8, 989, [https://doi.org/10.1038/s41467-](https://doi.org/10.1038/s41467-017-01038-w)
 605 017-01038-w, 2017.
- Flach, M., Brenning, A., Gans, F., Reichstein, M., Sippel, S., and Mahecha, M. D.: Vegetation modulates the impact of climate extremes on
 gross primary production, *Biogeosciences*, 18, 39–53, <https://doi.org/10.5194/bg-18-39-2021>, 2021.
- Gentine, P., Green, J. K., Guérin, M., Humphrey, V., Seneviratne, S. I., Zhang, Y., and Zhou, S.: Coupling between the terrestrial carbon and
 water cycles—a review, *Environmental Research Letters*, 14, 083 003, <https://doi.org/10.1088/1748-9326/ab22d6>, 2019.
- 610 Gharun, M., Shekhar, A., Xiao, J., Li, X., and Buchmann, N.: Effect of the 2022 summer drought across forest types in Europe, *Biogeo-*
sciences, 21, 5481–5494, <https://doi.org/10.5194/bg-21-5481-2024>, 2024.
- Green, J. K., Seneviratne, S. I., Berg, A. M., Findell, K. L., Hagemann, S., Lawrence, D. M., and Gentine, P.: Large influence of soil moisture
 on long-term terrestrial carbon uptake, *Nature*, 565, 476–479, <https://doi.org/10.1038/s41586-018-0848-x>, 2019.
- Groner, V. P., Raddatz, T., Reick, C. H., and Claussen, M.: Plant functional diversity affects climate–vegetation interaction, *Biogeosciences*,
 615 15, 1947–1968, <https://doi.org/10.5194/bg-15-1947-2018>, 2018.
- Guan, K., Pan, M., Li, H., Wolf, A., Wu, J., Medvigy, D., Caylor, K. K., Sheffield, J., Wood, E. F., Malhi, Y., Liang, M., Kimball, J. S.,
 Saleska, S., Berry, J., Joiner, J., and Lyapustin, A. I.: Photosynthetic seasonality of global tropical forests constrained by hydroclimate,
Nature Geoscience, 8, 284–289, <https://doi.org/10.1038/ngeo2382>, 2015.
- Hao, Z., Hao, F., Xia, Y., Feng, S., Sun, C., Zhang, X., Fu, Y., Hao, Y., Zhang, Y., and Meng, Y.: Compound
 620 droughts and hot extremes: Characteristics, drivers, changes, and impacts, *Earth-Science Reviews*, 235, 104 241,
<https://doi.org/https://doi.org/10.1016/j.earscirev.2022.104241>, 2022.
- Haren, R. V., Haarsma, R. J., Vries, H. D., Oldenborgh, G. J. V., and Hazeleger, W.: Resolution dependence of circulation forced future
 central European summer drying, *Environmental Research Letters*, 10, 055 002, <https://doi.org/10.1088/1748-9326/10/5/055002>, 2015.
- Harris, B. L., Taylor, C. M., Weedon, G. P., Talib, J., Dorigo, W., and Van Der Schalie, R.: Satellite-Observed Vegetation Responses to In-
 traseasonal Precipitation Variability, *Geophysical Research Letters*, 49, e2022GL099 635, <https://doi.org/10.1029/2022GL099635>, 2022.
- 625 Harris, B. L., Quaife, T., Taylor, C. M., and Harris, P. P.: Contrasting responses of vegetation productivity to intraseasonal rainfall in Earth
 system models, *Earth System Dynamics*, 15, 1019–1035, <https://doi.org/10.5194/esd-15-1019-2024>, 2024.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Sim-
 mons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G. D., Dahlgren,
 630 P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J.,
 Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P. d., Rozum, I., Vamborg, F., Vil-
 laume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049,
<https://doi.org/10.1002/qj.3803>, 2020.
- Hurt, G. C., Chini, L., Sahajpal, R., Frolking, S., Bodirsky, B. L., Calvin, K., Doelman, J. C., Fisk, J., Fujimori, S., Klein Goldewijk, K.,
 635 Hasegawa, T., Havlik, P., Heinemann, A., Humpenöder, F., Jungclaus, J., Kaplan, J. O., Kennedy, J., Krisztin, T., Lawrence, D., Lawrence,
 P., Ma, L., Mertz, O., Pongratz, J., Popp, A., Poulter, B., Riahi, K., Shevliakova, E., Stehfest, E., Thornton, P., Tubiello, F. N., Van Vuuren,



- D. P., and Zhang, X.: Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6, *Geoscientific Model Development*, 13, 5425–5464, <https://doi.org/10.5194/gmd-13-5425-2020>, 2020.
- Iturbide, M., Gutiérrez, J. M., Alves, L. M., Bedia, J., Cerezo-Mota, R., Gimadevilla, E., Cofiño, A. S., Di Luca, A., Faria, S. H., Gorodetskaya, I. V., Hauser, M., Herrera, S., Hennessy, K., Hewitt, H. T., Jones, R. G., Krakovska, S., Manzanar, R., Martínez-Castro, D., Narisma, G. T., Nurhati, I. S., Pinto, I., Seneviratne, S. I., Van Den Hurk, B., and Vera, C. S.: An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets, *Earth System Science Data*, 12, 2959–2970, <https://doi.org/10.5194/essd-12-2959-2020>, 2020.
- Jain, P., Castellanos-Acuna, D., Coogan, S. C. P., Abatzoglou, J. T., and Flannigan, M. D.: Observed increases in extreme fire weather driven by atmospheric humidity and temperature, *Nature Climate Change*, 12, 63–70, <https://doi.org/10.1038/s41558-021-01224-1>, 2022.
- Jung, M., Schwalm, C., Migliavacca, M., Walther, S., Camps-Valls, G., Koirala, S., Anthoni, P., Besnard, S., Bodesheim, P., Carvalhais, N., Chevallier, F., Gans, F., Goll, D. S., Haverd, V., Köhler, P., Ichii, K., Jain, A. K., Liu, J., Lombardozzi, D., Nabel, J. E. M. S., Nelson, J. A., O’Sullivan, M., Pallandt, M., Papale, D., Peters, W., Pongratz, J., Rödenbeck, C., Sitch, S., Tramontana, G., Walker, A., Weber, U., and Reichstein, M.: Scaling carbon fluxes from eddy covariance sites to globe: synthesis and evaluation of the FLUXCOM approach, *Biogeosciences*, 17, 1343–1365, <https://doi.org/10.5194/bg-17-1343-2020>, 2020.
- Kim, Y.-H., Min, S.-K., Zhang, X., Sillmann, J., and Sandstad, M.: Evaluation of the CMIP6 multi-model ensemble for climate extreme indices, *Weather and Climate Extremes*, 29, 100269, <https://doi.org/10.1016/j.wace.2020.100269>, 2020.
- Kolus, H. R., Huntzinger, D. N., Schwalm, C. R., Fisher, J. B., McKay, N., Fang, Y., Michalak, A. M., Schaefer, K., Wei, Y., Poulter, B., Mao, J., Parazoo, N. C., and Shi, X.: Land carbon models underestimate the severity and duration of drought’s impact on plant productivity, *Scientific Reports*, 9, 2758, <https://doi.org/10.1038/s41598-019-39373-1>, 2019.
- Kou-Giesbrecht, S., Reis Ely, C. R., Perakis, S. S., Cleveland, C. C., Menge, D. N. L., Reed, S. C., Taylor, B. N., Batterman, S. A., Crews, T. E., Dynarski, K. A., Gei, M., Gundale, M. J., Herridge, D. F., Jovan, S. E., Peoples, M. B., Piipponen, J., Rodríguez-Caballero, E., Salmon, V. G., Soper, F. M., Staccone, A. P., Weber, B., Williams, C. A., and Wurzbarger, N.: Overestimated natural biological nitrogen fixation translates to an exaggerated CO₂ fertilization effect in Earth system models, *Proceedings of the National Academy of Sciences*, 122, e2514628 122, <https://doi.org/10.1073/pnas.2514628122>, 2025.
- Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G., Collier, N., Ghimire, B., Van Kampenhout, L., Kennedy, D., Kluzek, E., Lawrence, P. J., Li, F., Li, H., Lombardozzi, D., Riley, W. J., Sacks, W. J., Shi, M., Vertenstein, M., Wieder, W. R., Xu, C., Ali, A. A., Badger, A. M., Bisht, G., Van Den Broeke, M., Brunke, M. A., Burns, S. P., Buzan, J., Clark, M., Craig, A., Dahlin, K., Drewniak, B., Fisher, J. B., Flanner, M., Fox, A. M., Gentine, P., Hoffman, F., Keppel-Aleks, G., Knox, R., Kumar, S., Lenaerts, J., Leung, L. R., Lipscomb, W. H., Lu, Y., Pandey, A., Pelletier, J. D., Perket, J., Randerson, J. T., Ricciuto, D. M., Sanderson, B. M., Slater, A., Subin, Z. M., Tang, J., Thomas, R. Q., Val Martin, M., and Zeng, X.: The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty, *Journal of Advances in Modeling Earth Systems*, 11, 4245–4287, <https://doi.org/10.1029/2018MS001583>, 2019.
- Li, J., Bevacqua, E., Chen, C., Wang, Z., Chen, X., Myneni, R. B., Wu, X., Xu, C.-Y., Zhang, Z., and Zscheischler, J.: Regional asymmetry in the response of global vegetation growth to springtime compound climate events, *Communications Earth & Environment*, 3, 123, <https://doi.org/10.1038/s43247-022-00455-0>, 2022.
- Li, J., Zhang, Y., Bevacqua, E., Zscheischler, J., Keenan, T. F., Lian, X., Zhou, S., Zhang, H., He, M., and Piao, S.: Future increase in compound soil drought-heat extremes exacerbated by vegetation greening, *Nature Communications*, 15, 10875, <https://doi.org/10.1038/s41467-024-55175-0>, 2024.



- 675 Lorenz, R., Argüeso, D., Donat, M. G., Pitman, A. J., Van Den Hurk, B., Berg, A., Lawrence, D. M., Chéruiy, F., Ducharne, A., Hagemann, S., Meier, A., Milly, P. C. D., and Seneviratne, S. I.: Influence of land-atmosphere feedbacks on temperature and precipitation extremes in the GLACE-CMIP5 ensemble, *Journal of Geophysical Research: Atmospheres*, 121, 607–623, <https://doi.org/10.1002/2015JD024053>, 2016.
- Mahecha, M. D., Bastos, A., Bohn, F. J., Eisenhauer, N., Feilhauer, H., Hickler, T., Kalesse-Los, H., Migliavacca, M., Otto, F. E. L., Peng, J., Sippel, S., Tegen, I., Weigelt, A., Wendisch, M., Wirth, C., Al-Halbouni, D., Deneke, H., Doktor, D., Dunker, S., Duveiller, G., Ehrlich, A., Foth, A., García-García, A., Guerra, C. A., Guimarães-Steinicke, C., Hartmann, H., Henning, S., Herrmann, H., Hu, P., Ji, C., Kattenborn, T., Kolleck, N., Kretschmer, M., Kühn, I., Luttikus, M. L., Maahn, M., Mönks, M., Mora, K., Pöhlker, M., Reichstein, M., Rüger, N., Sánchez-Parra, B., Schäfer, M., Stratmann, F., Tesche, M., Wehner, B., Wieneke, S., Winkler, A. J., Wolf, S., Zaehle, S., Zscheischler, J., and Quaas, J.: Biodiversity and Climate Extremes: Known Interactions and Research Gaps, *Earth's Future*, 12, e2023EF003963, <https://doi.org/10.1029/2023EF003963>, 2024.
- 680 Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., Brovkin, V., Claussen, M., Crueger, T., Esch, M., Fast, I., Fiedler, S., Fläschner, D., Gayler, V., Giorgetta, M., Goll, D. S., Haak, H., Hagemann, S., Hedemann, C., Hohenegger, C., Ilyina, T., Jahns, T., Jimenez-de-la Cuesta, D., Jungclaus, J., Kleinen, T., Kloster, S., Kracher, D., Kinne, S., Kleberg, D., Lasslop, G., Kornblueh, L., Marotzke, J., Matei, D., Meraner, K., Mikolajewicz, U., Modali, K., Möbis, B., Müller, W. A., Nabel, J. E., Nam, C. C., Notz, D., Nyawira, S. S., Paulsen, H., Peters, K., Pincus, R., Pohlmann, H., Pongratz, J., Popp, M., Raddatz, T. J. u., Rast, S., Redler, R., Reick, C. H., Rohrschneider, T., Schemann, V., Schmidt, H., Schnur, R., Schulzweida, U., Six, K. D., Stein, L., Stemmler, I., Stevens, B., Storch, J. S. v., Tian, F., Voigt, A., Vrese, P., Wieners, K. H., Wilkenskjaeld, S., Winkler, A., and Roeckner, E.: Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and Its Response to Increasing CO₂, *Journal of Advances in Modeling Earth Systems*, 11, 998–1038, <https://doi.org/10.1029/2018ms001400>, 2019.
- 690 McColl, K. A., Roderick, M. L., Berg, A., and Scheff, J.: The terrestrial water cycle in a warming world, *Nature Climate Change*, 12, 604–606, <https://doi.org/10.1038/s41558-022-01412-7>, 2022.
- Muñoz Sabater, J.: ERA5-Land hourly data from 1950 to present, <https://doi.org/10.24381/cds.e2161bac>, 2019.
- Norris, J., Hall, A., Neelin, J. D., Thackeray, C. W., and Chen, D.: Evaluation of the Tail of the Probability Distribution of Daily and Subdaily Precipitation in CMIP6 Models, *Journal of Climate*, 34, 2701–2721, <https://doi.org/10.1175/JCLI-D-20-0182.1>, 2021.
- 700 O'Donnell, A. J., Renton, M., Allen, K. J., and Grierson, P. F.: The role of extreme rain events in driving tree growth across a continental-scale climatic range in Australia, *Ecography*, 44, 1086–1097, <https://doi.org/10.1111/ecog.05671>, 2021.
- Reichstein, M., Bahn, M., Ciais, P., Frank, D., Mahecha, M. D., Seneviratne, S. I., Zscheischler, J., Beer, C., Buchmann, N., Frank, D. C., Papale, D., Rammig, A., Smith, P., Thonicke, K., Van Der Velde, M., Vicca, S., Walz, A., and Wattenbach, M.: Climate extremes and the carbon cycle, *Nature*, 500, 287–295, <https://doi.org/10.1038/nature12350>, 2013.
- 705 Reick, C. H., Raddatz, T., Brovkin, V., and Gayler, V.: Representation of natural and anthropogenic land cover change in MPI-ESM, *Journal of Advances in Modeling Earth Systems*, 5, 459–482, <https://doi.org/10.1002/jame.20022>, 2013.
- Ridder, N. N., Ukkola, A. M., Pitman, A. J., and Perkins-Kirkpatrick, S. E.: Increased occurrence of high impact compound events under climate change, *npj Climate and Atmospheric Science*, 5, 3, <https://doi.org/10.1038/s41612-021-00224-4>, 2022.
- Seiler, C., Melton, J. R., Arora, V. K., Sitch, S., Friedlingstein, P., Anthoni, P., Goll, D., Jain, A. K., Joetzjer, E., Lienert, S., Lombardozzi, D., Luyssaert, S., Nabel, J. E. M. S., Tian, H., Vuichard, N., Walker, A. P., Yuan, W., and Zaehle, S.: Are Terrestrial Biosphere Models Fit for Simulating the Global Land Carbon Sink?, *Journal of Advances in Modeling Earth Systems*, 14, e2021MS002946, <https://doi.org/10.1029/2021MS002946>, 2022.



- 715 Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F.,
 Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., and Zhou, B.: Weather and Climate Extreme Events in a Changing Climate,
 in: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the In-*
tergovernmental Panel on Climate Change, edited by Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S.,
 Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T.,
 Yelekçi, O., Yu, R., and Zhou, B., pp. 1513–1766, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,
<https://doi.org/10.1017/9781009157896.013>, 2021.
- 720 Sharma, B., Kumar, J., Ganguly, A. R., and Hoffman, F. M.: Carbon cycle extremes accelerate weakening of the land carbon sink in the late
 21st century, *Biogeosciences*, 20, 1829–1841, <https://doi.org/10.5194/bg-20-1829-2023>, 2023.
- Simpson, I. R., Shaw, T. A., Ceppi, P., Clement, A. C., Fischer, E., Grise, K. M., Pendergrass, A. G., Screen, J. A., Wills, R. C. J., Woollings,
 T., Blackport, R., Kang, J. M., and Po-Chedley, S.: Confronting Earth System Model trends with observations, *Science Advances*, 11,
 eadt8035, <https://doi.org/10.1126/sciadv.adt8035>, 2025.
- 725 Tokarska, K. B., Stolpe, M. B., Sippel, S., Fischer, E. M., Smith, C. J., Lehner, F., and Knutti, R.: Past warming trend constrains future
 warming in CMIP6 models, *SCIENCE ADVANCES*, 2020.
- Tramontana, G., Jung, M., Schwalm, C. R., Ichii, K., Camps-Valls, G., Ráduly, B., Reichstein, M., Arain, M. A., Cescatti, A., Kiely, G.,
 Merbold, L., Serrano-Ortiz, P., Sickert, S., Wolf, S., and Papale, D.: Predicting carbon dioxide and energy fluxes across global FLUXNET
 sites with regression algorithms, *Biogeosciences*, 13, 4291–4313, <https://doi.org/10.5194/bg-13-4291-2016>, 2016.
- 730 Tschumi, E., Lienert, S., Bastos, A., Ciais, P., Gregor, K., Joos, F., Knauer, J., Papastefanou, P., Rammig, A., Van Der Wiel, K.,
 Williams, K., Xu, Y., Zaehle, S., and Zscheischler, J.: Large Variability in Simulated Response of Vegetation Composition and Car-
 bon Dynamics to Variations in Drought-Heat Occurrence, *Journal of Geophysical Research: Biogeosciences*, 128, e2022JG007332,
<https://doi.org/10.1029/2022JG007332>, 2023.
- Van Der Woude, A. M., Peters, W., Joetzjer, E., Lafont, S., Koren, G., Ciais, P., Ramonet, M., Xu, Y., Bastos, A., Botfa, S., Sitch, S., De Kok,
 735 R., Kneuer, T., Kubistin, D., Jacotot, A., Loubet, B., Herig-Coimbra, P.-H., Loustau, D., and Luijkx, I. T.: Temperature extremes of 2022
 reduced carbon uptake by forests in Europe, *Nature Communications*, 14, 6218, <https://doi.org/10.1038/s41467-023-41851-0>, 2023.
- Villalobos-Herrera, R., Bevacqua, E., Ribeiro, A. F. S., Auld, G., Crocetti, L., Mircheva, B., Ha, M., Zscheischler, J., and De Michele, C.:
 Towards a compound-event-oriented climate model evaluation: a decomposition of the underlying biases in multivariate fire and heat
 stress hazards, *Natural Hazards and Earth System Sciences*, 21, 1867–1885, <https://doi.org/10.5194/nhess-21-1867-2021>, 2021.
- 740 Vogel, J., Paton, E., and Aich, V.: Seasonal ecosystem vulnerability to climatic anomalies in the Mediterranean, *Biogeosciences*, 18, 5903–
 5927, <https://doi.org/10.5194/bg-18-5903-2021>, 2021.
- Wang, Z., Zhan, C., Ning, L., and Guo, H.: Evaluation of global terrestrial evapotranspiration in CMIP6 models, *Theoretical and Applied
 Climatology*, 143, 521–531, <https://doi.org/10.1007/s00704-020-03437-4>, 2021.
- Wieners, K.-H., Giorgetta, M., Jungclaus, J., Reick, C., Esch, M., Bittner, M., Legutke, S., Schupfner, M., Wachsmann, F., Gayler, V.,
 745 Haak, H., Vrese, P. d., Raddatz, T., Mauritsen, T., Storch, J.-S. v., Behrens, J., Brovkin, V., Claussen, M., Crueger, T., Fast, I., Fiedler,
 S., Hagemann, S., Hohenegger, C., Jahns, T., Kloster, S., Kinne, S., Lasslop, G., Kornbluh, L., Marotzke, J., Matei, D., Meraner, K.,
 Mikolajewicz, U., Modali, K., Müller, W., Nabel, J., Notz, D., Gehlen, K. P.-v., Pincus, R., Pohlmann, H., Pongratz, J., Rast, S., Schmidt,
 H., Schnur, R., Schulzweida, U., Six, K., Stevens, B., Voigt, A., and Roeckner, E.: MPI-M MPI-ESM1.2-LR model output prepared for
 CMIP6 CMIP historical, <https://doi.org/10.22033/ESGF/CMIP6.6595>, 2019.



- 750 Wu, M., Manzoni, S., Vico, G., Bastos, A., De Vries, F. T., and Messori, G.: Drought Legacy in Sub-Seasonal Vegetation State and Sensitivity to Climate Over the Northern Hemisphere, *Geophysical Research Letters*, 49, e2022GL098700, <https://doi.org/10.1029/2022GL098700>, 2022.
- Wu, Y., Miao, C., Sun, Y., AghaKouchak, A., Shen, C., and Fan, X.: Global Observations and CMIP6 Simulations of Compound Extremes of Monthly Temperature and Precipitation, *GeoHealth*, 5, e2021GH000390, <https://doi.org/10.1029/2021GH000390>, 2021.
- 755 Zhou, S., Zhang, Y., Park Williams, A., and Gentile, P.: Projected increases in intensity, frequency, and terrestrial carbon costs of compound drought and aridity events, *Science Advances*, 5, eaau5740, <https://doi.org/10.1126/sciadv.aau5740>, 2019.
- Zscheischler, J. and Fischer, E. M.: The record-breaking compound hot and dry 2018 growing season in Germany, *Weather and Climate Extremes*, 29, 100270, <https://doi.org/10.1016/j.wace.2020.100270>, 2020.
- Zscheischler, J., Mahecha, M. D., Von Buttlar, J., Harmeling, S., Jung, M., Rammig, A., Randerson, J. T., Schölkopf, B., Seneviratne, S. I., Tomelleri, E., Zaehle, S., and Reichstein, M.: A few extreme events dominate global interannual variability in gross primary production, *Environmental Research Letters*, 9, 035001, <https://doi.org/10.1088/1748-9326/9/3/035001>, 2014a.
- 760 Zscheischler, J., Michalak, A. M., Schwalm, C., Mahecha, M. D., Huntzinger, D. N., Reichstein, M., Berthier, G., Ciais, P., Cook, R. B., El-Masri, B., Huang, M., Ito, A., Jain, A., King, A., Lei, H., Lu, C., Mao, J., Peng, S., Poulter, B., Ricciuto, D., Shi, X., Tao, B., Tian, H., Viovy, N., Wang, W., Wei, Y., Yang, J., and Zeng, N.: Impact of large-scale climate extremes on biospheric carbon fluxes: An intercomparison based on MsTMIP data, *Global Biogeochemical Cycles*, 28, 585–600, <https://doi.org/10.1002/2014GB004826>, publisher: John Wiley & Sons, Ltd, 2014b.
- 765

This chapter gathers insights into simulated vegetation resilience, effects of aerosol variability, and potential constraints on future anthropogenic interventions for climate change mitigation. We summarize the main findings from **P1–P3** (Sect. 9.1) and discuss common limitations (Sect. 9.2), which entail suggestions for the next generation of comprehensive ESMs projections and future research (Sect. 9.3).

9.1 Results of the manuscripts

P1: M. Adam, T. Kleinen, M. M. May, and K. Rehfeld (2025) “Land conversions not climate effects are the dominant indirect consequence of sun-driven CO₂ capture, conversion, and sequestration” (**P1**) explores Earth system interactions of large-scale CO₂ capture and electrochemical conversion into a sink product, all driven by solar power (sDACCCS). A spatially explicit implementation of CO₂ removal and associated renewable energy harvest in the Max Planck Institute for Meteorology Earth System Model (MPI-ESM) is leveraged to quantify side effects on climate, carbon cycle, and land use. The study probes major uncertainties around CDR including technological efficiency, spatial localization, and global CDR demand in scenarios stabilizing planetary temperature at the end of the century. Considerable negative consequences on surface climate cannot be found. A slight decline in natural carbon stocks is only temporal and not significantly offsetting the CO₂ removal potential of sDACCCS. However, conversion of agricultural and forested lands for CO₂ capture, conversion, and associated energy harvest is substantial in all experiments. In an experiment with extreme CDR demand, only moderate land use efficiency, and burden sharing according to historical emissions, this land conversion culminates in the equivalent of 40 % of the European Union’s agricultural lands being used. Land demand for sDACCCS scales approximately linearly with process chain efficiency, almost irrespective of the spatial deployment pattern.

P2: M. Adam, T. Schürmann, and K. Rehfeld (2026b) “Future volcanic eruptions shift the timing of net-zero emissions” (**P2**) quantifies uncertainties of future surface climate and carbon uptake arising from realistically varying volcanic aerosol forcing. A set of comprehensive MPI-ESM simulations forced with paleo-informed, stochastically occurring volcanic eruptions is employed along with an efficient emulator of MPI-ESM’s dominant spatial response modes. This approach provides statistically stable and spatially resolved uncertainty estimates. With varying aerosol forcing included, uncertainty of the global mean surface air temperature pathway is increased by 89 %. This increase varies regionally, but is particularly strong in the densely populated areas of southern and eastern Asia. Increased uncertainties in surface climate propagate into uncertainty in natural carbon uptake, especially in temperate to arid mid-latitude to subtropical climate zones. The supplementary uncertainties in surface climate and carbon uptake result in enhanced likelihoods of delayed or advanced achievement of planetary temperature stabilization and net-zero emissions.

P3: M. Adam, E. Ziegler, B. Gonzalez, N. Weitzel, and K. Rehfeld (2026a) In **P3**, “Earth system models might overestimate the local plant productivity response to temperature–moisture extremes”, the abilities of two ESMs to represent consequences of weather and climate extremes on gross primary production are gauged. Strength and timing of the statistical relationship between temperature–moisture and productivity extremes in the simulations are compared with observation-based data. Agreement between the datasets depends on the spatial aggregation. Globally, strength and timing conform well, but this agreement weakens on regional and especially on local scales. Both models overestimate strength and regional extent of the statistical relation between an external disturbance and the response of the simulated vegetation, which can be interpreted as underestimated resilience. Regional performance tends to be slightly superior outside the tropical latitudes. Both models exhibit a profound impact of the variable serving as moisture state indicator (soil moisture or precipitation) on regional spread and bias. Despite the biases, all datasets coherently represent patterns of beneficial and detrimental impacts of temperature–moisture compound events on vegetation extremes.

9.2 Limitations and uncertainties

The manuscripts **P1–P3** specifically discuss limitations and uncertainties of data and methods used in the case studies. Here, we aggregate common limitations, which imply recommendations for future modeling work (Sect. 9.3). Limitations arise from uncertainties in scenarios, boundary conditions, and forcings (Sect. 9.2.1), and from model shortcomings that constrain the transferability of results to real-world climate change (Sect. 9.2.2).

9.2.1 Uncertain scenarios, boundary conditions, and forcings

P1 and **P2** probe Earth system resilience to anthropogenic interventions and varying external forcing along plausible storylines (Sect. 4.1). In Earth system simulations of past or present climate, boundary conditions are strict and usually well-informed by observations or the paleoclimate record. For future projections, uncertainties from boundary conditions are less controllable, and applicability can only be judged in retrospect. Boundary conditions, such as land-use, greenhouse gas emissions, and the timing of volcanic or anthropogenic aerosol injections, all turn into uncertainty dimensions. As a result, a substantial share of decadal-scale projection uncertainty arises from scenario uncertainty (Hawkins and Sutton, 2009). Scenario uncertainty starts to play a substantial role for decadal projections and dominates over uncertainties from internal variability and model inaccuracy on timescales of three to four decades onwards (Hawkins and Sutton, 2009). In **P1** and **P2**, scenario uncertainties are mainly due to unknowns surrounding future anthropogenic interventions and sporadic volcanic forcing.

P1 demonstrates that high conversion efficiencies from atmospheric to captured CO₂ are essential for minimizing environmental consequences through land cover change. Modeling impacts requires accurate efficiency estimates. However, efficiency data from lab-scale or in-field demonstrators are often unpublished. Some studies or company reports only disclose efficiencies of individual process steps rather than conversion rates of whole process chains, which would allow relating energy demand to removed CO₂. At the same

time, development of CDR approaches and impact assessments is ongoing and designs constantly evolve. This complicates model calibration, assessments of energy requirements, and scenario design. To cope with these difficulties, the CDR submodel in **P1** is calibrated to a combination of reported, theoretical, and assumed values with an additional discount on overall system efficiency. The technology scenarios in **P1** also bracket some of the said uncertainty, but require recalibration for other technological assumptions.

The storylines in **P1** take scalable and land-use-efficient CDR as a given. In reality, successful technological developments are pending. For example, in-field DACCS demonstrators have attracted substantial investments, but currently struggle to achieve the targeted efficiencies (Terlouw et al., 2021). Electrocatalytic conversion of CO₂ to storable products has been successfully demonstrated at the lab scale (Bogdanoff et al., 2024; Esrafilzadeh et al., 2019; Lörch et al., 2024), but a production-grade sun-powered direct air capture with (electro)chemical conversion of captured CO₂ into sink products for storage (sDACCS) process demonstrator is unlikely to be available soon. Whether sufficient amounts of necessary catalysts can be sustainably sourced is also unknown. Similar uncertainties affect all CDR approaches with theoretical removal potentials in the Gt CO₂ range.

The most plausible and likely scenario for future interventions is a portfolio of mitigation measures (Rueda et al., 2021; S. M. Smith et al., 2024; Stremler et al., 2021b). Such a portfolio could include simultaneous deployment of several CDR approaches or a combination of CDR and aerosol injections (IPCC, 2018). The composition of a portfolio would be co-determined by economic and land use constraints, variable external forcing, and the ambition of ongoing decarbonization measures. Compared to such a detailed portfolio, the storylines in **P1** and **P2** are simplistic. However, macroeconomic integrated assessment models (IAMs) face the challenge to include many novel CDR approaches (Rickels et al., 2019), for example, ideas in the building sector (neustark AG, 2025), use of marine electrolysis (EcoEngineers, 2024; Equatic, 2023), or leveraging multi-purpose agricultural practices (Maslouski et al., 2025). It is unlikely that a majority of these ideas will turn into scalable and marketable CDR technologies. Still, portfolios in current CDR scenarios have almost no granularity and many missing socioeconomic interdependencies (Rickels et al., 2019). Likewise, operationalizing CDR portfolios in ESMs is a step-wise process that takes time (Sect. 9.3.3). And while modeling a full portfolio would allow for studying the interactions and co-dependencies of mitigation measures, attributing direct effects of individual measures requires isolated simulations, in the first place.

Results of **P2** can be interpreted as an analog for intermittent, but deliberate aerosol injections into the stratosphere, assuming a scenario with abrupt terminations and resumption. However, whether such a scenario would emerge is questionable, given the many detrimental consequences for ecosystem services and agricultural yields that are expected (Sect. 4.1). The results of **P2** support this objection against a scenario with strongly varying injections. Despite ongoing impact assessments, large-scale radiation management techniques remain hypothetical, leaving further scenario uncertainties unresolved. These include, for example, the location, amount, and type of aerosol injected.

Although human activity has a major influence on the future climate trajectory, variability arising from natural forcing will continue to shape it too (**P2**, Sect. 4.1). **P2** takes the statistics of past eruptions as a direct analog for future volcanic activity. However, there is evidence that melting glacier ice promotes volcanic activity and may even feed back

into global warming by releasing volcanic CO₂ (Huybers and Langmuir, 2009). It is also imaginable that rare but exceptionally strong events occur, inducing non-linear knock-on effects that are not necessarily well-represented in ESMs (Segschneider et al., 2013). Therefore, the uncertainty increases in surface climate and carbon uptake suggested by **P2** could potentially be underestimated, especially because the employed MPI-ESM has a low to average climate sensitivity compared to other CMIP models (Nijse et al., 2020).

The large number of unknowns in future scenarios leads to some vagueness in the results and interpretations, which could be criticized. However, this reflects one of the core trade-offs of ESM projections, which do not aim for precise forecasts but seek to identify potential general bottlenecks or show-stoppers. Still, there are plausible “What if?” scenarios that are not within the option space of IAMs and SSP-type scenarios, especially sudden societal shifts. These *social tipping dynamics* could, in theory, change global socioeconomic incentives (Otto et al., 2020; Winkelmann et al., 2022) and thus constitute a known unknown for future Earth system dynamics.

9.2.2 Transferability of modeling results to the real world

ESMs are sophisticated but imperfect reflections of reality, echoing the famous aphorism “all models are wrong, but some are useful” (Box, 1979; Hand, 2014). They integrate decades of research (Sect. 4.2), explain much of the past and present climate change trends and patterns, and support decision-making (e.g., Flato et al., 2013; IPCC, 2018). They also provide accurate estimates of carbon stocks and fluxes, and are able to represent many Earth system feedbacks such as CO₂ fertilization and atmosphere–ocean interactions (e.g., Arora et al., 2020; Friedlingstein et al., 2026). Despite these successes, ESMs have room for improvement, especially in projecting Earth system variability under climate change mitigation.

Mean projections of global and regional temperature evolution, mean circulation patterns, or the global carbon budget are mostly robust (Arora et al., 2020; I. R. Simpson et al., 2025). In contrast, ESMs underestimate the magnitude of weather and climate variability, from multi-day extremes to millennial climate modes (Lorenz et al., 2016; Norris et al., 2021; I. R. Simpson et al., 2025; van Haren et al., 2015). This may eventually lead to an underappreciation of the damaging potential associated with weather extremes and longer-term climate fluctuations (**P2**; Ellerhoff, 2023; Norris et al., 2021; Reichstein et al., 2013). There are many starting points to correct these biases, ranging from underestimated sub-scale convective precipitation to missing destabilizing feedbacks on centennial to millennial time scales (Klein et al., 2021; Laepple et al., 2023; Norris et al., 2021; Ziegler et al., 2025). In this context, **P2** underlines the stimulating effect of variable external forcing on decadal variability. The findings of **P3** further indicate that inaccuracies in simulated variability also extend into biosphere compartments, concurring with previous studies (Seiler et al., 2022). Utilizing ESMs to examine Earth system variability thus warrants careful case-by-case bias assessments and model–data validation.

Results of **P3** provide another example for the necessity to carefully interpret model results. In this case, modeled water availability is an incomplete representation of what a plant would experience in the field under a changing climate. Hydroclimatic conditions determine plant growth and, generally, root zone water availability is a direct indicator

for plant-available moisture (Johnston et al., 2025; McColl et al., 2022). By contrast, **P3** demonstrated that mismatches between observations and models get strongly reduced with precipitation as an indirect indicator for soil moisture extremes. Because field studies support moisture availability as an indicator for drying/wetting (McColl et al., 2022), this is an indication for biased model calibration or inaccurate process representations. However, it is likely that the difference in time that precipitation and soil moisture take to integrate atmospheric drought or extreme wetness contribute to the discrepancies between precipitation and soil moisture-based results (**P3**).

Leveraging Earth system models to assess the risks of anthropogenic interventions for climate change mitigation is an ongoing development over the recent decade. This work began with CO₂ removal implicitly contained in the emission forcing (Koven et al., 2022; Melnikova et al., 2021; O'Neill et al., 2016). Currently the development is expanding to spatially represented CDR (**P1**; Moustakis et al., 2024). These representations are somewhat pioneering work and pay only limited attention to detail and realism in the involved parametrizations. This includes the high-level parametrization of CO₂ removal processes (**P1**) and either prescribed land use scenarios (Moustakis et al., 2024) or land allocation dynamics (**P1**). However, in the rapidly evolving context of anthropogenic interventions into the Earth system, ESM simulations can contribute only part of a comprehensive assessment, because they can model segments of, but not the full CDR life cycle. Nevertheless, their contribution to publicly accessible knowledge on Earth system interactions of human action is fundamental in light of ongoing technological developments, build-up of carbon removal markets, and global change.

Earth's land surface hosts anthropogenic drivers of planetary change, natural buffers of change, and, prospectively, interventions for climate change mitigation. This is why land surface models (LSMs) are central for risk assessments under climate stabilization scenarios. However, the number of land processes that may influence ecosystem resilience, carbon uptake, and human activity is huge. Many of these processes are a lot less fundamentally constrained than the physical laws of the atmosphere and ocean, requiring parametrization (Sect. 4.2). Some parametrizations are crude and overly generalizing, for example, regarding vegetation competition, forest demography, and bioclimatic constraints for plant growth (Blyth et al., 2021; Bonan et al., 2024; Reick et al., 2013). The same goes for heterogeneities of soils, root-zone soil–plant interactions, and soil microbial activity. For regionally constrained cases studies, specialized process models are often a superior choice (e.g., Brown et al., 2022; Han et al., 2024). However, results of **P3** are an example for the predictive power of well-calibrated LSMs for aggregated carbon cycle dynamics on regional to global scales.

9.3 Implications and outlook

Results of **P1–P3** demonstrate substantial effects of anthropogenic interventions, variability, and process model design on the future Earth system trajectory simulated by ESMs. This section scrutinizes how the three case studies expand our knowledge of Earth system resilience under climate change mitigation trajectories (Sect. 9.3.1). Climate change risk assessments benefit from well-characterized, expanded, and newly-developed ESMs capabilities. Therefore, the findings also feed into recommendations for examining portfolios

of climate change mitigation and engineering options (Sect. 9.3.2). Finally, drawing on the limitations identified in Sect. 9.2, this section also outlines potential future research to build on the methods and results explored within this thesis (Sect. 9.3.3).

9.3.1 Earth system resilience under climate change mitigation

A high buffering capacity of the carbon cycle is crucial for climate change mitigation scenarios (Chapt. 4.1). Land carbon stocks appear to be resilient to multi-decadal deployment of highly-efficient, land-based CDR and associated energy harvest (**P1**). Overall depletions in vegetation and soil carbon stocks in the order of a couple gigatons of Carbon (**P1**) are negligible compared to the total stocks (450 GtC and 1700 GtC, respectively; Friedlingstein et al., 2025), and the removed CO₂. In the projections, they recover once CDR is reduced (**P1**). However, recovery of soil carbon stocks in the simulations is almost symmetrical and omits any knock-on effects that could result from disturbing vegetation–soil interactions or priming of microbial dynamics. Therefore, terrestrial CDR might lead to a longer legacy than simulated by an ESM. At the same time, ecological co-benefits are possible but not represented in the model. For example, **P1** assumes a high, technically required spacing between CDR devices and photovoltaic modules, but does not consider the potential of using this space synergetically for agriculture or vegetation cover.

Through many climate–biosphere interactions, carbon cycle variability is intertwined with external Earth system forcing. Considering sporadic volcanic forcing in projections along an overshoot scenario increases the global uncertainty of the pivotal carbon sink by a third (**P2**). While the surface air temperature response to varying aerosol forcing is virtually exclusively cooling, uncertainties of net carbon uptake increase on both sides, albeit asymmetrically (**P2**). Thus, with realistic volcanic forcing, there is less certainty in the timing of net-zero emissions. This complicates planning of emission budgets and appropriate scaling of climate change mitigation measures. Even though the MPI-ESM version employed in **P2** is state-of-the-art in the CMIP6 cycle, it also misses important carbon cycle dynamics that might influence at least the local to regional net carbon flux response, for example, through permafrost thawing (Schädel et al., 2024), incomplete feedbacks from disturbances like wildfires (F. Li et al., 2024), or vegetation dynamics (Winkler et al., 2019). And given MPI-ESM’s tendency to overestimate vegetation sensitivity to climate extremes (**P3**), it is unclear if this bias could also affect simulated (multi-)annual carbon cycle variability in response to varying aerosols. However, there is also the challenge of clearly attributing volcanic effects on carbon cycle variability due to non-linear feedbacks and knock-on effects. This is demonstrated by a higher likelihood for an El Niño/La Niña-like ocean state following volcanic eruptions, which, in turn, has a strong imprint on tropical GPP (Holmgren et al., 2001; Sippel et al., 2018; Zhang et al., 2019).

Resilience of vegetation to disturbances is essential for preserving the terrestrial carbon sink. Since already a limited number of extremes can already significantly alter the annual net carbon uptake (Zscheischler et al., 2014b), inaccurate projections of the GPP response to temperature–moisture extremes could result in biased emission budgets. Drawing on the comprehensive assessment of **P3**, the simulated regional to global scale productivity response to such extremes appears reliable, at least for the two ESMs assessed here. The models’ performances on a local grid scale level are weaker, requiring bias corrections and model refinements. This ambivalent finding could be an indication that local biases

level out to produce global carbon flux estimates that remain reasonable. The two models assessed in **P3** are among the best-performing ESMs in CMIP6 with respect to the global carbon cycle (Arora et al., 2020), so care has been taken in their calibrations to achieve this global-scale performance. However, given the observed discrepancies between data and models in the soil moisture response to wettening and drying (**P3**), global estimates may partially be “right for the wrong reasons”. However, this hypothesis demands further investigation (Sect. 9.3.3) and should ideally be tested on a larger ensemble of ESMs for confidence in the generality of the results (**P3**).

Since natural carbon sinks provide a key ecosystem service for climate change mitigation, there is an intelligible focus on detrimental types of temperature–moisture extremes. However, beneficial conditions for vegetation productivity can also be identified in many regions with medium to high net carbon uptake (**P3**). The planetary state currently transitions to a warmer but also wetter mean climate, an increasing likelihood of dry and wet extreme conditions, and strengthened CO₂ fertilization (Mahony and Cannon, 2018; Norris et al., 2021; Zhu et al., 2016). Therefore, it is unclear how regionally opposing climate–vegetation interactions will be reflected in the variability of regional to global carbon fluxes in the future. Although applying the framework of **P3** to Earth system projections is left to future research (Sect. 9.3.3), the beneficial and detrimental effects identified by that work can provide the basis for building hypotheses on this issue. With climate change, wettening is expected in western North America, northeastern Europe, central and northern Africa, and south Asia (Stevenson et al., 2022). Over the recent past, many of these regions are associated with detrimental conditions for vegetation productivity through hot–dry and cold–dry extremes, especially in the mid- to high latitudes (**P3**). Wettening under climate change could potentially reduce the vapor pressure deficit under (extremely) dry conditions and reduce stressors. In contrast, climate projections agree well in suggesting drying across South and Central America, northern Eurasia, the Mediterranean region, and South Africa (Stevenson et al., 2022; K. Trenberth, 2011). This could further aggravate growth-damaging stressors for vegetation. Crucially for the land carbon sink, South American tropical rainforests are already showing signs of becoming increasingly vulnerable and will likely experience drying in the future (Chapt. 4.1). Their ability to act as a net carbon sink is expected to be gradually lost with warming above 1.5 to 2 °C (Nath et al., 2024). This is less clear for African rainforest (Nath et al., 2024), pointing to potential future studies (Sect. 9.3.3).

9.3.2 Climate engineering as part of the climate change mitigation toolbox

Anthropogenic interventions into the Earth system intent to exert a net stabilizing effect on planetary temperature and, thereby, on climate, carbon cycle, and ecosystems (Chapt. 4). Large-scale, high-efficiency CDR process chains could fulfill this aim (**P1**), provided they can be scaled up sufficiently. Detrimental effects on terrestrial carbon stocks through land conversion are temporary and small compared to the CDR removal potential (**P1**). While not addressing the root cause of unsustainable atmospheric CO₂ concentrations (Chapt. 4), aerosol forcing also has a strong global cooling effect (**P2**) and could be scaled to counter-balance the global warming effect of anthropogenic greenhouse gases. To fulfill this purpose, deliberate aerosol injections do not necessarily have to follow along the

choreography of a smooth, continuous scenario. Taking sporadic stratospheric aerosol forcing from volcanic eruptions as an analog demonstrates that varying aerosol loads also result in net cooling of the planet (**P2**), but likely at the expense of ecosystem stability (Sect. 4.1, 9.3.2) and temporal certainty of emission pathways (**P2**).

Both climate engineering measures can contribute to halting climate change, and mitigate some of its negative consequences on societies and ecosystems (**P1**, **P2**). However, this relies on ambitious decarbonization in the first place. SSP1-2.6, used as “low CDR deployment” scenario in **P1**, requires current CO₂ emissions of ~40 GtCO₂ yr⁻¹ (Chapt. 4.1) to be reduced to ~10 GtCO₂ yr⁻¹ by the middle of this century, to then achieve net-negative emissions of approximately -5 GtCO₂ yr⁻¹ with large-scale CDR during the subsequent decades. In contrast, the “high deployment” scenario of **P2** demands ~40 GtCO₂ yr⁻¹ of CO₂ removals with almost no additional decarbonization. While such a scenario may be theoretically feasible from a land use perspective, it is unrealistic, even when leaving environmental concerns aside. Achieving this scale of highly efficient removals demands scale-up rates far above the most optimistic expectations (S. M. Smith et al., 2024) and industrial-scale deployment would have to start at present day. Ambitious decarbonization is equally essential for SAIs. Variable aerosol forcing increases the likelihood of stabilizing planetary temperature at levels that are compatible with the Paris Climate Agreement (**P2**; Bethke et al., 2017). However, the cooling potential of a couple of teragrams of sulfate aerosols injections (Quaglia et al., 2022) is still small compared to the anthropogenic greenhouse effect assumed in the overshoot scenario of **P2**. Thus, stalling decarbonization and hoping for CDR and SAI as primary measures for mitigating climate change risks missing out on global temperature stabilization if interventions do not scale as expected. This may entail a lock-in on environmentally costly CO₂ removal and SAI technology (Fuss et al., 2014; McDonald, 2023; Nauels et al., 2025; Schleussner et al., 2024).

The findings of **P1** and **P2** assess potential consequences of anthropogenic interventions on climate and vegetation resilience. However, societal and socioeconomic aspects of such interventions could be as much of a concern for planning climate change mitigation measures. In this context, the findings of **P1** contribute to previous characterizations of potential tradeoffs arising from climate engineering measures (e.g., Kravitz et al., 2016; W. Lee et al., 2020). **P1** demonstrates that even a land use efficient CDR approach takes up a substantial amount of land when scaled up to a multi-gigaton removal. If CDR required more energy than originally expected or CO₂ storage was less durable than assumed, land demand for deployment and energy harvest can quickly scale up.

Compared to all biomass-based approaches suggested to date, the sDACCS approach assumed in **P1** is still highly land use efficient. Achieving annual removals in the order of 10 GtCO₂ yr⁻¹ exclusively through photosynthesis is likely impossible within the planetary boundaries (Heck et al., 2018). At the same time, the result underlines that there is no terrestrial CDR approach without an environmental and societal burden through land cover change. The implications of this extend beyond the approach specifically modeled as part of **P1**, because land is a limited and precious resource (Lambin and Meyfroidt, 2011). Relying on large-scale CDR increases the likelihood for target conflicts sparked by the land requirements. CDR and associated energy harvest may compete for the same land required for food production, housing, and infrastructure, with water resources needed for irrigation, and with ecosystem services. These assets are already pressured by climate change. Prioritizing marine over land-based CDR could lift some pressure off land

resources, but this has detrimental consequences for marine ecosystems and uncertain scaling potential (Boyd et al., 2024; Roberts et al., 2026). Marine-based CDR may not be sufficiently durable on decadal to centennial time scale with the ocean carbon cycle essentially representing a non-linear and semi-open system (Arzeno-Soltero et al., 2023; Siegel et al., 2021). A portfolio of different CDR methods could also help balancing different target conflicts (Fuhrman et al., 2023; IPCC, 2018; Strefler et al., 2021b). However, to avoid these conflicts in the first place, ambitious decarbonization remains the most critical and sustainable option for climate change mitigation.

9.3.3 Open questions and potential for future research

This dissertation explored opportunities to expand ESM capabilities to better represent future anthropogenic interventions and drivers of climate and carbon cycle variability. The future climate and Earth system state depend on a multitude of natural and anthropogenic constraints (Chapt. 4, Sect. 9.3.1). In addition, drivers of environmental change evolve, as does the scientific understanding of their physical, chemical, and biological implications. The case studies presented here contribute to this evolving understanding, but also raise new research questions. At the same time, they only cover a small subset of possible future Earth system dynamics.

Numerous uncertainties and drivers may affect our understanding of Earth system resilience under climate change mitigation pathways. Many of these factors are only broached by **P1–P3** or not addressed at all, but several of them have been covered elsewhere. For example, aerosol–cloud interactions can be better resolved by explicit models of aerosol chemistry than by parametrizations along the concept of an effective optical depth (Fan et al., 2016; Malavelle et al., 2017). Similarly, detrimental side effects and co-benefits of large-scale photosynthesis-based CDR have been demonstrated through land use inventory modeling (Heck et al., 2016, 2018). And drivers, scale dependence, and persistence of climate variability have been studied in great detail (Ellerhoff and Rehfeld, 2021; Ellerhoff et al., 2022; Hawkins and Sutton, 2009; Huybers and Curry, 2006; Laepple et al., 2023; Ziegler et al., 2025). Incorporating these and other insights into ESMs parametrizations and calibrations is an iterative process. Therefore, the following sections elaborate on unresolved issues that this work could help to address.

Variability of the terrestrial biosphere and land–atmosphere interactions

The motivation for studying vegetation resilience under climate change as part of this work (**P3**) is the importance of plant growth to the land carbon sink (Sect. 4). Besides affecting climate indirectly through altered land carbon fluxes, climate-induced changes in vegetation cover also directly feed back onto weather and climate through shifts in radiative and moisture budgets. In this context, investigating combined climate and carbon cycle effects of extremes in vegetation productivity under stratospheric aerosol forcing may yield new insights into carbon cycle dynamics under climate change mitigation scenarios. Aerosol-induced cooling can raise the likelihood of El Niño/La Niña-like modes in the tropical Pacific (Pausata et al., 2015; Ward et al., 2021). The exact type of mode depends on the place of aerosol injection (D’Agostino et al., 2026; Pausata et al., 2015; Ward et al., 2021). At the same time, variability of land carbon uptake and the likelihood

of temperature–moisture extremes are also connected to these climatic modes through temperature and hydroclimate feedbacks (**P2**; K. Trenberth, 2011; K. E. Trenberth and Dai, 2007).

There is general agreement between observations and models about how vegetation productivity responds to temperature–moisture extremes (**P3**). Future work could quantify how the statistical link between climate and vegetation extremes may change under future climate change. With global warming, a higher frequency, duration, and severity of drought conditions are likely to amplify damaging effects. It is unclear whether regionally higher moisture abundance from changing precipitation patterns could counterbalance some of these effects. Over the long term, relative shifts in the likelihood of beneficial and damaging extremes would diminish net land carbon uptake. This strongly encourages applying the analysis of **P3** to future scenarios.

Soils store about three times as much carbon as vegetation (Friedlingstein et al., 2026), and soil carbon cycling is vital for biomass-based CDR such as biochar and enhanced mineral weathering. Both the model–data comparison from **P3** and the symmetric recovery of soil carbon stocks after land use disturbances observed in **P1** raise questions about soil moisture and carbon dynamics in the JSBACH3.2 land surface model of MPI-ESM. Therefore, it appears worthwhile to more closely examine the performance of soil models contained in ESMs and MPI-ESM in particular. For example, advancing our understanding about how plant nutrients affect land carbon uptake in ESMs might improve these models under rising atmospheric CO₂ levels (Cambron et al., 2025). Currently, JSBACH is undergoing substantial development with the aim of improved soil carbon dynamics and soil–vegetation interactions as part of ICON-ESM (Jungclaus et al., 2022). It is pivotal that such developments recognize the historical focus of ESMs on geophysical interactions and substantially raise the level of detail and accuracy of simulated land ecosystem dynamics (Bonan et al., 2024).

Towards modeling Earth system impacts, mutual interactions, and life cycles of CDR portfolios

Socioeconomic, environmental, and technological constraints for CDR scale-up might best be addressed with a portfolio of measures (IPCC, 2018; S. M. Smith et al., 2024; Stremler et al., 2021b). Early scale-up could focus on biomass-based approaches, such as soil carbon sequestration or afforestation, as these approaches do not require extensive technological development (Chapt. 4.1). Around mid-century, they could be complemented by novel CDR methods. These promise high scalability and land use efficiency but demand two to three further decades of development (Minx et al., 2024). Assessing potential mutual interactions, including co-benefits, of these CO₂ removal methods under climate change, requires explicit models. In this context, **P1** provides a proof-of-concept for spatially explicit and dynamically coupled CDR modeling in an ESM. This representation enabled studying potential side effects from land–atmosphere interactions, carbon cycle dynamics, and land cover change. This blueprint and recent to prospective anthropogenic interventions and work on photosynthesis-based and marine CDR (Moustakis et al., 2024) can inform the development of additional process models.

At the same time as explicit CDR models in climate projections emerge, the limited availability of data on the efficiencies of CDR technologies could impede model development and scenario building (**P1**, Sect. 9.2). Crucial parameters include energy conversion rates during the removal process as well as resilience and durability of long-term storage. Incentives for sharing efficiency data are low, even when this data is aggregated, and complicated by economic competition. Nonetheless, openly reported and verifiable efficiencies are essential for credible carbon removal credits. They also benefit the accuracy of CDR process models. For example, this would enable a logical improvement to the specific CDR model developed in **P1**, namely the integration of dependencies of direct air capture and conversion process steps on environmental parameters, such as ambient temperature and humidity.

Net Earth system effects of CDR deployment go beyond the deployment phase covered by the ESM projections of **P1**. They also encompass direct and indirect environmental and climatic effects of sourcing raw materials, manufacturing, setup, maintenance, and destruction, as well as the permanence of CO₂ storage. For credible carbon removal crediting, results from ESM projections must be complemented by full life cycle assessments (e.g., Chauvy and Dubois, 2022; Terlouw et al., 2021). Similar to ESM development, high accuracy and the availability of conversion efficiencies and uncertainties of process designs are essential for life cycle assessment. Establishing data-sharing requirements as part of monitoring, reporting, and verification frameworks (S. M. Smith et al., 2023) could facilitate this essential research.

Advancing future scenarios and analogs for anthropogenic interventions

A substantial fraction of the uncertainty in Earth system projections arises from scenario uncertainty (Sect. 9.2). To first order, this uncertainty stems from socioeconomic dynamics and political decisions. These factors are hard to anticipate and have to be bracketed with storyline trajectories. However, drawing from this thesis, there are opportunities to narrow secondary uncertainties and make ESM projections of anthropogenic interventions comparable across models. For example, spatial scenarios that are constrained by macroeconomic dynamics and are inherently coherent with emission trajectories only exist for a limited subset of biomass-based CDR, especially BECCS. A higher level of granularity for CDR methods in these land use scenarios is essential for meaningful projections of future anthropogenic interventions. This requires economic integrated assessment models (IAMs) to be expanded (Rickels et al., 2019), particularly by including novel CDR approaches such as sDACCS. Yet, these models face the challenge of keeping up with recent technological developments and regularly updating boundary conditions, parameters, and scenarios.

To overcome the lack of spatial scenarios for CDR deployment, **P1** drew on deployment scenarios which were built around equity considerations (Fyson et al., 2020; Pozo et al., 2020). Yet, aside from static land use constraints (**P1**), this approach omits target conflicts between CDR and sustainable land use, food production, and renewable energy harvesting. IPCC and ScenarioMIP storylines do not capture these future land use dynamics in great detail either. So far, IAM and land use scenarios also do not sufficiently account for renewable energy harvesting needed for novel CDR. Efforts are ongoing to model target conflicts around land use with agent-based models (Zeng et al., 2025) and to incorporate socioeconomic dynamics directly into ESMs (Donges et al., 2020). These developments

could eventually represent both economic and environmental co-dependencies among CDR approaches, agriculture, and energy harvest, but remain in early stages.

Another aspect currently overlooked in scenario building are interactions between CDR and deliberate aerosol injections. Individual model-based or theoretical assessments already studied the possibility of combining CO₂ removals and aerosol injections (Sonntag et al., 2018; Vaughan and Lenton, 2011). However, model intercomparisons predominantly focus either on emission budgets or deliberate interventions into the radiative balance, but not on both simultaneously. Identifying potential show-stoppers from interactions of climate engineering measures can help steer future research, technology developments, and investments.

Complementary to developing new modeling capabilities is to fully leverage the existing body of simulation data, observations, and paleoclimate archives as analogs for anthropogenic interventions. **P2** provides a promising example by incorporating uncertainties from intermittent aerosol forcing into existing model ensembles of future climate change. Expanding its emulation approach to multi-model ensembles only requires a limited number of sensitivity tests. Future work could utilize existing VolMIP simulations (Zanchettin et al., 2016) to expand ScenarioMIP multi-model ensembles (Tebaldi et al., 2021; van Vuuren et al., 2025) with the added uncertainty envelope from intermittent aerosol forcing.

Human livelihoods depend on the resilience of climate, biosphere, and ecosystems to disturbances. Anthropogenic climate and land use change shift the Earth system state and dynamics, challenging these livelihoods. As current decarbonization rates are insufficient to stabilize planetary temperature over the long term, large-scale artificial CO₂ removal and deliberate aerosol injections into the stratosphere are becoming a virtual necessity. However, these interventions bear environmental, socioeconomic, and climatic risks. It is thus essential that Earth system projections capture the dominant interactions of these prospective interventions. At the same time, ensuring that Earth system models accurately approximate real-world dynamics is vital for climate change mitigation and carbon management strategies, necessitating thorough comparisons of simulations and observations. High accuracy is especially important for gauging impacts of climate variability on other Earth system compartments such as the biosphere, since rare extreme conditions may strongly influence resilience under climate change mitigation.

This dissertation aimed to expand and advance projections of future Earth system trajectories, including potential anthropogenic interventions for stabilizing climate. Three case studies examined different aspects for improvements, namely, novel explicit modeling of technological carbon dioxide removal, non-stationary aerosol forcing, and simulated vegetation stability to external disturbances. With reference to the research objectives O1–O4 (Chapt. 5), we conclude (key findings *in italics*):

O1: To gauge Earth system interactions of a fully technological CO₂ removal approach in net-negative emission and temperature stabilization scenarios

Earth system projections that explicitly included a novel, renewably powered sDACCS approach for large-scale CO₂ removal prompt two main conclusions. On the one hand, *no show-stoppers for sDACCS could be identified regarding unintended impacts on local to global climate or the resilience of natural carbon stocks*. This finding contrasts with many CDR methods based on natural photosynthesis and encourages further development of sDACCS and similar technologies. On the other hand, *land use for CDR deployment and energy harvesting through photovoltaics can be substantial*. Although sDACCS process chains are proposed to be at least an order of magnitude more efficient than natural photosynthesis, their net land footprint could be considerable when removals are scaled up to a gigaton scale. Drawing on this conclusion, it appears unlikely that there is any sustainably powered, terrestrial CDR without substantial land use burden. This may provoke target conflicts, especially if land use efficiencies are lower than currently anticipated or if insufficient decarbonization result in a lock-in to excessive CDR. These conclusions, combined with the fact that saved emissions offer energetic, environmental, and climatic benefits, highlight the *importance of strengthening ongoing decarbonization efforts*.

O2: To quantify uncertainties imposed by realistically varying volcanic aerosol forcing on future surface climate and carbon uptake

Simulation and emulation ensembles along a temperature overshoot scenario, which included varying levels of stratospheric aerosols from volcanic eruptions, confirm

that *intermittent aerosol forcing significantly increases multi-annual to multi-decadal variability of surface climate and land carbon uptake*. Increases in global annual mean temperature uncertainty of 0.20 °C (simulations only) and 0.32 °C (full emulation ensemble) validate previous studies (Bethke et al., 2017; Chim et al., 2025). The rise in temperature uncertainty is spatially heterogeneous and *disproportionately affects densely populated regions*. More variable surface climate can be reflected in raised likelihoods of weather and climate extremes, both locally and non-locally. Therefore, future assessments of interventions into the radiative balance should scrutinize this regional focus within appropriate forcing scenarios. Supplementary uncertainties in surface climate, propagated to natural carbon sinks using a linear covariance-based approach, point to substantially raised regional uncertainties in terrestrial carbon uptake. On an aggregated level, **P2** thus concludes that aerosol-induced variability of climate and carbon cycle could *delay or advance temperature stabilization and carbon negativity*. This conclusion could be further supported by explicitly emulating the response of land carbon uptake to intermittent aerosol injections. Still, these findings underline the importance of accounting for varying aerosol concentrations in Earth system projections by default, which has not been done so far and is not planned for the upcoming seventh CMIP cycle. Emulation techniques, such as the one employed in **P2**, could help operationalize uncertainty assessments in multi-model ensembles, because they offer a reasonable balance between statistical rigor and computational cost.

O3: To assess the abilities of ESMs to represent effects of temperature–moisture extremes on vegetation productivity

Comparisons with observation-based data generally validate the ability of the CESM2 and MPI-ESM models to produce reliable characteristics of statistical relations between temperature–moisture and GPP extremes. In particular, *both ESMs reproduce the strength of the statistical link between temperature–moisture and GPP extremes reasonably well for all types of event combinations. This holds at both regional and global scales*. This builds confidence in present-day estimates of the carbon cycle’s response to weather and climate extremes, as well as in the variability of simulated terrestrial carbon uptake. The *models struggle with the timing between extreme climatic conditions and vegetation response, as well as the strength and timing of local responses in general*. Even though precipitation is the less direct indicator of moisture conditions, biases with precipitation as a moisture indicator are lower. Future research and model development should address whether modeled soil moisture responds overly sensitive to climatic drivers. Decreasing moisture evaporation and infiltration rates in process model parametrizations could readjust evaporative feedbacks and reduce discrepancies with observations. When categorizing responses of vegetation productivity to extreme conditions into advantageous and adverse effects, local biases are less concerning, even at smaller scales. Models and observations suggest *coherent regional patterns of positive and negative effects of climate extremes on vegetation growth*. These patterns could shift under global warming and may help identify potential relative asymmetries between the two types of effects, supporting the assessment of consequences for land carbon sinks.

O4: To advance modeling capabilities of prospective anthropogenic interventions into the Earth system for climate change mitigation

This research objective spans across **O1–O3** and synthesizes their methodological

advancements. **P1** leverages novel modeling features for spatially explicit CDR, while **P2** includes a proof-of-concept for operationalizing uncertainty assessments around realistically varying radiative aerosol forcing in ensembles of Earth system projections. Together, they demonstrate the feasibility of expanding ESMs and storylines to resolve anthropogenic interventions and additional external forcings. By contrast, omitting the potential for land use conflicts in implicit emission scenarios that do not specify type, scale, and location of CO₂ removals would mask a substantial environmental burden and could influence decision-making. Similarly, not accounting for varying volcanic eruptions in projections might suggest an inappropriately high level of confidence in the precise timing of future trajectories. In addition, uncertainties in future projections also arise from inaccuracies in process models of ESMs. In this context, **P3** recommends ways forward for mitigating biases in soil components and moisture extremes.

This work contributed to more detailed and accurate projections of Earth system resilience under climate change mitigation trajectories. Methodological advancements expanded the range of possible scenarios that can be studied with comprehensive Earth system models and made some anthropogenic interventions in the MPI-ESM model more explicit. Model-observation comparisons built confidence in the simulated regional to global response of vegetation productivity to extreme conditions. They also suggested potential causes of local model biases. Further, the results offer encouraging insights into the resilience of climate and carbon stocks to scale-up of renewable-powered, high-efficiency CO₂ removal and conversion. However, even land use efficient CDR methods may cause target conflicts when deployed for gigaton-scale removals, highlighting the necessity for ambitious zero greenhouse gas emissions. Based on these findings, comprehensive model-based assessments of CDR should recognize the benefits of simulating land-atmosphere interactions, carbon cycle impacts, and target conflicts from land cover change for CDR explicitly. Future work should continue to expand explicit modeling capabilities for anthropogenic interventions. Potential mutual interactions within prospective portfolios of mitigation measures should also be scrutinized. The results of this work also underscore the importance of varying sulfate aerosol injections for the variability of surface climate and natural carbon uptake. This could be critical for climate change mitigation scenarios and warrants better representation in model-based assessments. Gauging Earth system resilience to anthropogenic interventions, disturbances from climate and weather extremes, and varying external forcings has limitations, even with the current generation of ESMs. Addressing shortcomings in soil moisture and carbon cycling is likely to further improve model reliability. Altogether, the research presented in this work informs the development of next-generation Earth system models and facilitates climate change research and policy, from anticipating the risks posed by climatic extremes to developing mitigation strategies and constraining the global emission budget.

References

- Adam, M. et al. (2025). ‘Land conversions not climate effects are the dominant indirect consequence of sun-driven CO₂ capture, conversion, and sequestration’. *Environmental Research Letters* 20.3, p. 034011. DOI: [10.1088/1748-9326/ada971](https://doi.org/10.1088/1748-9326/ada971) (cited on pages 4, 99).
- Adam, M. et al. (2026a). ‘Earth system models might overestimate the local plant productivity response to temperature–moisture extremes’. *EGUsphere* [preprint, under review]. DOI: [10.5194/egusphere-2026-626](https://doi.org/10.5194/egusphere-2026-626) (cited on pages 4, 100).
- Adam, M. et al. (2026b). ‘Future volcanic eruptions shift the timing of net-zero emissions’. *EarthArXiv* [preprint, accepted: PLOS Climate]. DOI: [10.31223/X5946V](https://doi.org/10.31223/X5946V) (cited on pages 4, 99).
- Anderegg, W. R. L. et al. (2015). ‘Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models’. *Science* 349.6247, pp. 528–532. DOI: [10.1126/science.aab1833](https://doi.org/10.1126/science.aab1833) (cited on page 16).
- Andernach, M. et al. (2026). ‘Stabilizing feedbacks allow for multiple states of the Greenland Ice Sheet in a fully coupled Earth System – Ice Sheet Model’. *The Cryosphere* 20.2, pp. 1047–1069. DOI: [10.5194/tc-20-1047-2026](https://doi.org/10.5194/tc-20-1047-2026) (cited on page 8).
- Archer, D. et al. (2009). ‘Atmospheric Lifetime of Fossil Fuel Carbon Dioxide’. *Annual Review of Earth and Planetary Sciences* 37.1, pp. 117–134. DOI: [10.1146/annurev.earth.031208.100206](https://doi.org/10.1146/annurev.earth.031208.100206) (cited on page 20).
- Arora, V. K. et al. (2020). ‘Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models’. *Biogeosciences* 17.16, pp. 4173–4222. DOI: [10.5194/bg-17-4173-2020](https://doi.org/10.5194/bg-17-4173-2020) (cited on pages 20, 102, 105).
- Arzeno-Soltero, I. B. et al. (2023). ‘Large global variations in the carbon dioxide removal potential of seaweed farming due to biophysical constraints’. *Communications Earth & Environment* 4.1, p. 185. DOI: [10.1038/s43247-023-00833-2](https://doi.org/10.1038/s43247-023-00833-2) (cited on page 107).
- Aubry, T. J. et al. (2025). ‘Stratospheric aerosol forcing for CMIP7 (part 1): Optical properties for pre-industrial, historical, and scenario simulations (version 2.2.1)’. *EGUsphere* 2025, pp. 1–53. DOI: [10.5194/egusphere-2025-4990](https://doi.org/10.5194/egusphere-2025-4990) (cited on pages 7, 21).
- Babiker, M. et al. (2022). ‘Cross-sectoral Perspectives’. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY, USA: Cambridge University Press. DOI: [10.1017/9781009157926.005](https://doi.org/10.1017/9781009157926.005) (cited on pages 5, 12, 13).
- Banwart, S. A. et al. (2016). ‘Soil Functions: Connecting Earth’s Critical Zone’. *Annual Review of Earth and Planetary Sciences* 47.1, pp. 1–27. DOI: [10.1146/annurev-earth-063016-020544](https://doi.org/10.1146/annurev-earth-063016-020544) (cited on page 8).
- Bastos, A. et al. (2023). ‘A joint framework for studying compound ecoclimatic events’. *Nature Reviews Earth & Environment* 4.5, pp. 333–350. DOI: [10.1038/s43017-023-00410-3](https://doi.org/10.1038/s43017-023-00410-3) (cited on pages 5, 6).
- Bell, M. L. et al. (2024). ‘Climate Change, Extreme Heat, and Health’. *New England Journal of Medicine* 390.19, pp. 1793–1801. DOI: [10.1056/nejmra2210769](https://doi.org/10.1056/nejmra2210769) (cited on page 5).

- Bethke, I. et al. (2017). 'Potential volcanic impacts on future climate variability'. *Nature Climate Change* 7.11, pp. 799–805. DOI: [10.1038/nclimate3394](https://doi.org/10.1038/nclimate3394) (cited on pages 16, 21, 106, 112).
- Betts, R. A. (2000). 'Offset of the potential carbon sink from boreal forestation by decreases in surface albedo'. *Nature* 408.6809, pp. 187–190. DOI: [10.1038/35041545](https://doi.org/10.1038/35041545) (cited on page 14).
- Bluth, G. J. S. et al. (1992). 'Global tracking of the SO₂ clouds from the June, 1991 Mount Pinatubo eruptions'. *Geophysical Research Letters* 19.2, pp. 151–154. DOI: [10.1029/91gl02792](https://doi.org/10.1029/91gl02792) (cited on page 15).
- Blyth, E. M. et al. (2021). 'Advances in Land Surface Modelling'. *Current Climate Change Reports* 7.2, pp. 45–71. DOI: [10.1007/s40641-021-00171-5](https://doi.org/10.1007/s40641-021-00171-5) (cited on pages 18, 19, 103).
- Bogdanoff, P. et al. (2024). 'Electrochemical Studies on CO₂ Reduction at Liquid GaInSn Alloy Electrodes'. *Electrochemical Society Meeting Abstracts* MA2024-02.56, pp. 3751–3751. DOI: [10.1149/ma2024-02563751mtgabs](https://doi.org/10.1149/ma2024-02563751mtgabs) (cited on page 101).
- Bonan, G. B. (2008). 'Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests'. *Science* 320.5882, pp. 1444–1449. DOI: [10.1126/science.1155121](https://doi.org/10.1126/science.1155121) (cited on pages 6, 16, 19).
- Bonan, G. B. et al. (2024). 'Reimagining Earth in the Earth System'. *Journal of Advances in Modeling Earth Systems* 16.8. DOI: [10.1029/2023ms004017](https://doi.org/10.1029/2023ms004017) (cited on pages 7, 103, 108).
- Box, G. (1979). 'Robustness in the Strategy of Scientific Model Building'. *Robustness in Statistics*, Academic Press. Ed. by R. L. Launer and G. N. Wilkinson, pp. 201–236. DOI: [10.1016/b978-0-12-438150-6.50018-2](https://doi.org/10.1016/b978-0-12-438150-6.50018-2) (cited on page 102).
- Boyd, P. W. et al. (2024). 'Limited understanding of basic ocean processes is hindering progress in marine carbon dioxide removal'. *Environmental Research Letters* 19.6, p. 061002. DOI: [10.1088/1748-9326/ad502f](https://doi.org/10.1088/1748-9326/ad502f) (cited on pages 13, 107).
- Boysen, L. R. et al. (2020). 'Global climate response to idealized deforestation in CMIP6 models'. *Biogeosciences* 17.22, pp. 5615–5638. DOI: [10.5194/bg-17-5615-2020](https://doi.org/10.5194/bg-17-5615-2020) (cited on page 16).
- Brown, C. et al. (2022). 'Agent-Based Modeling of Alternative Futures in the British Land Use System'. *Earth's Future* 10.11. DOI: [10.1029/2022ef002905](https://doi.org/10.1029/2022ef002905) (cited on page 103).
- Buck, H. J. (2020). 'Should carbon removal be treated as waste management? Lessons from the cultural history of waste'. *Interface Focus* 10.5, p. 20200010. DOI: [10.1098/rsfs.2020.0010](https://doi.org/10.1098/rsfs.2020.0010) (cited on page 13).
- Budyko, M. I. (1969). 'The effect of solar radiation variations on the climate of the Earth'. *Tellus A* 21.5, p. 611. DOI: [10.3402/tellusa.v21i5.10109](https://doi.org/10.3402/tellusa.v21i5.10109) (cited on page 20).
- Cambron, T. W. et al. (2025). 'Plant nutrient acquisition under elevated CO₂ and implications for the land carbon sink'. *Nature Climate Change* 15.9, pp. 935–946. DOI: [10.1038/s41558-025-02386-y](https://doi.org/10.1038/s41558-025-02386-y) (cited on page 108).
- Carton, W. et al. (2020). 'Negative emissions and the long history of carbon removal'. *Wiley Interdisciplinary Reviews: Climate Change* 11.6. DOI: [10.1002/wcc.671](https://doi.org/10.1002/wcc.671) (cited on page 13).
- CDRterra (Oct. 2023). *CDRterra: Forschungsprogramm zu landbasierten Methoden der Kohlendioxidentnahme*. Version V1.0. DOI: [10.5281/zenodo.10603985](https://doi.org/10.5281/zenodo.10603985) (cited on page 9).
- Chauvy, R. and L. Dubois (2022). 'Life cycle and techno-economic assessments of direct air capture processes: An integrated review'. *International Journal of Energy Research* 46.8, pp. 10320–10344. DOI: [10.1002/er.7884](https://doi.org/10.1002/er.7884) (cited on page 109).

- Chen, Y. et al. (2023). ‘Northern-high-latitude permafrost and terrestrial carbon response to two solar geoengineering scenarios’. *Earth System Dynamics* 14.1, pp. 55–79. DOI: [10.5194/esd-14-55-2023](https://doi.org/10.5194/esd-14-55-2023) (cited on page 15).
- Chen, Y. et al. (2020). ‘Mitigation of Arctic permafrost carbon loss through stratospheric aerosol geoengineering’. *Nature Communications* 11.1, p. 2430. DOI: [10.1038/s41467-020-16357-8](https://doi.org/10.1038/s41467-020-16357-8) (cited on page 15).
- Chim, M. M. et al. (2025). ‘Neglecting future sporadic volcanic eruptions underestimates climate uncertainty’. *Communications Earth & Environment* 6.1, p. 236. DOI: [10.1038/s43247-025-02208-1](https://doi.org/10.1038/s43247-025-02208-1) (cited on pages 7, 16, 112).
- Ciais, P. et al. (2013). ‘Carbon and Other Biogeochemical Cycles’. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by T. F. Stocker et al. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press (cited on pages 7, 16, 18, 20).
- Clarke, B. et al. (2022). ‘Extreme weather impacts of climate change: an attribution perspective’. *Environmental Research: Climate* 1.1, p. 012001. DOI: [10.1088/2752-5295/ac6e7d](https://doi.org/10.1088/2752-5295/ac6e7d) (cited on page 5).
- Collatz, G. et al. (1992). ‘Coupled Photosynthesis-Stomatal Conductance Model for Leaves of C4 Plants’. *Functional Plant Biology* 19.5, pp. 519–538. DOI: [10.1071/pp9920519](https://doi.org/10.1071/pp9920519) (cited on page 17).
- Crutzen, P. J. (2002). ‘The “anthropocene”’. *Journal de Physique IV France* 12.10, pp. 1–5. DOI: [10.1051/jp4:20020447](https://doi.org/10.1051/jp4:20020447) (cited on page 5).
- Crutzen, P. J. (2006). ‘Albedo Enhancement by Stratospheric Sulfur Injections: A Contribution to Resolve a Policy Dilemma?’ *Climatic Change* 77.3-4, p. 211. DOI: [10.1007/s10584-006-9101-y](https://doi.org/10.1007/s10584-006-9101-y) (cited on pages 5, 14).
- D’Agostino, R. et al. (2026). ‘The Impact of Volcanic Eruptions on Tropical Hydroclimate’. *Annual Review of Earth and Planetary Sciences*. DOI: [10.1146/annurev-earth-071025-112048](https://doi.org/10.1146/annurev-earth-071025-112048) (cited on page 107).
- de Coninck, H. et al. (2018). ‘Strengthening and Implementing the Global Response’. *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. Ed. by V. Masson-Delmotte et al. Cambridge, UK and New York, NY, USA: Cambridge University Press, pp. 313–444 (cited on pages 5, 14–16).
- De Hertog, S. J. et al. (2022). ‘The biogeophysical effects of idealized land cover and land management changes in Earth system models’. *Earth System Dynamics* 13.3, pp. 1305–1350. DOI: [10.5194/esd-13-1305-2022](https://doi.org/10.5194/esd-13-1305-2022) (cited on page 14).
- Dellink, R. et al. (2017). ‘Long-term economic growth projections in the Shared Socioeconomic Pathways’. *Global Environmental Change* 42, pp. 200–214. DOI: [10.1016/j.gloenvcha.2015.06.004](https://doi.org/10.1016/j.gloenvcha.2015.06.004) (cited on page 10).
- Deser, C. et al. (2020). ‘Insights from Earth system model initial-condition large ensembles and future prospects’. *Nature Climate Change* 10.4, pp. 277–286. DOI: [10.1038/s41558-020-0731-2](https://doi.org/10.1038/s41558-020-0731-2) (cited on page 20).
- Desonie, D. (2007). *Geosphere: The land and its uses*. Infobase Publishing (cited on page 8).
- Doney, S. C. et al. (2025). ‘The Science, Engineering, and Validation of Marine Carbon Dioxide Removal and Storage’. *Annual Review of Marine Science* 17.1, pp. 55–81. DOI: [10.1146/annurev-marine-040523-014702](https://doi.org/10.1146/annurev-marine-040523-014702) (cited on page 13).

- Donges, J. F. et al. (2020). ‘Earth system modeling with endogenous and dynamic human societies: the copan: CORE open World–Earth modeling framework’. *Earth System Dynamics* 11.2, pp. 395–413. DOI: [10.5194/esd-11-395-2020](https://doi.org/10.5194/esd-11-395-2020) (cited on page 109).
- Donner, L. J. and W. G. Large (2008). ‘Climate Modeling’. *Annual Review of Environment and Resources* 33.1, pp. 1–17. DOI: [10.1146/annurev.envIRON.33.020707.160752](https://doi.org/10.1146/annurev.envIRON.33.020707.160752) (cited on page 17).
- Dowell, N. M. et al. (2017). ‘The role of CO₂ capture and utilization in mitigating climate change’. *Nature Climate Change* 7.4, pp. 243–249. DOI: [10.1038/nclimate3231](https://doi.org/10.1038/nclimate3231) (cited on page 13).
- EcoEngineers (2024). *Methodology for Measurement, Reporting, and Verification of Electrolytic Oceanic Carbon Dioxide Removal*. URL: <https://www.equatic.tech/the-equatic-process#measurement-reporting-and-verification> (visited on 04/10/2026) (cited on page 101).
- Ellerhoff, B. (2023). ‘Structure and Causes of Variability in Earth’s Surface Air Temperature at the Local to Global Level’. PhD thesis. University of Tübingen. DOI: [10.15496/publikation-83926](https://doi.org/10.15496/publikation-83926) (cited on pages 9, 102).
- Ellerhoff, B. and K. Rehfeld (2021). ‘Probing the timescale dependency of local and global variations in surface air temperature from climate simulations and reconstructions of the last millennia’. *Physical Review E* 104.6, p. 064136. DOI: [10.1103/physreve.104.064136](https://doi.org/10.1103/physreve.104.064136) (cited on page 107).
- Ellerhoff, B. et al. (2022). ‘Contrasting State-Dependent Effects of Natural Forcing on Global and Local Climate Variability’. *Geophysical Research Letters* 49.10. DOI: [10.1029/2022gl098335](https://doi.org/10.1029/2022gl098335) (cited on pages 6, 15, 20, 21, 107).
- Equatic (2023). *White Paper: Equatic’s Measurement, Reporting, and Verification Methodology*. URL: <https://www.equatic.tech/the-equatic-process#measurement-reporting-and-verification> (visited on 04/10/2026) (cited on page 101).
- Erb, M. P. et al. (2013). ‘The Contribution of Radiative Feedbacks to Orbitally Driven Climate Change’. *Journal of Climate* 26.16, p. 130218123451008. DOI: [10.1175/jcli-d-12-00419.1](https://doi.org/10.1175/jcli-d-12-00419.1) (cited on page 7).
- Esrafilzadeh, D. et al. (2019). ‘Room temperature CO₂ reduction to solid carbon species on liquid metals featuring atomically thin ceria interfaces’. *Nature Communications* 10.1, p. 865. DOI: [10.1038/s41467-019-08824-8](https://doi.org/10.1038/s41467-019-08824-8) (cited on page 101).
- Eyring, V. et al. (2019). ‘Taking climate model evaluation to the next level’. *Nature Climate Change* 9.2, pp. 102–110. DOI: [10.1038/s41558-018-0355-y](https://doi.org/10.1038/s41558-018-0355-y) (cited on page 20).
- Fahrenbach, N. L. S. et al. (2025). ‘Mechanistic insights into tropical circulation and hydroclimate responses to future forest cover change’. *Weather and Climate Dynamics* 6.4, pp. 1461–1477. DOI: [10.5194/wcd-6-1461-2025](https://doi.org/10.5194/wcd-6-1461-2025) (cited on page 16).
- Fan, J. et al. (2016). ‘Review of Aerosol–Cloud Interactions: Mechanisms, Significance, and Challenges’. *Journal of the Atmospheric Sciences* 73.11, pp. 4221–4252. DOI: [10.1175/jas-d-16-0037.1](https://doi.org/10.1175/jas-d-16-0037.1) (cited on page 107).
- Farquhar, G. D. et al. (1980). ‘A Biochemical Model of Photosynthetic CO₂ Assimilation in Leaves of C₃ Species’. *Planta*. 1st ser. 149, pp. 78–90 (cited on page 17).
- Feldl, N. and G. H. Roe (2013). ‘The Nonlinear and Nonlocal Nature of Climate Feedbacks’. *Journal of Climate* 26.21, p. 130506141914009. DOI: [10.1175/jcli-d-12-00631.1](https://doi.org/10.1175/jcli-d-12-00631.1) (cited on page 7).

- Fisher, R. A. et al. (2018). 'Vegetation demographics in Earth System Models: A review of progress and priorities'. *Global Change Biology* 24.1, pp. 35–54. DOI: [10.1111/gcb.13910](https://doi.org/10.1111/gcb.13910) (cited on page 8).
- Flato, G. et al. (2013). 'Evaluation of Climate Models'. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by T. Stocker et al. Cambridge, UK and New York, NY, USA: Cambridge University Press (cited on pages 17, 20, 102).
- Flato, G. (2011). 'Earth system models: an overview'. *Wiley Interdisciplinary Reviews: Climate Change* 2.6, pp. 783–800. DOI: [10.1002/wcc.148](https://doi.org/10.1002/wcc.148) (cited on pages 7, 8, 18).
- Forkel, M. et al. (2016). 'Enhanced seasonal CO₂ exchange caused by amplified plant productivity in northern ecosystems'. *Science* 351.6274, pp. 696–699. DOI: [10.1126/science.aac4971](https://doi.org/10.1126/science.aac4971) (cited on page 16).
- Frank, D. et al. (2015). 'Effects of climate extremes on the terrestrial carbon cycle: concepts, processes and potential future impacts'. *Global Change Biology* 21.8, pp. 2861–2880. DOI: [10.1111/gcb.12916](https://doi.org/10.1111/gcb.12916) (cited on page 17).
- Friedlingstein, P. (2015). 'Carbon cycle feedbacks and future climate change'. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 373.2054, p. 20140421. DOI: [10.1098/rsta.2014.0421](https://doi.org/10.1098/rsta.2014.0421) (cited on page 20).
- Friedlingstein, P. et al. (2023). 'Global Carbon Budget 2023'. *Earth System Science Data* 15.12, pp. 5301–5369. DOI: [10.5194/essd-15-5301-2023](https://doi.org/10.5194/essd-15-5301-2023) (cited on page 11).
- Friedlingstein, P. et al. (2025). 'Global Carbon Budget 2024'. *Earth System Science Data* 17.3, pp. 965–1039. DOI: [10.5194/essd-17-965-2025](https://doi.org/10.5194/essd-17-965-2025) (cited on pages 7, 104).
- Friedlingstein, P. et al. (2026). 'Emerging climate impact on carbon sinks in a consolidated carbon budget'. *Nature* 649.8095, pp. 98–103. DOI: [10.1038/s41586-025-09802-5](https://doi.org/10.1038/s41586-025-09802-5) (cited on pages 5, 11, 16, 17, 22, 102, 108).
- Fu, B. et al. (2015). 'Ecosystem services in changing land use'. *Journal of Soils and Sediments* 15.4, pp. 833–843. DOI: [10.1007/s11368-015-1082-x](https://doi.org/10.1007/s11368-015-1082-x) (cited on page 5).
- Fuhrman, J. et al. (2023). 'Diverse carbon dioxide removal approaches could reduce impacts on the energy–water–land system'. *Nature Climate Change* 13.4, pp. 341–350. DOI: [10.1038/s41558-023-01604-9](https://doi.org/10.1038/s41558-023-01604-9) (cited on page 107).
- Fuss, S. et al. (2024). 'Chapter 4: The Voluntary Carbon Market, The State of Carbon Dioxide Removal - 2nd Edition.' *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. Smith et al. DOI: [10.17605/OSF.IO/MG3CY](https://doi.org/10.17605/OSF.IO/MG3CY) (cited on page 13).
- Fuss, S. et al. (2014). 'Betting on negative emissions'. *Nature Climate Change* 4.10, pp. 850–853. DOI: [10.1038/nclimate2392](https://doi.org/10.1038/nclimate2392) (cited on pages 5, 13, 106).
- Fuss, S. et al. (2018). 'Negative emissions - Part 2: Costs, potentials and side effects'. *Environmental Research Letters* 13.6, p. 063002. DOI: [10.1088/1748-9326/aabf9f](https://doi.org/10.1088/1748-9326/aabf9f) (cited on pages 6, 13).
- Futerman, G. et al. (2025). 'The interaction of solar radiation modification with Earth system tipping elements'. *Earth System Dynamics* 16.4, pp. 939–978. DOI: [10.5194/esd-16-939-2025](https://doi.org/10.5194/esd-16-939-2025) (cited on pages 6, 15).
- Fyke, J. et al. (2018). 'An Overview of Interactions and Feedbacks Between Ice Sheets and the Earth System'. *Reviews of Geophysics* 56.2, pp. 361–408. DOI: [10.1029/2018rg000600](https://doi.org/10.1029/2018rg000600) (cited on page 7).
- Fyson, C. L. et al. (2020). 'Fair-share carbon dioxide removal increases major emitter responsibility'. *Nature Climate Change* 10.9, pp. 836–841. DOI: [10.1038/s41558-020-0857-2](https://doi.org/10.1038/s41558-020-0857-2) (cited on pages 21, 109).

- Gabrielli, P. et al. (2020). 'The Role of Carbon Capture and Utilization, Carbon Capture and Storage, and Biomass to Enable a Net-Zero-CO₂ Emissions Chemical Industry'. *Industrial & Engineering Chemistry Research* 59.15, pp. 7033–7045. DOI: [10.1021/acs.iecr.9b06579](https://doi.org/10.1021/acs.iecr.9b06579) (cited on page 13).
- Gasser, T. et al. (2015). 'Negative emissions physically needed to keep global warming below 2 °C'. *Nature Communications* 6.1, p. 7958. DOI: [10.1038/ncomms8958](https://doi.org/10.1038/ncomms8958) (cited on page 5).
- Gatti, L. V. et al. (2021). 'Amazonia as a carbon source linked to deforestation and climate change'. *Nature* 595.7867, pp. 388–393. DOI: [10.1038/s41586-021-03629-6](https://doi.org/10.1038/s41586-021-03629-6) (cited on pages 16, 17).
- Geden, O. et al. (2024). 'Chapter 1: Introduction, The State of Carbon Dioxide Removal - 2nd Edition'. *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. Smith et al. DOI: [10.17605/OSF.IO/E5M86](https://doi.org/10.17605/OSF.IO/E5M86) (cited on page 13).
- Goelzer, H. et al. (2025). 'Interactive coupling of a Greenland ice sheet model in NorESM2'. *Geoscientific Model Development* 18.20, pp. 7853–7867. DOI: [10.5194/gmd-18-7853-2025](https://doi.org/10.5194/gmd-18-7853-2025) (cited on page 8).
- Gomes, S. D. et al. (2025). 'Rising atmospheric CO₂ concentrations: the overlooked factor promoting SW Iberian Forest development across the LGM and the last deglaciation?'. *Biogeosciences* 22.21, pp. 6631–6650. DOI: [10.5194/bg-22-6631-2025](https://doi.org/10.5194/bg-22-6631-2025) (cited on page 16).
- Gu, L. et al. (2003). 'Response of a Deciduous Forest to the Mount Pinatubo Eruption: Enhanced Photosynthesis'. *Science* 299.5615, pp. 2035–2038. DOI: [10.1126/science.1078366](https://doi.org/10.1126/science.1078366) (cited on page 16).
- Guo, S. et al. (2004). 'Particles in the great Pinatubo volcanic cloud of June 1991: The role of ice'. *Geochemistry, Geophysics, Geosystems* 5.5. DOI: [10.1029/2003gc000655](https://doi.org/10.1029/2003gc000655) (cited on page 15).
- Hacke, U. G. et al. (2001). 'Cavitation Fatigue. Embolism and Refilling Cycles Can Weaken the Cavitation Resistance of Xylem1'. *Plant Physiology* 125.2, pp. 779–786. DOI: [10.1104/pp.125.2.779](https://doi.org/10.1104/pp.125.2.779) (cited on page 17).
- Han, M. et al. (2024). 'Modeling biochar effects on soil organic carbon on croplands in a microbial decomposition model (MIMICS-BC_v1.0)'. *Geoscientific Model Development* 17.12, pp. 4871–4890. DOI: [10.5194/gmd-17-4871-2024](https://doi.org/10.5194/gmd-17-4871-2024) (cited on page 103).
- Hand, D. J. (2014). 'Wonderful Examples, but Let's not Close Our Eyes'. *Statistical Science* 29.1. DOI: [10.1214/13-sts446](https://doi.org/10.1214/13-sts446) (cited on page 102).
- Hasselmann, K. (1976). 'Stochastic climate models Part I. Theory'. *Tellus* 28.6, pp. 473–485. DOI: [10.1111/j.2153-3490.1976.tb00696.x](https://doi.org/10.1111/j.2153-3490.1976.tb00696.x) (cited on page 8).
- Hawkins, E. and R. Sutton (2009). 'The Potential to Narrow Uncertainty in Regional Climate Predictions'. *Bulletin of the American Meteorological Society* 90.8, pp. 1095–1107. DOI: [10.1175/2009bams2607.1](https://doi.org/10.1175/2009bams2607.1) (cited on pages 5, 6, 100, 107).
- Heck, V. et al. (2016). 'Is extensive terrestrial carbon dioxide removal a 'green' form of geoengineering? A global modelling study'. *Global and Planetary Change* 137, pp. 123–130. DOI: [10.1016/j.gloplacha.2015.12.008](https://doi.org/10.1016/j.gloplacha.2015.12.008) (cited on page 107).
- Heck, V. et al. (2018). 'Biomass-based negative emissions difficult to reconcile with planetary boundaries'. *Nature Climate Change* 8.2, pp. 151–155. DOI: [10.1038/s41558-017-0064-y](https://doi.org/10.1038/s41558-017-0064-y) (cited on pages 14, 106, 107).

- Hinkel, J. et al. (2014). 'Coastal flood damage and adaptation costs under 21st century sea-level rise'. *Proceedings of the National Academy of Sciences* 111.9, pp. 3292–3297. DOI: [10.1073/pnas.1222469111](https://doi.org/10.1073/pnas.1222469111) (cited on page 6).
- Hirota, M. et al. (2011). 'Global Resilience of Tropical Forest and Savanna to Critical Transitions'. *Science* 334.6053, pp. 232–235. DOI: [10.1126/science.1210657](https://doi.org/10.1126/science.1210657) (cited on page 8).
- Holmgren, M. et al. (2001). 'El Niño effects on the dynamics of terrestrial ecosystems'. *Trends in Ecology & Evolution* 16.2, pp. 89–94. DOI: [10.1016/S0169-5347\(00\)02052-8](https://doi.org/10.1016/S0169-5347(00)02052-8) (cited on page 104).
- Hu, A. et al. (2016). 'Impact of solar panels on global climate'. *Nature Climate Change* 6.3, pp. 290–294. DOI: [10.1038/nclimate2843](https://doi.org/10.1038/nclimate2843) (cited on page 14).
- Hubau, W. et al. (2020). 'Asynchronous carbon sink saturation in African and Amazonian tropical forests'. *Nature* 579.7797, pp. 80–87. DOI: [10.1038/s41586-020-2035-0](https://doi.org/10.1038/s41586-020-2035-0) (cited on page 17).
- Hurt, G. C. et al. (2020). 'Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6'. *Geoscientific Model Development* 13.11, pp. 5425–5464. DOI: [10.5194/gmd-13-5425-2020](https://doi.org/10.5194/gmd-13-5425-2020) (cited on page 5).
- Huybers, P. and W. Curry (2006). 'Links between annual, Milankovitch and continuum temperature variability'. *Nature* 441.7091, pp. 329–332. DOI: [10.1038/nature04745](https://doi.org/10.1038/nature04745) (cited on pages 5, 20, 107).
- Huybers, P. and C. Langmuir (2009). 'Feedback between deglaciation, volcanism, and atmospheric CO₂'. *Earth and Planetary Science Letters* 286.3–4, pp. 479–491. DOI: [10.1016/j.epsl.2009.07.014](https://doi.org/10.1016/j.epsl.2009.07.014) (cited on page 102).
- Illing, S. et al. (2018). 'Assessing the impact of a future volcanic eruption on decadal predictions'. *Earth System Dynamics* 9.2, pp. 701–715. DOI: [10.5194/esd-9-701-2018](https://doi.org/10.5194/esd-9-701-2018) (cited on page 14).
- Infante-Amate, J. et al. (2024). 'Unsustainable prosperity? Decoupling wellbeing, economic growth, and greenhouse gas emissions over the past 150 years'. *World Development* 184, p. 106754. DOI: [10.1016/j.worlddev.2024.106754](https://doi.org/10.1016/j.worlddev.2024.106754) (cited on page 5).
- IPCC (1990). *Climate Change: The IPCC Scientific Assessment*. Ed. by J. T. Houghton et al. Cambridge: Cambridge University Press (cited on page 5).
- (2005). *IPCC Special Report on Carbon Dioxide Capture and Storage. Prepared by Working Group III of the Intergovernmental Panel on Climate Change*. Ed. by B. Metz et al. Cambridge, UK and New York, NY, USA: Cambridge University Press (cited on page 5).
 - (2018). 'Summary for Policymakers'. *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. Ed. by V. Masson-Delmotte et al. Geneva, Switzerland: World Meteorological Organization (cited on pages 101, 102, 107, 108).
 - (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by The Core Writing Team, H. Lee, and J. Romero. Geneva, Switzerland: IPCC. DOI: [10.59327/ipcc/ar6-9789291691647](https://doi.org/10.59327/ipcc/ar6-9789291691647) (cited on pages 5, 8, 15).
- Jeevanjee, N. et al. (2025). 'A Holistic View of Climate Sensitivity'. *Annual Review of Earth and Planetary Sciences* 53.1, pp. 367–396. DOI: [10.1146/annurev-earth-040523-014302](https://doi.org/10.1146/annurev-earth-040523-014302) (cited on page 20).

- Jiang, J. et al. (2025). ‘Mitigation efforts to reduce carbon dioxide emissions and meet the Paris Agreement have been offset by economic growth’. *Communications Earth & Environment* 6.1, p. 823. DOI: [10.1038/s43247-025-02743-x](https://doi.org/10.1038/s43247-025-02743-x) (cited on page 5).
- Johnston, M. R. et al. (2025). ‘Effects of Hot Versus Dry Vapor Pressure Deficit on Ecosystem Carbon and Water Fluxes’. *Journal of Geophysical Research: Biogeosciences* 130.1. DOI: [10.1029/2024jg008146](https://doi.org/10.1029/2024jg008146) (cited on pages 16, 103).
- Jungclaus, J. H. et al. (2022). ‘The ICON Earth System Model Version 1.0’. *Journal of Advances in Modeling Earth Systems* 14.4. DOI: [10.1029/2021ms002813](https://doi.org/10.1029/2021ms002813) (cited on page 108).
- Junge, C. E. and J. E. Manson (1961). ‘Stratospheric aerosol studies’. *Journal of Geophysical Research (1896-1977)* 66.7, pp. 2163–2182. DOI: [10.1029/jz066i007p02163](https://doi.org/10.1029/jz066i007p02163) (cited on page 14).
- Keith, D. W. and D. G. MacMartin (2015). ‘A temporary, moderate and responsive scenario for solar geoengineering’. *Nature Climate Change* 5.3, pp. 201–206. DOI: [10.1038/nclimate2493](https://doi.org/10.1038/nclimate2493) (cited on page 15).
- Klein, C. et al. (2021). ‘Combining CMIP data with a regional convection-permitting model and observations to project extreme rainfall under climate change’. *Environmental Research Letters* 16.10, p. 104023. DOI: [10.1088/1748-9326/ac26f1](https://doi.org/10.1088/1748-9326/ac26f1) (cited on page 102).
- Kolus, H. R. et al. (2019). ‘Land carbon models underestimate the severity and duration of drought’s impact on plant productivity’. *Scientific Reports* 9.1, p. 2758. DOI: [10.1038/s41598-019-39373-1](https://doi.org/10.1038/s41598-019-39373-1) (cited on page 16).
- Koven, C. D. et al. (2022). ‘Multi-century dynamics of the climate and carbon cycle under both high and net negative emissions scenarios’. *Earth System Dynamics* 13.2, pp. 885–909. DOI: [10.5194/esd-13-885-2022](https://doi.org/10.5194/esd-13-885-2022) (cited on pages 6, 12, 103).
- Kravitz, B. et al. (2016). ‘Geoengineering as a design problem’. *Earth System Dynamics* 7.2, pp. 469–497. DOI: [10.5194/esd-7-469-2016](https://doi.org/10.5194/esd-7-469-2016) (cited on page 106).
- Kremser, S. et al. (2016). ‘Stratospheric aerosol—Observations, processes, and impact on climate’. *Reviews of Geophysics* 54.2, pp. 278–335. DOI: [10.1002/2015rg000511](https://doi.org/10.1002/2015rg000511) (cited on pages 14, 15, 21).
- Laepfle, T. et al. (2023). ‘Regional but not global temperature variability underestimated by climate models at supradecadal timescales’. *Nature Geoscience* 16.11, pp. 958–966. DOI: [10.1038/s41561-023-01299-9](https://doi.org/10.1038/s41561-023-01299-9) (cited on pages 21, 102, 107).
- Lambin, E. F. and P. Meyfroidt (2011). ‘Global land use change, economic globalization, and the looming land scarcity’. *Proceedings of the National Academy of Sciences* 108.9, pp. 3465–3472. DOI: [10.1073/pnas.1100480108](https://doi.org/10.1073/pnas.1100480108) (cited on pages 5, 6, 106).
- Lee, K. et al. (2021). ‘Fair distributions of carbon dioxide removal obligations and implications for effective national net-zero targets’. *Environmental Research Letters* 16.9, p. 094001. DOI: [10.1088/1748-9326/ac1970](https://doi.org/10.1088/1748-9326/ac1970) (cited on page 21).
- Lee, W. et al. (2020). ‘Expanding the design space of stratospheric aerosol geoengineering to include precipitation-based objectives and explore trade-offs’. *Earth System Dynamics* 11.4, pp. 1051–1072. DOI: [10.5194/esd-11-1051-2020](https://doi.org/10.5194/esd-11-1051-2020) (cited on page 106).
- Lenton, T. M. et al. (2008). ‘Tipping elements in the Earth’s climate system’. *Proceedings of the National Academy of Sciences* 105.6, pp. 1786–1793. DOI: [10.1073/pnas.0705414105](https://doi.org/10.1073/pnas.0705414105) (cited on page 17).
- Lewis, S. L. and M. A. Maslin (2015). ‘Defining the Anthropocene’. *Nature* 519.7542, pp. 171–180. DOI: [10.1038/nature14258](https://doi.org/10.1038/nature14258) (cited on page 5).

- Li, F. et al. (2024). ‘Evaluation of global fire simulations in CMIP6 Earth system models’. *Geoscientific Model Development* 17.23, pp. 8751–8771. DOI: [10.5194/gmd-17-8751-2024](https://doi.org/10.5194/gmd-17-8751-2024) (cited on page 104).
- Li, J. et al. (2024). ‘Future increase in compound soil drought-heat extremes exacerbated by vegetation greening’. *Nature Communications* 15.1, p. 10875. DOI: [10.1038/s41467-024-55175-0](https://doi.org/10.1038/s41467-024-55175-0) (cited on page 16).
- Li, T. et al. (2000). ‘Dynamic and Thermodynamic Regulation of Ocean Warming’. *Journal of the Atmospheric Sciences* 57.20, pp. 3353–3365. DOI: [10.1175/1520-0469\(2000\)057%3C3353:DATR00%3E2.0.CO;2](https://doi.org/10.1175/1520-0469(2000)057%3C3353:DATR00%3E2.0.CO;2) (cited on page 7).
- Li, Y. et al. (2018). ‘Climate model shows large-scale wind and solar farms in the Sahara increase rain and vegetation’. *Science* 361.6406, pp. 1019–1022. DOI: [10.1126/science.aar5629](https://doi.org/10.1126/science.aar5629) (cited on page 14).
- Lörch, D. et al. (2024). ‘From CO₂ to Solid Carbon: Reaction Mechanism, Active Species, and Conditioning the Ce-Alloyed GaInSn Catalyst’. *The Journal of Physical Chemistry C* 128.49, pp. 20827–20840. DOI: [10.1021/acs.jpcc.4c05482](https://doi.org/10.1021/acs.jpcc.4c05482) (cited on page 101).
- Lorenz, R. et al. (2016). ‘Influence of land-atmosphere feedbacks on temperature and precipitation extremes in the GLACE-CMIP5 ensemble’. *Journal of Geophysical Research: Atmospheres* 121.2, pp. 607–623. DOI: [10.1002/2015jd024053](https://doi.org/10.1002/2015jd024053) (cited on page 102).
- Loughran, T. F. et al. (2023). ‘Limited Mitigation Potential of Forestation Under a High Emissions Scenario: Results From Multi-Model and Single Model Ensembles’. *Journal of Geophysical Research: Biogeosciences* 128.12. DOI: [10.1029/2023jg007605](https://doi.org/10.1029/2023jg007605) (cited on page 14).
- Low, S. and H. J. Buck (2020). ‘The practice of responsible research and innovation in “climate engineering”’. *Wiley Interdisciplinary Reviews: Climate Change* 11.3, pp. 1–17. DOI: [10.1002/wcc.644](https://doi.org/10.1002/wcc.644) (cited on page 5).
- Lu, Z. et al. (2021). ‘Impacts of Large-Scale Sahara Solar Farms on Global Climate and Vegetation Cover’. *Geophysical Research Letters* 48.2, pp. 1–10. DOI: [10.1029/2020gl090789](https://doi.org/10.1029/2020gl090789) (cited on page 17).
- Määttänen, A. et al. (2024). ‘Uncertainties and confidence in stratospheric aerosol injection modelling: a systematic literature review’. *Oxford Open Climate Change* 4.1, kgae007. DOI: [10.1093/oxfclm/kgae007](https://doi.org/10.1093/oxfclm/kgae007) (cited on page 15).
- MacMartin, D. G. et al. (2016). ‘Geoengineering with stratospheric aerosols: What do we not know after a decade of research?’ *Earth’s Future* 4.11, pp. 543–548. DOI: [10.1002/2016ef000418](https://doi.org/10.1002/2016ef000418) (cited on pages 15, 16).
- Mahecha, M. D. et al. (2022). ‘Biodiversity loss and climate extremes – study the feedbacks’. *Nature* 612.7938, pp. 30–32. DOI: [10.1038/d41586-022-04152-y](https://doi.org/10.1038/d41586-022-04152-y) (cited on pages 6, 16).
- Mahony, C. R. and A. J. Cannon (2018). ‘Wetter summers can intensify departures from natural variability in a warming climate’. *Nature Communications* 9.1, p. 783. DOI: [10.1038/s41467-018-03132-z](https://doi.org/10.1038/s41467-018-03132-z) (cited on page 105).
- Malavelle, F. F. et al. (2017). ‘Strong constraints on aerosol–cloud interactions from volcanic eruptions’. *Nature* 546.7659, pp. 485–491. DOI: [10.1038/nature22974](https://doi.org/10.1038/nature22974) (cited on page 107).
- Malhi, Y. (2017). ‘The Concept of the Anthropocene’. *Annual Review of Environment and Resources* 42.1, pp. 77–104. DOI: [10.1146/annurev-environ-102016-060854](https://doi.org/10.1146/annurev-environ-102016-060854) (cited on page 5).

- Manabe, S. et al. (1965). 'Simulated Climatology of a general circulation model with a hydrologic cycle'. *Monthly Weather Review* 93.12, pp. 769–798. DOI: [10.1175/1520-0493\(1965\)093<0769:scoagc>2.3.co;2](https://doi.org/10.1175/1520-0493(1965)093<0769:scoagc>2.3.co;2) (cited on page 8).
- Maslouski, M. et al. (2025). 'Soil and vegetation responses to biochar application in terms of its feedback on carbon sequestration under different environmental conditions—LiDELS model overview'. *Environmental Research Letters* 20.4, p. 044020. DOI: [10.1088/1748-9326/adbfa6](https://doi.org/10.1088/1748-9326/adbfa6) (cited on page 101).
- Matthews, H. D. and S. Wynes (2022). 'Current global efforts are insufficient to limit warming to 1.5°C'. *Science* 376.6600, pp. 1404–1409. DOI: [10.1126/science.abo3378](https://doi.org/10.1126/science.abo3378) (cited on page 5).
- Mauritsen, T. et al. (2013). 'Tuning the climate of a global model'. *Journal of Advances in Modeling Earth Systems* 4.3. DOI: [10.1029/2012ms000154](https://doi.org/10.1029/2012ms000154) (cited on page 19).
- May, M. M. and K. Rehfeld (2019). 'ESD Ideas: Photoelectrochemical carbon removal as negative emission technology'. *Earth System Dynamics* 10.1, pp. 1–7. DOI: [10.5194/esd-10-1-2019](https://doi.org/10.5194/esd-10-1-2019) (cited on page 13).
- May, R. M. (1977). 'Thresholds and breakpoints in ecosystems with a multiplicity of stable states'. *Nature* 269.5628, pp. 471–477. DOI: [10.1038/269471a0](https://doi.org/10.1038/269471a0) (cited on page 8).
- McColl, K. A. et al. (2022). 'The terrestrial water cycle in a warming world'. *Nature Climate Change* 12.7, pp. 604–606. DOI: [10.1038/s41558-022-01412-7](https://doi.org/10.1038/s41558-022-01412-7) (cited on page 103).
- McCormack, C. G. et al. (2016). 'Key impacts of climate engineering on biodiversity and ecosystems, with priorities for future research'. *Journal of Integrative Environmental Sciences* 13.2-4, pp. 103–128. DOI: [10.1080/1943815x.2016.1159578](https://doi.org/10.1080/1943815x.2016.1159578) (cited on page 15).
- McDonald, M. (2023). 'Geoengineering, climate change and ecological security'. *Environmental Politics* 32.4, pp. 565–585. DOI: [10.1080/09644016.2022.2113606](https://doi.org/10.1080/09644016.2022.2113606) (cited on page 106).
- McMichael, A. J. et al. (2006). 'Climate change and human health: present and future risks'. *The Lancet* 367.9513, pp. 859–869. DOI: [10.1016/s0140-6736\(06\)68079-3](https://doi.org/10.1016/s0140-6736(06)68079-3) (cited on page 7).
- McMichael, C. et al. (2020). 'A review of estimating population exposure to sea-level rise and the relevance for migration'. *Environmental Research Letters* 15.12, p. 123005. DOI: [10.1088/1748-9326/abb398](https://doi.org/10.1088/1748-9326/abb398) (cited on page 5).
- Meierrieks, D. (2021). 'Weather shocks, climate change and human health'. *World Development* 138, p. 105228. DOI: [10.1016/j.worlddev.2020.105228](https://doi.org/10.1016/j.worlddev.2020.105228) (cited on page 7).
- Melnikova, I. et al. (2021). 'Carbon Cycle Response to Temperature Overshoot Beyond 2°C: An Analysis of CMIP6 Models'. *Earth's Future* 9.5, pp. 1–19. DOI: [10.1029/2020ef001967](https://doi.org/10.1029/2020ef001967) (cited on pages 12, 103).
- Mengis, N. et al. (2020). 'Evaluation of the University of Victoria Earth System Climate Model version 2.10 (UVic ESCM 2.10)'. *Geoscientific Model Development* 13.9, pp. 4183–4204. DOI: [10.5194/gmd-13-4183-2020](https://doi.org/10.5194/gmd-13-4183-2020) (cited on page 9).
- Mercado, L. M. et al. (2009). 'Impact of changes in diffuse radiation on the global land carbon sink'. *Nature* 458.7241, pp. 1014–1017. DOI: [10.1038/nature07949](https://doi.org/10.1038/nature07949) (cited on page 16).
- Meyer, A. L. S. et al. (2022). 'Risks to biodiversity from temperature overshoot pathways'. *Philosophical Transactions of the Royal Society B* 377.1857, p. 20210394. DOI: [10.1098/rstb.2021.0394](https://doi.org/10.1098/rstb.2021.0394) (cited on page 12).

- Minx, J. et al. (2024). 'Chapter 2: Research and Development, The State of Carbon Dioxide Removal - 2nd Edition.' *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. Smith et al. DOI: [10.17605/OSF.IO/4FGHP](https://doi.org/10.17605/OSF.IO/4FGHP) (cited on page 108).
- Moustakis, Y. et al. (2024). 'Temperature overshoot responses to ambitious forestation in an Earth System Model'. *Nature Communications* 15.1, p. 8235. DOI: [10.1038/s41467-024-52508-x](https://doi.org/10.1038/s41467-024-52508-x) (cited on pages 21, 103, 108).
- Mühlbauer, A. et al. (2025). 'Assessment of technologies and economics for carbon dioxide removal from a portfolio perspective'. *International Journal of Greenhouse Gas Control* 141, p. 104297. DOI: [10.1016/j.ijggc.2024.104297](https://doi.org/10.1016/j.ijggc.2024.104297) (cited on page 13).
- Nath, D. et al. (2024). 'Faster dieback of rainforests altering tropical carbon sinks under climate change'. *npj Climate and Atmospheric Science* 7.1, p. 235. DOI: [10.1038/s41612-024-00793-0](https://doi.org/10.1038/s41612-024-00793-0) (cited on page 105).
- Nauels, A. et al. (2025). 'Multi-century global and regional sea-level rise commitments from cumulative greenhouse gas emissions in the coming decades'. *Nature Climate Change* 15.11, pp. 1198–1204. DOI: [10.1038/s41558-025-02452-5](https://doi.org/10.1038/s41558-025-02452-5) (cited on pages 5, 106).
- Nemet, G. F. et al. (2024). 'Chapter 3: Demonstration and Upscaling, The State of Carbon Dioxide Removal - 2nd Edition.' *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. Smith et al. DOI: [10.17605/OSF.IO/DPKSB](https://doi.org/10.17605/OSF.IO/DPKSB) (cited on pages 6, 13).
- Nemet, G. F. et al. (2018). 'Negative emissions - Part 3: Innovation and upscaling'. *Environmental Research Letters* 13.6, p. 063003. DOI: [10.1088/1748-9326/aabff4](https://doi.org/10.1088/1748-9326/aabff4) (cited on pages 6, 13).
- neustark AG (2025). *Carbon mineralisation using reactive mineral waste*. URL: <https://globalgoals.goldstandard.org/432-cdr-carbon-mineralisation-using-reactive-mineral-waste/> (visited on 04/10/2026) (cited on page 101).
- Nijse, F. J. M. M. et al. (2020). 'Emergent constraints on transient climate response (TCR) and equilibrium climate sensitivity (ECS) from historical warming in CMIP5 and CMIP6 models'. *Earth System Dynamics* 11.3, pp. 737–750. DOI: [10.5194/esd-11-737-2020](https://doi.org/10.5194/esd-11-737-2020) (cited on page 102).
- Norby, R. J. et al. (2005). 'Forest response to elevated CO₂ is conserved across a broad range of productivity'. *Proceedings of the National Academy of Sciences* 102.50, pp. 18052–18056. DOI: [10.1073/pnas.0509478102](https://doi.org/10.1073/pnas.0509478102) (cited on page 16).
- Norris, J. et al. (2021). 'Evaluation of the Tail of the Probability Distribution of Daily and Subdaily Precipitation in CMIP6 Models'. *Journal of Climate* 34.7, pp. 2701–2721. DOI: [10.1175/jcli-d-20-0182.1](https://doi.org/10.1175/jcli-d-20-0182.1) (cited on pages 102, 105).
- O'Neill, B. C. et al. (2016). 'The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6'. *Geoscientific Model Development* 9.9, pp. 3461–3482. DOI: [10.5194/gmd-9-3461-2016](https://doi.org/10.5194/gmd-9-3461-2016) (cited on pages 10, 12, 103).
- Olonscheck, D. et al. (2023). 'The New Max Planck Institute Grand Ensemble With CMIP6 Forcing and High-Frequency Model Output'. *Journal of Advances in Modeling Earth Systems* 15.10. DOI: [10.1029/2023ms003790](https://doi.org/10.1029/2023ms003790) (cited on page 11).
- Otto, I. M. et al. (2020). 'Social tipping dynamics for stabilizing Earth's climate by 2050'. *Proceedings of the National Academy of Sciences* 117.5, pp. 2354–2365. DOI: [10.1073/pnas.1900577117](https://doi.org/10.1073/pnas.1900577117) (cited on page 102).
- Ozkan, M. (2021). 'Direct air capture of CO₂: A response to meet the global climate targets'. *MRS Energy & Sustainability* 8.2, pp. 51–56. DOI: [10.1557/s43581-021-00005-9](https://doi.org/10.1557/s43581-021-00005-9) (cited on page 13).

- Pan, Y. et al. (2011). 'A Large and Persistent Carbon Sink in the World's Forests'. *Science* 333.6045, pp. 988–993. DOI: [10.1126/science.1201609](https://doi.org/10.1126/science.1201609) (cited on page 16).
- Papież, M. et al. (2022). 'Decoupling is not enough - Evidence from fossil fuel use in over 130 countries'. *Journal of Cleaner Production* 379, p. 134856. DOI: [10.1016/j.jclepro.2022.134856](https://doi.org/10.1016/j.jclepro.2022.134856) (cited on page 5).
- Pathak, M. et al. (2022). 'Technical Summary'. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY, USA: Cambridge University Press. DOI: [10.1017/9781009157926.002](https://doi.org/10.1017/9781009157926.002) (cited on pages 5, 7).
- Patz, J. A. et al. (2005). 'Impact of regional climate change on human health'. *Nature* 438.7066, pp. 310–317. DOI: [10.1038/nature04188](https://doi.org/10.1038/nature04188) (cited on page 7).
- Pausata, F. S. R. et al. (2015). 'Impacts of high-latitude volcanic eruptions on ENSO and AMOC'. *Proceedings of the National Academy of Sciences* 112.45, pp. 13784–13788. DOI: [10.1073/pnas.1509153112](https://doi.org/10.1073/pnas.1509153112) (cited on pages 14, 107).
- Peng, S.-S. et al. (2014). 'Afforestation in China cools local land surface temperature'. *Proceedings of the National Academy of Sciences* 111.8, pp. 2915–2919. DOI: [10.1073/pnas.1315126111](https://doi.org/10.1073/pnas.1315126111) (cited on page 14).
- Piao, S. et al. (2020). 'Characteristics, drivers and feedbacks of global greening'. *Nature Reviews Earth & Environment* 1.1, pp. 14–27. DOI: [10.1038/s43017-019-0001-x](https://doi.org/10.1038/s43017-019-0001-x) (cited on page 17).
- Pongratz, J. et al. (2024). 'Chapter 7: Current levels of CDR, The State of Carbon Dioxide Removal - 2nd Edition.' *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. Smith et al. DOI: [10.17605/OSF.IO/ZXSKB](https://doi.org/10.17605/OSF.IO/ZXSKB) (cited on page 13).
- Pope, F. D. et al. (2012). 'Stratospheric aerosol particles and solar-radiation management'. *Nature Climate Change* 2.10, pp. 713–719. DOI: [10.1038/nclimate1528](https://doi.org/10.1038/nclimate1528) (cited on pages 6, 14, 15).
- Popp, A. et al. (2017). 'Land-use futures in the shared socio-economic pathways'. *Global Environmental Change* 42, pp. 331–345. DOI: [10.1016/j.gloenvcha.2016.10.002](https://doi.org/10.1016/j.gloenvcha.2016.10.002) (cited on pages 5, 6, 14).
- Port, U. et al. (2012). 'The influence of vegetation dynamics on anthropogenic climate change'. *Earth System Dynamics* 3.2, pp. 233–243. DOI: [10.5194/esd-3-233-2012](https://doi.org/10.5194/esd-3-233-2012) (cited on page 18).
- Pozo, C. et al. (2020). 'Equity in allocating carbon dioxide removal quotas'. *Nature Climate Change* 10.7, pp. 640–646. DOI: [10.1038/s41558-020-0802-4](https://doi.org/10.1038/s41558-020-0802-4) (cited on page 109).
- Quaglia, I. et al. (2022). 'Interactive stratospheric aerosol models' response to different amounts and altitudes of SO₂ injection during the 1991 Pinatubo eruption'. *Atmospheric Chemistry and Physics* 23.2, pp. 921–948. DOI: [10.5194/acp-23-921-2023](https://doi.org/10.5194/acp-23-921-2023) (cited on pages 15, 106).
- Rast, S. et al. (2013). *User manual for ECHAM6*. Reports on Earth System Science / Max Planck Institute for Meteorology. Max Planck Institute for Meteorology (cited on page 18).
- Reichstein, M. et al. (2013). 'Climate extremes and the carbon cycle'. *Nature* 500.7462, pp. 287–295. DOI: [10.1038/nature12350](https://doi.org/10.1038/nature12350) (cited on pages 5, 6, 17, 22, 102).
- Reick, C. H. et al. (2013). 'Representation of natural and anthropogenic land cover change in MPI-ESM'. *Journal of Advances in Modeling Earth Systems* 5.3, pp. 459–482. DOI: [10.1002/jame.20022](https://doi.org/10.1002/jame.20022) (cited on pages 18, 19, 103).

- Reick, C. H. et al. (2021). *JSBACH 3: The land component of the MPI Earth System Model - Documentation of version 3.2*. Reports on Earth System Science / Max Planck Institute for Meteorology. Max Planck Institute for Meteorology. DOI: [10.17617/2.3279802](https://doi.org/10.17617/2.3279802) (cited on pages 18, 19).
- Reith, F. et al. (2016). 'Revisiting ocean carbon sequestration by direct injection: a global carbon budget perspective'. *Earth System Dynamics* 7.4, pp. 797–812. DOI: [10.5194/esd-7-797-2016](https://doi.org/10.5194/esd-7-797-2016) (cited on page 16).
- Riahi, K. et al. (2022). 'Mitigation pathways compatible with long-term goals'. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by P. Shukla et al. Cambridge, UK and New York, NY, USA: Cambridge University Press. DOI: [10.1017/9781009157926.005](https://doi.org/10.1017/9781009157926.005) (cited on pages 5, 10–12).
- Riahi, K. et al. (2017). 'The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview'. *Global Environmental Change* 42, pp. 153–168. DOI: [10.1016/j.gloenvcha.2016.05.009](https://doi.org/10.1016/j.gloenvcha.2016.05.009) (cited on pages 5, 8, 10, 11).
- Riahi, K. et al. (2021). 'Cost and attainability of meeting stringent climate targets without overshoot'. *Nature Climate Change* 11.12, pp. 1063–1069. DOI: [10.1038/s41558-021-01215-2](https://doi.org/10.1038/s41558-021-01215-2) (cited on page 5).
- Ricke, K. et al. (2023). 'Hydrological Consequences of Solar Geoengineering'. *Annual Review of Earth and Planetary Sciences* 51.1, pp. 447–470. DOI: [10.1146/annurev-earth-031920-083456](https://doi.org/10.1146/annurev-earth-031920-083456) (cited on pages 8, 14).
- Ricke, K. L. et al. (2010). 'Regional climate response to solar-radiation management'. *Nature Geoscience* 3.8, pp. 537–541. DOI: [10.1038/ngeo915](https://doi.org/10.1038/ngeo915) (cited on pages 6, 15).
- Rickels, W. et al. (2019). '(Mis)conceptions about modeling of negative emissions technologies'. *Environmental Research Letters* 14.10, p. 104004. DOI: [10.1088/1748-9326/ab3ab4](https://doi.org/10.1088/1748-9326/ab3ab4) (cited on pages 6, 13, 14, 101, 109).
- Ridder, N. N. et al. (2022). 'Increased occurrence of high impact compound events under climate change'. *npj Climate and Atmospheric Science* 5.1, p. 3. DOI: [10.1038/s41612-021-00224-4](https://doi.org/10.1038/s41612-021-00224-4) (cited on page 16).
- Ritchie, P. D. L. et al. (2026). 'The implications of overshooting 1.5 °C on Earth system tipping elements—a review'. *Environmental Research Letters* 21.4, p. 043001. DOI: [10.1088/1748-9326/ae3cad](https://doi.org/10.1088/1748-9326/ae3cad) (cited on page 12).
- Roberts, K. E. et al. (2026). 'Potential Impacts of Climate Interventions on Marine Ecosystems'. *Reviews of Geophysics* 64.1. DOI: [10.1029/2024rg000876](https://doi.org/10.1029/2024rg000876) (cited on page 107).
- Roe, S. et al. (2019). 'Contribution of the land sector to a 1.5 °C world'. *Nature Climate Change* 9.11, pp. 817–828. DOI: [10.1038/s41558-019-0591-9](https://doi.org/10.1038/s41558-019-0591-9) (cited on page 5).
- Rosen, J. (2018). 'The carbon harvest'. *Science* 359.6377, pp. 733–737. DOI: [10.1126/science.359.6377.733](https://doi.org/10.1126/science.359.6377.733) (cited on page 12).
- Rougier, J. and M. Goldstein (2014). 'Climate Simulators and Climate Projections'. *Annual Review of Statistics and Its Application* 1.1, pp. 103–123. DOI: [10.1146/annurev-statistics-022513-115652](https://doi.org/10.1146/annurev-statistics-022513-115652) (cited on pages 8, 20).
- Ruddiman, W. F. (2008). *Earth's Climate: Past and Future*. New York, US and Houndmills, England: W. H. Freeman and Company (cited on pages 7, 8).
- (2013). 'The Anthropocene'. *Annual Review of Earth and Planetary Sciences* 41.1, pp. 45–68. DOI: [10.1146/annurev-earth-050212-123944](https://doi.org/10.1146/annurev-earth-050212-123944) (cited on page 5).

- Rueda, O. et al. (2021). ‘Negative-emissions technology portfolios to meet the 1.5°C target’. *Global Environmental Change* 67, p. 102238. DOI: [10.1016/j.gloenvcha.2021.102238](https://doi.org/10.1016/j.gloenvcha.2021.102238) (cited on page 101).
- Saatchi, S. et al. (2013). ‘Persistent effects of a severe drought on Amazonian forest canopy’. *Proceedings of the National Academy of Sciences* 110.2, pp. 565–570. DOI: [10.1073/pnas.1204651110](https://doi.org/10.1073/pnas.1204651110) (cited on page 17).
- Schädel, C. et al. (Feb. 2024). ‘Earth system models must include permafrost carbon processes’. *Nature Climate Change* 14.2, pp. 114–116. DOI: [10.1038/s41558-023-01909-9](https://doi.org/10.1038/s41558-023-01909-9) (cited on page 104).
- Schillinger, M. et al. (2022). ‘Separating internal and externally forced contributions to global temperature variability using a Bayesian stochastic energy balance framework’. *Chaos: An Interdisciplinary Journal of Nonlinear Science* 32.11, p. 113146. DOI: [10.1063/5.0106123](https://doi.org/10.1063/5.0106123) (cited on page 15).
- Schindlbeck-Belo, J. C. et al. (2023). ‘PalVol v1: a proxy-based semi-stochastic ensemble reconstruction of volcanic stratospheric sulfur injection for the last glacial cycle (140 000–50 BP)’. *Earth System Science Data* 16.2, pp. 1063–1081. DOI: [10.5194/essd-16-1063-2024](https://doi.org/10.5194/essd-16-1063-2024) (cited on page 21).
- Schleussner, C.-F. et al. (2024). ‘Overconfidence in climate overshoot’. *Nature* 634.8033, pp. 366–373. DOI: [10.1038/s41586-024-08020-9](https://doi.org/10.1038/s41586-024-08020-9) (cited on page 106).
- Schmidt, G. A. et al. (2017). ‘Practice and philosophy of climate model tuning across six US modeling centers’. *Geoscientific Model Development* 10.9, pp. 3207–3223. DOI: [10.5194/gmd-10-3207-2017](https://doi.org/10.5194/gmd-10-3207-2017) (cited on page 19).
- Schulte, I. et al. (2024). ‘Chapter 10: Monitoring, Reporting and Verification, The State of Carbon Dioxide Removal - 2nd Edition’. *The State of Carbon Dioxide Removal - 2nd Edition*. Ed. by S. M. S. et al. (cited on page 13).
- Schwalm, C. R. et al. (2017). ‘Global patterns of drought recovery’. *Nature* 548.7666, pp. 202–205. DOI: [10.1038/nature23021](https://doi.org/10.1038/nature23021) (cited on page 17).
- Schwinger, J. et al. (2022a). ‘Emit now, mitigate later? Earth system reversibility under overshoots of different magnitudes and durations’. *Earth System Dynamics* 13.4, pp. 1641–1665. DOI: [10.5194/esd-13-1641-2022](https://doi.org/10.5194/esd-13-1641-2022) (cited on page 12).
- Schwinger, J. et al. (2022b). ‘Possibility for strong northern hemisphere high-latitude cooling under negative emissions’. *Nature Communications* 13.1, p. 1095. DOI: [10.1038/s41467-022-28573-5](https://doi.org/10.1038/s41467-022-28573-5) (cited on page 12).
- Segschneider, J. et al. (2013). ‘Impact of an extremely large magnitude volcanic eruption on the global climate and carbon cycle estimated from ensemble Earth System Model simulations’. *Biogeosciences* 10.2, pp. 669–687. DOI: [10.5194/bg-10-669-2013](https://doi.org/10.5194/bg-10-669-2013) (cited on page 102).
- Seiler, C. et al. (2022). ‘Are Terrestrial Biosphere Models Fit for Simulating the Global Land Carbon Sink?’ *Journal of Advances in Modeling Earth Systems* 14.5. DOI: [10.1029/2021ms002946](https://doi.org/10.1029/2021ms002946) (cited on page 102).
- Sharma, B. et al. (2023). ‘Carbon cycle extremes accelerate weakening of the land carbon sink in the late 21st century’. *Biogeosciences* 20.10, pp. 1829–1841. DOI: [10.5194/bg-20-1829-2023](https://doi.org/10.5194/bg-20-1829-2023) (cited on page 7).
- Shepherd, T. G. et al. (2018). ‘Storylines: an alternative approach to representing uncertainty in physical aspects of climate change’. *Climatic Change* 151.3–4, pp. 555–571. DOI: [10.1007/s10584-018-2317-9](https://doi.org/10.1007/s10584-018-2317-9) (cited on pages 8, 10).

- Sherwood, S. C. et al. (2014). ‘Spread in model climate sensitivity traced to atmospheric convective mixing’. *Nature* 505.7481, pp. 37–42. DOI: [10.1038/nature12829](https://doi.org/10.1038/nature12829) (cited on page 8).
- Shi, Y. et al. (2019). ‘How parameter specification of an Earth system model of intermediate complexity influences its climate simulations’. *Progress in Earth and Planetary Science* 6.1, p. 46. DOI: [10.1186/s40645-019-0294-x](https://doi.org/10.1186/s40645-019-0294-x) (cited on page 19).
- Siegel, D. A. et al. (2021). ‘Assessing the sequestration time scales of some ocean-based carbon dioxide reduction strategies’. *Environmental Research Letters* 16.10, p. 104003. DOI: [10.1088/1748-9326/ac0be0](https://doi.org/10.1088/1748-9326/ac0be0) (cited on page 107).
- Simpson, I. R. et al. (2025). ‘Confronting Earth System Model trends with observations’. *Science Advances* 11.11, eadt8035. DOI: [10.1126/sciadv.adt8035](https://doi.org/10.1126/sciadv.adt8035) (cited on pages 20, 102).
- Simpson, N. P. et al. (2021). ‘A framework for complex climate change risk assessment’. *One Earth* 4.4, pp. 489–501. DOI: [10.1016/j.oneear.2021.03.005](https://doi.org/10.1016/j.oneear.2021.03.005) (cited on page 6).
- Sippel, S. et al. (2018). ‘Drought, Heat, and the Carbon Cycle: a Review’. *Current Climate Change Reports* 4.3, pp. 266–286. DOI: [10.1007/s40641-018-0103-4](https://doi.org/10.1007/s40641-018-0103-4) (cited on page 104).
- Sitch, S. et al. (2014). ‘Recent trends and drivers of regional sources and sinks of carbon dioxide’. *Biogeosciences* 12.3, pp. 653–679. DOI: [10.5194/bg-12-653-2015](https://doi.org/10.5194/bg-12-653-2015) (cited on page 16).
- Smith, L. J. and M. S. Torn (2013). ‘Ecological limits to terrestrial biological carbon dioxide removal’. *Climatic Change* 118.1, pp. 89–103. DOI: [10.1007/s10584-012-0682-3](https://doi.org/10.1007/s10584-012-0682-3) (cited on page 12).
- Smith, P. et al. (2016). ‘Biophysical and economic limits to negative CO₂ emissions’. *Nature Climate Change* 6.1, pp. 42–50. DOI: [10.1038/nclimate2870](https://doi.org/10.1038/nclimate2870) (cited on pages 6, 14).
- Smith, S. M. et al. (2023). *The state of carbon dioxide removal*. DOI: [10.17605/osf.io/w3b4z](https://doi.org/10.17605/osf.io/w3b4z) (cited on pages 11, 13, 109).
- Smith, S. M. et al. (2024). *The state of Carbon Dioxide Removal - 2nd Edition*. DOI: [10.17605/OSF.IO/F85QJ](https://doi.org/10.17605/OSF.IO/F85QJ) (cited on pages 5, 101, 106, 108).
- Sonntag, S. et al. (2018). ‘Quantifying and Comparing Effects of Climate Engineering Methods on the Earth System’. *Earth’s Future* 6.2, pp. 149–168. DOI: [10.1002/2017ef000620](https://doi.org/10.1002/2017ef000620) (cited on page 110).
- Stevens, B. et al. (2013). ‘Atmospheric component of the MPI-M Earth System Model: ECHAM6’. *Journal of Advances in Modeling Earth Systems* 5.2, pp. 146–172. DOI: [10.1002/jame.20015](https://doi.org/10.1002/jame.20015) (cited on page 18).
- Stevenson, S. et al. (2022). ‘Twenty-first century hydroclimate: A continually changing baseline, with more frequent extremes’. *Proceedings of the National Academy of Sciences* 119.12, e2108124119. DOI: [10.1073/pnas.2108124119](https://doi.org/10.1073/pnas.2108124119) (cited on page 105).
- Strefler, J. et al. (2021a). ‘Alternative carbon price trajectories can avoid excessive carbon removal’. *Nature Communications* 12.1, pp. 1–8. DOI: [10.1038/s41467-021-22211-2](https://doi.org/10.1038/s41467-021-22211-2) (cited on page 13).
- Strefler, J. et al. (2021b). ‘Carbon dioxide removal technologies are not born equal’. *Environmental Research Letters* 16.7, p. 074021. DOI: [10.1088/1748-9326/ac0a11](https://doi.org/10.1088/1748-9326/ac0a11) (cited on pages 13, 101, 107, 108).
- Svenning, J.-C. and B. Sandel (2013). ‘Disequilibrium vegetation dynamics under future climate change’. *American Journal of Botany*. DOI: [10.3732/ajb.1200469](https://doi.org/10.3732/ajb.1200469) (cited on page 16).

- Tebaldi, C. et al. (2021). ‘Climate model projections from the Scenario Model Intercomparison Project (ScenarioMIP) of CMIP6’. *Earth System Dynamics* 12.1, pp. 253–293. DOI: [10.5194/esd-12-253-2021](https://doi.org/10.5194/esd-12-253-2021) (cited on pages 10, 11, 110).
- Terlouw, T. et al. (2021). ‘Life Cycle Assessment of Direct Air Carbon Capture and Storage with Low-Carbon Energy Sources’. *Environmental Science & Technology* 55.16, pp. 11397–11411. DOI: [10.1021/acs.est.1c03263](https://doi.org/10.1021/acs.est.1c03263) (cited on pages 101, 109).
- Tharammal, T. et al. (2019). ‘A review of the major drivers of the terrestrial carbon uptake: model-based assessments, consensus, and uncertainties’. *Environmental Research Letters* 14.9, p. 093005. DOI: [10.1088/1748-9326/ab3012](https://doi.org/10.1088/1748-9326/ab3012) (cited on page 16).
- Tilmes, S. et al. (2013). ‘The hydrological impact of geoengineering in the Geoengineering Model Intercomparison Project (GeoMIP)’. *Journal of Geophysical Research: Atmospheres* 118.19, pp. 11, 036–11, 058. DOI: [10.1002/jgrd.50868](https://doi.org/10.1002/jgrd.50868) (cited on page 15).
- Tilmes, S. et al. (2020). ‘Reaching 1.5 and 2.0 °C global surface temperature targets using stratospheric aerosol geoengineering’. *Earth System Dynamics* 11.3, pp. 579–601. DOI: [10.5194/esd-11-579-2020](https://doi.org/10.5194/esd-11-579-2020) (cited on page 15).
- Tjiputra, J. F. et al. (2016). ‘Impact of idealized future stratospheric aerosol injection on the large-scale ocean and land carbon cycles’. *Journal of Geophysical Research: Biogeosciences* 121.1, pp. 2–27. DOI: [10.1002/2015jg003045](https://doi.org/10.1002/2015jg003045) (cited on page 16).
- Toohey, M. et al. (2016). ‘Easy Volcanic Aerosol (EVA v1.0): an idealized forcing generator for climate simulations’. *Geoscientific Model Development* 9.11, pp. 4049–4070. DOI: [10.5194/gmd-9-4049-2016](https://doi.org/10.5194/gmd-9-4049-2016) (cited on page 18).
- Trenberth, K. (2011). ‘Changes in precipitation with climate change’. *Climate Research* 47.1, pp. 123–138. DOI: [10.3354/cr00953](https://doi.org/10.3354/cr00953) (cited on pages 105, 108).
- Trenberth, K. E. and A. Dai (2007). ‘Effects of Mount Pinatubo volcanic eruption on the hydrological cycle as an analog of geoengineering’. *Geophysical Research Letters* 34.15. DOI: [10.1029/2007gl030524](https://doi.org/10.1029/2007gl030524) (cited on pages 14, 108).
- Trisos, C. H. et al. (2018). ‘Potentially dangerous consequences for biodiversity of solar geoengineering implementation and termination’. *Nature Ecology & Evolution* 2.3, pp. 475–482. DOI: [10.1038/s41559-017-0431-0](https://doi.org/10.1038/s41559-017-0431-0) (cited on page 15).
- United Nations Development Programme (UNDP) (2024). *Peoples’ Climate Vote 2024*. URL: <https://peoplesclimate.vote/download> (visited on 03/02/2026) (cited on page 5).
- Urban Climate Change Research Network (UCCRN) (2018). *The future we don’t want*. URL: <https://www.c40.org/what-we-do/scaling-up-climate-action/water-heat-nature/the-future-we-dont-want/> (visited on 03/02/2026) (cited on page 5).
- van Dijk, E. J. C. et al. (2024). ‘High-frequency climate forcing causes prolonged cold periods in the Holocene’. *Communications Earth & Environment* 5.1, p. 242. DOI: [10.1038/s43247-024-01380-0](https://doi.org/10.1038/s43247-024-01380-0) (cited on page 16).
- van Haren, R. et al. (2015). ‘Resolution dependence of circulation forced future central European summer drying’. *Environmental Research Letters* 10.5, p. 055002. DOI: [10.1088/1748-9326/10/5/055002](https://doi.org/10.1088/1748-9326/10/5/055002) (cited on page 102).
- van Soest, H. L. et al. (2021). ‘Net-zero emission targets for major emitting countries consistent with the Paris Agreement’. *Nature Communications* 12.1, p. 2140. DOI: [10.1038/s41467-021-22294-x](https://doi.org/10.1038/s41467-021-22294-x) (cited on page 5).
- van Vuuren, D. et al. (2025). ‘The Scenario Model Intercomparison Project for CMIP7 (ScenarioMIP-CMIP7)’. *EGUsphere* 2025, pp. 1–38. DOI: [10.5194/egusphere-2024-3765](https://doi.org/10.5194/egusphere-2024-3765) (cited on pages 10, 110).

- Vaughan, N. E. and T. M. Lenton (2011). ‘A review of climate geoengineering proposals’. *Climatic Change* 109.3-4, pp. 745–790. DOI: [10.1007/s10584-011-0027-7](https://doi.org/10.1007/s10584-011-0027-7) (cited on page 110).
- (2012). ‘Interactions between reducing CO₂ emissions, CO₂ removal and solar radiation management’. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 370.1974, pp. 4343–4364. DOI: [10.1098/rsta.2012.0188](https://doi.org/10.1098/rsta.2012.0188) (cited on page 6).
- Verschuur, J. et al. (2024). ‘Quantifying climate risks to infrastructure systems: A comparative review of developments across infrastructure sectors’. *PLOS Climate* 3.4, e0000331. DOI: [10.1371/journal.pclm.0000331](https://doi.org/10.1371/journal.pclm.0000331) (cited on page 7).
- Walker, J. C. G. et al. (1981). ‘A negative feedback mechanism for the long-term stabilization of Earth’s surface temperature’. *Journal of Geophysical Research* (cited on page 8).
- Wang, S. et al. (2020). ‘Recent global decline of CO₂ fertilization effects on vegetation photosynthesis’. *Science* 370.6522, pp. 1295–1300. DOI: [10.1126/science.abb7772](https://doi.org/10.1126/science.abb7772) (cited on page 17).
- Ward, B. et al. (2021). ‘The sensitivity of the El Niño–Southern Oscillation to volcanic aerosol spatial distribution in the MPI Grand Ensemble’. *Earth System Dynamics* 12.3, pp. 975–996. DOI: [10.5194/esd-12-975-2021](https://doi.org/10.5194/esd-12-975-2021) (cited on page 107).
- Whitby, K. T. (2007). ‘The physical characteristics of sulfur aerosols’. *Atmospheric Environment* 41, pp. 25–49. DOI: [10.1016/j.atmosenv.2007.10.057](https://doi.org/10.1016/j.atmosenv.2007.10.057) (cited on page 14).
- Wieder, W. R. et al. (2015). ‘Future productivity and carbon storage limited by terrestrial nutrient availability’. *Nature Geoscience* 8.6, pp. 441–444. DOI: [10.1038/ngeo2413](https://doi.org/10.1038/ngeo2413) (cited on page 17).
- Wieners, K.-H. et al. (2019a). ‘MPI-M MPI-ESM1.2-LR model output prepared for CMIP6 CMIP historical (Versions 20190911, 20230321)’. *Earth System Grid Federation*. DOI: [10.22033/esgf/cmip6.6595](https://doi.org/10.22033/esgf/cmip6.6595) (cited on page 11).
- Wieners, K.-H. et al. (2019b). ‘MPI-M MPI-ESM1.2-LR model output prepared for CMIP6 ScenarioMIP (Versions 20191029, 20191105, 20230712, 20231017)’. *Earth System Grid Federation*. DOI: [10.22033/esgf/cmip6.793](https://doi.org/10.22033/esgf/cmip6.793) (cited on page 11).
- Wiens, J. A. et al. (2009). ‘Niches, models, and climate change: Assessing the assumptions and uncertainties’. *Proceedings of the National Academy of Sciences* 106, pp. 19729–19736. DOI: [10.1073/pnas.0901639106](https://doi.org/10.1073/pnas.0901639106) (cited on page 16).
- Willeit, M. et al. (2014). ‘Time-scale and state dependence of the carbon-cycle feedback to climate’. *Climate Dynamics* 42.7-8, pp. 1699–1713. DOI: [10.1007/s00382-014-2102-z](https://doi.org/10.1007/s00382-014-2102-z) (cited on page 17).
- Windisch, M. G. et al. (Oct. 2021). ‘Prioritizing forestation based on biogeochemical and local biogeophysical impacts’. *Nature Climate Change* 11.10, pp. 867–871. DOI: [10.1038/s41558-021-01161-z](https://doi.org/10.1038/s41558-021-01161-z) (cited on page 14).
- Winkelmann, R. et al. (2022). ‘Social tipping processes towards climate action: A conceptual framework’. *Ecological Economics* 192, p. 107242. DOI: [10.1016/j.ecolecon.2021.107242](https://doi.org/10.1016/j.ecolecon.2021.107242) (cited on page 102).
- Winkler, A. J. et al. (2019). ‘Earth system models underestimate carbon fixation by plants in the high latitudes’. *Nature Communications* 10.1, p. 885. DOI: [10.1038/s41467-019-08633-z](https://doi.org/10.1038/s41467-019-08633-z) (cited on page 104).
- Wunderling, N. et al. (2023). ‘Global warming overshoots increase risks of climate tipping cascades in a network model’. *Nature Climate Change* 13.1, pp. 75–82. DOI: [10.1038/s41558-022-01545-9](https://doi.org/10.1038/s41558-022-01545-9) (cited on pages 12, 17).

- Zanchettin, D. et al. (2016). ‘The Model Intercomparison Project on the climatic response to Volcanic forcing (VolMIP): experimental design and forcing input data for CMIP6’. *Geoscientific Model Development* 9.8, pp. 2701–2719. DOI: [10.5194/gmd-9-2701-2016](https://doi.org/10.5194/gmd-9-2701-2016) (cited on page 110).
- Zanchettin, D. et al. (2022). ‘Effects of forcing differences and initial conditions on inter-model agreement in the VolMIP volc-pinatubo-full experiment’. *Geoscientific Model Development* 15.5, pp. 2265–2292. DOI: [10.5194/gmd-15-2265-2022](https://doi.org/10.5194/gmd-15-2265-2022) (cited on pages 14, 15).
- Zarnetske, P. L. et al. (2021). ‘Potential ecological impacts of climate intervention by reflecting sunlight to cool Earth’. *Proceedings of the National Academy of Sciences* 118.15, e1921854118. DOI: [10.1073/pnas.1921854118](https://doi.org/10.1073/pnas.1921854118) (cited on pages 15, 16).
- Zeng, Y. et al. (2025). ‘InsNet-CRAFTY v1.0: integrating institutional network dynamics powered by large language models with land use change simulation’. *Geoscientific Model Development* 18.15, pp. 4983–5013. DOI: [10.5194/gmd-18-4983-2025](https://doi.org/10.5194/gmd-18-4983-2025) (cited on page 109).
- Zhang, X. et al. (2019). ‘Greenhouse Gas Concentration and Volcanic Eruptions Controlled the Variability of Terrestrial Carbon Uptake Over the Last Millennium’. *Journal of Advances in Modeling Earth Systems* 11.6, pp. 1715–1734. DOI: [10.1029/2018ms001566](https://doi.org/10.1029/2018ms001566) (cited on page 104).
- Zhu, Z. et al. (2016). ‘Greening of the Earth and its drivers’. *Nature Climate Change* 6.8, pp. 791–795. DOI: [10.1038/nclimate3004](https://doi.org/10.1038/nclimate3004) (cited on pages 16, 105).
- Zickfeld, K. et al. (2011). ‘Nonlinearity of Carbon Cycle Feedbacks’. *Journal of Climate* 24.16, pp. 4255–4275. DOI: [10.1175/2011jcli3898.1](https://doi.org/10.1175/2011jcli3898.1) (cited on page 7).
- Zickfeld, K. et al. (2021). ‘Asymmetry in the climate–carbon cycle response to positive and negative CO₂ emissions’. *Nature Climate Change* 11.7, pp. 613–617. DOI: [10.1038/s41558-021-01061-2](https://doi.org/10.1038/s41558-021-01061-2) (cited on pages 6, 12).
- Zickfeld, K. et al. (2023). ‘Net-zero approaches must consider Earth system impacts to achieve climate goals’. *Nature Climate Change* 13.12, pp. 1298–1305. DOI: [10.1038/s41558-023-01862-7](https://doi.org/10.1038/s41558-023-01862-7) (cited on pages 6, 7, 14, 21).
- Ziegler, E. et al. (2025). ‘Patterns of changing surface climate variability from the Last Glacial Maximum to present in transient model simulations’. *Climate of the Past* 21.3, pp. 627–659. DOI: [10.5194/cp-21-627-2025](https://doi.org/10.5194/cp-21-627-2025) (cited on pages 102, 107).
- Zscheischler, J. et al. (2014a). ‘Extreme events in gross primary production: a characterization across continents’. *Biogeosciences* 11.11, pp. 2909–2924. DOI: [10.5194/bg-11-2909-2014](https://doi.org/10.5194/bg-11-2909-2014) (cited on pages 6, 16, 17).
- Zscheischler, J. et al. (2013). ‘Detection and attribution of large spatiotemporal extreme events in Earth observation data’. *Ecological Informatics* 15, pp. 66–73. DOI: [10.1016/j.ecoinf.2013.03.004](https://doi.org/10.1016/j.ecoinf.2013.03.004) (cited on page 17).
- Zscheischler, J. et al. (2014b). ‘A few extreme events dominate global interannual variability in gross primary production’. *Environmental Research Letters* 9.3, p. 035001. DOI: [10.1088/1748-9326/9/3/035001](https://doi.org/10.1088/1748-9326/9/3/035001) (cited on pages 17, 104).

APPENDIX

Manuscript 1 — Supplementary Material | A

Supplementary Material to:

M. Adam, T. Kleinen, M. M. May, and K. Rehfeld (2025). “Land conversions not climate effects are the dominant indirect consequence of sun-driven CO₂ capture, conversion, and sequestration”. *Environmental Research Letters* 20.3, 034011. DOI: [10.1088/1748-9326/ada971](https://doi.org/10.1088/1748-9326/ada971).

Refer to Chapt. 6 for a declaration on author contributions.

Supplementary Information to “Land conversions not climate effects are the dominant consequence of Sun-driven CO₂ capture, conversion, and sequestration” by M. Adam et al.

In this Supplementary Information (SI), we describe the representation of sDACCCS in MPI-ESM step by step (Section S1) and discuss technology assumptions (Section S2), scenario design (Section S3), and model validation (Section S4). Furthermore, we include figures supplementing the results of the main manuscript (Figures S8–S31).

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S1 Details of the sDACCCS representation in MPI-ESM

CDR land cover on vegetated and bare land

JSBACH sub-divides every grid cell into tiles (see references Reick et al. [73] and Reick et al. [74] for any details on JSBACH). Each tile is associated with a type of land cover, with changing tile (cover) fractions resulting from natural or anthropogenic land cover change. Supported cover types include different plant functional types (PFTs), unvegetated (bare) land, and glaciers, assuming a well-mixed domain within the grid cell [73]. To represent sDACCCS land cover on the vegetated fraction of land, we expand the lookup table defining every land cover type’s parameters and introduce a new land cover class. This class allows to exclude sDACCCS from calculations dedicated to vegetation and to compute CDR-specific processes exclusively on the sDACCCS tile. On unvegetated land, the pre-existing version of JSBACH cannot separate bare soil into different tiles, as it does for vegetated land. However, one could deploy sDACCCS on bare land where plants cannot grow because bioclimatic conditions exceed their capabilities. As an additional complication, JSBACH implicitly accounts for bare land when computing land surface properties like albedo for the vegetated land fraction. To accommodate these constraints within our modeling goals, we represent sDACCCS implicitly on the bare fraction. With this extension of JSBACH’s tiling concept, the overall sDACCCS land cover fraction in a grid cell, f_{CDR} , consists of the cover fractions c_{CDR}^v on vegetated land and c_{CDR}^b on bare land

$$f_{\text{CDR}} = c_{\text{CDR}}^v f_{v, \max} + c_{\text{CDR}}^b f_b \quad (21)$$

Here, $f_b = 1 - f_{v, \max}$ denotes the fraction of bare land, and $f_{v, \max}$ the potential vegetation extent.

sDACCCS land cover class

We implement the sDACCCS land cover class (Figure S1i-ii) with masks t^k building on JSBACH’s land cover lookup table. These masks help to separate processes taking place on CDR tiles and on vegetation tiles ($t^{v \vee \text{CDR}}$) from those exclusively involving sDACCCS (t^{CDR}) or vegetation tiles (t^v). Based on the t^k , we exclude sDACCCS chains from processes like carbon allocation through photosynthesis, vegetation dynamics, dynamic phenology, and disturbances. Calculations involving both vegetation and CDR tiles include (bio-)physical surface properties, radiative balances, soil hydrology, and land use transitions. Processes exclusive to sDACCCS CDR cover are the CO_2 withdrawal through (photo-)electrochemical reduction, fill-up of the sink product pool, and coupling of the CDR cover to the spatiotemporal target.

Land surface properties

Through solar energy harvest and CO_2 capturing facilities, large-scale sDACCCS would alter the surface albedo and the surface roughness lengths. Changes in these properties can modify the absorption of shortwave radiation, the back-scattering of short- and longwave radiation, and the transport of heat and momentum through the atmospheric boundary layer. In this study, we assume an effective albedo of 0.27 for sDACCCS tiles, similar to previous studies on the climatic effects of photovoltaics within general circulation models [75]. As roughness

lengths we assume 1m, the same as JSBACH does for tropical deciduous and extra-tropical trees. This assumption is motivated by the expected size of DAC facilities and large-scale solar parks.

sDACCCS land cover could be deployed both on vegetated and bare land. However, JSBACH's tiling scheme [74, 73] focusses on resolving different surface types on the vegetated fraction of land. Therefore, treating the bare land's properties implicitly in many computations is handy in the default model, while it complicates representing sDACCCS as an additional surface cover on unvegetated land. To still account for CDR on unvegetated land implicitly, we modify JSBACH's albedo and roughness schemes to account for the implicit sDACCCS cover on the bare fraction of land. This approach allows to represent CO₂ withdrawal on bare land, land use through sDACCCS, and impacts of CDR on the surface energy balance (Figure S1). At the same time, we can keep JSBACH's default schemes, for example, for vegetation dynamics. However, bare land neither contains a soil model nor soil carbon stocks. Thus, CDR land use transitions only impact existing carbon stocks on the vegetated fraction of a grid cell.

Surface albedo

For each tile, JSBACH distinguishes between cover area and vegetation canopy area [73]. The canopy fraction can be smaller than or equal to the tile cover fraction. Without changing the tile fraction, this approach allows handling dynamically changing leaf area and the subsequent effect of exposing bare soil on the tiles' albedo. For CDR cover, we assume that (i) sDACCCS on bare soil does not get exposed through canopy gaps, (ii) sDACCCS cover is not subject to canopy gaps that are not already covered by its effective albedo (iii) the turnover of soil organic matter does not change the soil albedo on sDACCCS-covered land, (iv) tree stems do not affect the albedo of sDACCCS, and (v) sDACCCS does not impact the other tiles' surface properties.

JSBACH represents gaps in the canopy which expose bare soil on the vegetated fraction of land (Figure 4.1 in Reick et al. [74]) with the "sky view factor" [74] κ_k , $k \in K = \{\text{LCT}_i \mid \iota_i^v = \text{TRUE} \vee \iota_i^{\text{CDR}} = \text{TRUE}\}$, $i = 1, 2, \dots, N_{\text{LCT}}$. For vegetation, κ_k is a function of the dynamic leaf area index Λ_k [74]. Respecting (i), κ_k differs between vegetation and CDR cover

$$\kappa_k = \begin{cases} 1 - f_v, & \iota_k^{\text{CDR}} = \text{TRUE} \\ 1 - [f_v \cdot (1 - e^{-\Lambda_k/2})], & \text{else} \end{cases} \quad (22)$$

where f_v is the potentially vegetated cover fraction and we assume $\iota^v \vee \text{CDR} = \text{TRUE}$ here in the first place. JSBACH's sky view factor that includes the shading effect of tree stems for forest vegetation [74], $\kappa_{\text{stem},k}$, remains untouched, following (iii) and (iv)

$$\kappa_{\text{stem},k} = \kappa - [1 - f_v \cdot (1 - e^{-1/2(\Lambda_k + \Xi_k)})] \quad (23)$$

To now account for the implicit CDR cover on bare land, we split the contributions of sDACCCS on bare soil from the remaining bare land whose exposed fraction increases through canopy gaps. Thus, the "background albedo", a tile's albedo prior to considering snow cover and tree stems, is

$$\alpha_k^{\text{bg}} = \begin{cases} (1 - \kappa_k) \alpha_{c,k} + (\kappa_k - f_{\text{CDR}}^b) \alpha_{\text{soil}}, & \iota_k^F = \text{TRUE} \\ (1 - \kappa_k) \alpha_{c,k} + (\kappa_k - f_{\text{CDR}}^b) \alpha_{\text{soil}} & \text{else} \\ + \alpha_{\text{CDR}} \cdot f_{\text{CDR}}^b, & \end{cases} \quad (24)$$

Here, $\alpha_{c,k}$ denotes the canopy albedo of a land cover type's effective CDR albedo, α_{soil} the albedo of unvegetated land, and ι_k^F the mask for forest PFTs. Other than in JSBACH's default scheme, α_k^{bg} distinguishes between forested land and non-forest cover. This design choice simplifies applying (iv). Incorporating snow cover on the vegetation canopy and on sDACCCS,

as well as tree stems results in the albedo α_k for tile k on the vegetated fraction of land

$$\alpha_k = \begin{cases} \max \left[(\kappa_k - \kappa_{\text{stem},k} - f_{\text{CDR}}^b)(c_{\text{sn}}\alpha_{\text{sn}} + (1 - c_{\text{sn}})\alpha_{\text{soil}}) \right. \\ \quad \left. + \kappa_{\text{stem},k}(c_{\text{snc}}\alpha_{\text{snc}} + (1 - c_{\text{sn}})\alpha_{\text{soil}}) \right. \\ \quad \left. + (1 - \kappa_k)(c_{\text{snc}}\alpha_{\text{snc}} + (1 - c_{\text{snc}})\alpha_k^{bg}), \alpha_k^{bg} \right] & \iota_k^F = \text{TRUE} \\ \max \left[c_{\text{sn}}\alpha_{\text{snc}} + (1 - c_{\text{sn}})\alpha_k^{bg}, \alpha_k^{bg} \right], & \text{else} \end{cases} \quad (25)$$

In Equation (25), α_{sn} and α_{snc} denote the snow albedo on ground and on the canopy, c_{sn} and c_{snc} are the respective cover fractions. Again, (i) and (iv) result in separate terms for the contributions of sDACCSS on the fraction of bare land and on exposed soil itself. Equations (24) and (25) incorporate the unvegetated land into the albedo of vegetated tiles. Then, as in the default model [74], the aggregated albedo of a land grid box is

$$\alpha = \sum_{k \in K} c_k \alpha_k \quad (26)$$

Surface roughness

In JSBACH, contributions of the surface type $z_{0_m}^{\text{surf}}$ and the underlying orography $z_{0_m}^{\text{oro}}$ make up the effective roughness length for the turbulent transport of momentum [74] z_{0_m}

$$z_{0_m} = \sqrt{(z_{0_m}^{\text{surf}})^2 + (z_{0_m}^{\text{oro}})^2} \quad (27)$$

The turbulent heat transport only depends on the surface roughness of the land cover, $z_{0_h}^{\text{surf}}$. In both cases, the parameters for the surface roughness lengths have to be aggregated from the tile level to the grid cell resolution. JSBACH employs the concept of a blending height [76] to achieve this downscaling [74]. The reasoning behind this concept is that surface heat and momentum fluxes originating from multiple surface types cannot be distinguished above a certain blending height l_b . Similar to the albedo calculations, JSBACH handles bare soil implicitly when computing a grid cell's roughness length. We expand this approach for the implicit sDACCSS fraction on unvegetated land. The effective bare fraction f_{b_j} on a vegetated tile j and the effective fraction of implicit CDR that is deployed on bare soil f_{CDR_j} are

$$\begin{aligned} f_{b_j} &= (1 - f_v) \cdot c_j \cdot (1 - c_{\text{CDR}}^b) \\ f_{\text{CDR}_j} &= (1 - f_v) \cdot c_j \cdot c_{\text{CDR}}^b \end{aligned} \quad (28)$$

where the prefactor $1 - f_v$ spreads the implicit bare and sDACCSS-covered land fraction across all vegetated tiles, assuming a well-mixed domain [73]. c_{CDR}^b again denotes the fraction of sDACCSS cover on bare land and c_j the cover fraction of the respective tile j . Then, we can treat f_{b_j} and f_{CDR_j} separately when aggregating the surface roughness with the blending height approach. The roughness length for heat transport follows as [74, 76]

$$z_{0_h}^{\text{surf}} = l_b \exp \left\{ - \left(\sum_{j=1}^{N_{\text{tiles}}} \sum_{i \in \{j, b_j, \text{CDR}_j\}} \sum_{\{\text{sn}, \text{nsn}\}} \frac{f_i}{(\ln(l_b/z_{0_h}^i))^2} \right)^{-1/2} \right\} \quad (29)$$

with grid cell cover fractions f_i and blending height $l_b = 100$ m. The sum over $\{\text{sn}, \text{nsn}\}$ symbolizes that the surface roughness for heat transport changes if snow covers a surface (sn) compared to when it does not (nsn). An analogous calculation yields the roughness length for turbulent momentum transport. For $z_{0_m}^{\text{surf}}$, the only difference lies in the fact that JSBACH does not differentiate between snow-covered and snow-free surfaces [74].

CDR land cover dynamics

Two stages make up our CDR deployment scheme. First, we translate the global SSP-based CDR target into a spatially explicit target change of fractional sDACCCS area (Figure S2). Subsequently, we integrate these anticipated area changes into JSBACH's land use transition scheme. The transition scheme combines a set of priority rules for land conversion with a series of transition matrices converting between cover types. It resolves land use change including cyclic ("secondary") transitions at annual time scale and interpolates them linearly onto a daily resolution.

First stage – Converting spatiotemporal targets into anticipated changes in sDACCCS

We initially determine the globally integrated mismatch between the cumulated CDR target $\tilde{T}$ and cumulative simulated withdrawal through sDACCCS, $\tilde{W}$ (Figure S2). With a second-order Taylor expansion of this mismatch, we incorporate offsets from internal variability over time while smoothly changing sDACCCS cover a smooth effective forcing. The condition is supposed to hold after sDACCCS has been deployed over the course of year i while the computation takes place at the beginning of it, i.e. at the end of year $i - 1$.

$$\begin{aligned} 0 &\stackrel{!}{=} T(t) - W(t) \\ &= T_i - W_i + \partial_t T|_i - \partial_t W|_i + \frac{\partial_t^2 T|_i - \partial_t^2 W|_i}{2} + \sigma(\Delta t^3) \end{aligned} \quad (30)$$

To solve Equation (30) for the residual CDR deployment, denoted Δ_i , we reformulate it in terms of the annual target removal rates T_i and actual (simulated) rates W_i . To account for the linear interpolation of land cover changes over a year [74] which leads to a systematic lag of the W_i behind the T_i , we further introduce target removal rates $T_{i-1/2}^*$ that lag the T_i by half a year. Based on the $T_{i-1/2}^*$, we can eventually avoid a systematic bias in Equation (30). With these adjustments, the cumulative removal is

$$\tilde{T}_i = \sum_{j \leq i} T_j = \tilde{T}_{i-1/2}^* + \frac{T_{i+1/2}^* + T_{i-1/2}^*}{2} \quad (31)$$

with cumulative target removal at the middle of the previous simulation year $\tilde{T}_{i-1/2}^* = \sum_{j \leq i-1/2} T_j^*$. The second term in Equation (31) reflects the linear interpolation of land cover changes. Similarly, we obtain an expression for the first derivative

$$\partial_t \tilde{T}|_i = T_i = \frac{T_{i+1/2}^* + T_{i-1/2}^*}{2} \quad (32)$$

and the second derivative

$$\partial_t^2 \tilde{T}|_i = \tilde{T}_{i+1}^* - 2\tilde{T}_i^* + \tilde{T}_i^* \quad (33)$$

Inserting the definition (31) into Equation (33) yields an expression that is independent of the subsequent cumulative target

$$\partial_t^2 \tilde{T}|_i = \frac{1}{2}(T_{i+3/2}^* + T_{i+1/2}^* - 3T_{i-3/2}^* + T_{i-5/2}^*) \quad (34)$$

Then, the expressions (31)-(34) can all be computed from the global CDR scenario. For the realized, piece-wise linear cumulative CDR, we obtain

$$\tilde{W}_i = \sum_{j \leq i} W_j \quad (35)$$

Its first derivate can be expressed as a the sum of last year's CO₂ removal and the residual sDACCS deployment

$$\partial_t \tilde{W} = W_i = W_{i-1} + \Delta_i \quad (36)$$

and the second derivative can be discretized analogously to Equation (33)

$$\partial_t^2 \tilde{W} = \tilde{W}_{i+1} - 2\tilde{W}_i + \tilde{W}_{i-1} \simeq \tilde{T}_{i+1} - 2\tilde{W}_i + \tilde{W}_{i-1} \quad (37)$$

where we assume $\tilde{W}_{i+1} \rightarrow \tilde{T}_{i+1}$. Solving for Δ_i yields an expression

$$\Delta_i = \Delta_i \left(\tilde{T}_i, \partial_t \tilde{T}_i (T_{i+1/2}^*, T_{i-1/2}^*), \partial_t^2 \tilde{T}_i (T_{i+3/2}^*, T_{i+1/2}^*, T_{i-1/2}^*, T_{i-3/2}^*), \tilde{W}_i, \partial_t^2 \tilde{W}_i (\tilde{W}_{i+1}, \tilde{W}_i, \tilde{W}_{i-1}) \right) \quad (38)$$

To improve numerical stability, we test different linearization coefficients for the different orders in (38) and eventually draw on $1/2$ for the zeroth and first order term, and 1 for the second order term. Thus, we emphasize smoothness of the CDR pathway. For many parts of the deployment scheme it is irrelevant if $\Delta \geq 0$ or $\Delta < 0$ (index dropped in the following). Therefore, the scheme's steps apply to both cases, CDR establishment and dismantling, if not stated otherwise.

The withdrawal potential ψ_{ij} of every grid cell $(i, j) \in \{(1, 1), (1, 2), \dots, (n_{\text{lon}}, n_{\text{lat}})\}$ translates the spatiotemporal sDACCS target into anticipated changes of sDACCS land cover (Figure S2). However, the target change in CDR Δ_i is an extensive quantity. Thus, ψ_{ij} has to be scaled by the corresponding maximum CDR cover fraction to obtain the CDR in relation to changes in the cover fraction. The maximum CDR cover is $f_{\text{max}} - f_{\epsilon}$ with the technical lower limit to the grid cell cover fraction f_{ϵ} [74]. Therefore, the relative potential withdrawal ψ_{ij}^r is

$$\psi_{ij}^r = \frac{\psi_{ij}}{f_{\text{max}} - f_{\epsilon}} \quad (39)$$

Correcting for natural land cover dynamics δ (see below), the anticipated change in sDACCS grid cell fraction is

$$\Delta \tilde{f}_{ij} = \frac{(\Delta + \delta) \cdot w_{ij}^c}{\psi_{ij}^r} \quad (40)$$

As the concluding step of the first stage of sDACCS deployment (Figure S2), we iteratively spread the CDR deployment $\Delta_r = \Delta_i + \delta$ across all cells that are (i) involved in the deployment process in the sense of a contribution weight $w_{ij}^c > 0$ (see below), (ii) can support a growing (decreasing) CDR fraction because they have not reached the upper (lower) CDR fraction limit up to the current year, and (iii) have not reached the upper (lower) CDR limit in a previous step of the current iteration. The result of the iteration is the realizable fractional change in sDACCS cover Δf_{ij} and also covers numerical inaccuracies that occur from normalizations. The realized change can only be determined following the natural and anthropogenic land cover dynamics.

The iteration takes place as long as $\Delta_r > \delta_{\text{tol}}$ and the criterion $n_{\text{iter}} < n_{\text{iter, max}}$ for a finite loop is fulfilled. Here δ_{tol} is a tolerance parameter, $n_{\text{iter, max}}$ denotes the maximum number permitted iterations, and n_{iter} is the iteration counter. At the start of the iteration, the globally realizable CDR target $\Delta_{\text{iter}} = 0$. Drawing on (13), (i)-(iii) translate into

$$\Delta f_{ij} = \min \left[\Delta f + \frac{\Delta_r \cdot w_{ij}^c}{\psi_{ij}^r}, \Delta f_{ij}^{\text{max}} \right] \quad (41)$$

$$\forall (i, j) \in \{(1, 1), (1, 2), \dots, (n_{\text{lon}}, n_{\text{lon}}) \mid \Delta f_{ij} < \Delta f_{ij}^{\text{max}}\}$$

in the iteration step. To guarantee $W_i \geq 0$ and $\tilde{W}_i \geq 0$, the maximum change in sDACCCS cover fraction $\Delta f_{ij}^{\max}$ depends on the sign of the global change in CDR deployment

$$\Delta f_{ij}^{\max} = \begin{cases} \max[f_{ij}^{\max} - f_{ij}, 0], & \Delta_r > 0 \\ \max[f_{ij} - f_\epsilon, 0], & \text{else} \end{cases} \quad (42)$$

The $f_{ij}^{\max}$ account for additional land availability constraints due to inaccessible terrain, fresh-water cover, nature conservation, and settlements (Section S3). After each iteration step, the remaining CDR change gets updated as

$$\Delta_{\text{iter}} = \sum_{i=1}^{n_{\text{lon}}} \sum_{j=1}^{n_{\text{lat}}} \Delta f_{ij} \cdot \psi_{ij}^r \quad (43)$$

Consequently,

$$\Delta_r = \Delta + \delta - \Delta_{\text{iter}} \quad (44)$$

following each iteration step. Note that ψ_{ij}^r (Equation (39)) does not have to be updated in the iteration as $f_{ij}^{\max}$ and f_ϵ are fixed parameters. The model component handles the technical case $f_{ij} < f_\epsilon$ implicitly as changes in cover fractions only take place on CDR tiles with $f_{ij} \geq f_\epsilon$. This condition implies that sDACCCS deployment and potential destruction can only ever happen on a grid cell if that cell gets initialized with $t_{ij}^{\text{CDR}} = \text{TRUE}$.

While being spatially explicit and flexible to forward and backward conversions of land area to sDACCCS cover, this deployment scheme cannot compensate transient contribution weights that start out as $w_{ij}^c \neq 0$ and turn zero over time. The scheme will only remove the formerly installed sDACCCS cover from a cell when the $w_{ij}^c \neq 0$, as is evident from Equation (41). This behaviour can cause inconsistency with the contribution map. The issue is, however, only relevant if one wants to prescribe that CDR is not deployed anymore in a specific area where this was possible before, which is not the case in our study.

Second stage – determining contributions of vegetated and unvegetated land to sDACCCS cover

We translate every grid cell's anticipated change in sDACCCS cover fraction into land use transitions. On the vegetated fraction of land, this is realized through JSBACH's transition scheme. For bare land, we directly compute the new implicit CDR fraction from the anticipated change in cover fraction in Equation (40). We determine contributions of the vegetated and unvegetated land cover to sDACCCS cover, assuming that neither bare nor vegetated land is preferred for sDACCCS deployment. Formally, this assumption results in relatively equal contributions of the vegetated and bare land fraction, represented in the conditions

$$c_{\text{CDR}}^v \stackrel{!}{=} c_{\text{CDR}}^b \Leftrightarrow \frac{f_{\text{CDR}}^v}{f^v} \stackrel{!}{=} \frac{f_{\text{CDR}}^b}{1 - f^v} \quad (45)$$

Here, f^v is the vegetated fraction, c_{CDR}^b and c_{CDR}^v are the cover fractions of sDACCCS on bare and vegetated land, and f_{CDR}^b and f_{CDR}^v denote the respective grid cell cover fractions of the two contributions. Without dynamic vegetation, sDACCCS cover fractions on vegetated and bare land would directly result from (14)

$$\Delta c^v = \Delta f \quad \text{and} \quad \Delta c^b = \Delta f \quad (46)$$

This simple conversion from a change in grid cell fraction to a change in tile cover fraction is valid because

$$\Delta f = \Delta f^v + \Delta f^b = f^v \Delta c^v + (1 - f^v) \Delta c^b = f^v \Delta f + (1 - f^v) \Delta f \quad (47)$$

However, as f^v changes with shifting bioclimatic conditions [74], changes in sDACCCS cover at the same time cause a small but accumulating systematic imbalance between c_{CDR}^b and c_{CDR}^v (Figure S3). In addition, land use transitions can be partially unfulfilled due to the priority rules (see below), the conservation criterion of transition matrix elements [74], and numerical inaccuracies, causing imbalances between c_{CDR}^b and c_{CDR}^v . To prevent inconsistent CO₂ withdrawal *within* the year of occurring imbalances, we adjust the fraction of sDACCCS on bare land. This corrects the CO₂ withdrawal for an expanding/shrinking vegetated fraction but cannot respect condition (14). This is because JSBACH reads and computes agricultural land use transitions ahead of shifts in natural vegetation extent, which also fixes the timing of sDACCCS cover change. Then, at the beginning of the subsequent year(s), we correct *past* imbalances between sDACCCS cover on vegetated and bare land by adjusting anticipated cover changes. Drawing on Figure S3, the necessary adjustment to maintain the anticipated sDACCCS cover within the year of imbalances is

$$\Delta f_{\text{des}}^b = (c_{\text{CDR}}^b - c_{\text{CDR}}^v) \cdot \Delta f^v \quad (48)$$

which adds to (15). Here, $\Delta f^v = f_i^v - f_{i-1}^v$ is the shift in vegetation extent from the previous year $i - 1$ to i .

To re-adjust previous relatively unequal contributions between vegetated and bare land, the model adds (removes) a relatively higher share of sDACCCS on the under-represented (over-represented) land type while sDACCCS cover is increasing (shrinking) in three steps. First, we diagnose the imbalance between the relative cover fractions on vegetated and bare land as

$$\nu = \frac{1}{2} - \frac{c_{\text{CDR}}^b}{c_{\text{CDR}}^b + c_{\text{CDR}}^v} \quad (49)$$

This term is zero for no mismatch in the relative cover fractions, positive for $c_{\text{CDR}}^b < c_{\text{CDR}}^v$, and negative for $c_{\text{CDR}}^b > c_{\text{CDR}}^v$. The point of view chosen here is that of the sDACCCS cover on bare land. Note, however, that

$$-\nu = \frac{1}{2} - \frac{c_{\text{CDR}}^v}{c_{\text{CDR}}^b + c_{\text{CDR}}^v} \quad (50)$$

Thus, it is irrelevant if ν is defined in terms of the relative imbalance of c_{CDR}^b or c_{CDR}^v . The imbalance between sDACCCS cover fractions translates into fractional mismatches covered area on bare and vegetated land

$$\nu_b^f = \nu \cdot (c_{\text{CDR}}^b + c_{\text{CDR}}^v) \cdot (1 - f_{v,\text{max}}) \quad (51)$$

$$\nu_v^f = -\nu \cdot (c_{\text{CDR}}^b + c_{\text{CDR}}^v) \cdot f_{v,\text{max}} \quad (52)$$

In a second step, the anticipated change in sDACCCS area Δf (Equation (41)) can be corrected for these mismatches. To achieve this correction, compare each grid cell's ν_b^f and ν_v^f with the anticipated land use transitions. One can capture the compensation in these balancing terms:

Case 1: On grid cells with growing sDACCCS area ($\Delta f > 0$) grow the area more on the relatively under-represented surface type:

$$\Delta f_{b,\text{bal}} = \begin{cases} \min[f_{\text{CDR,max}}^b - f_{\text{CDR}}^b, \min[\Delta f, \nu_b^f]], & \nu > 0 \\ 0, & \text{else} \end{cases} \quad (53)$$

$$\Delta f_{v,\text{bal}} = \begin{cases} \min[f_{\text{CDR,max}}^v - f_{\text{CDR}}^v, \min[\Delta f, \nu_v^f]], & \nu < 0 \\ 0, & \text{else} \end{cases} \quad (54)$$

Case 2: On grid cells with shrinking sDACCCS area ($\Delta f < 0$), shrink the area more on the relatively over-represented surface type:

$$\Delta f_{b,bal} = \begin{cases} \max[\Delta f, \nu_b^f], & \nu < 0 \\ 0, & \text{else} \end{cases} \quad (55)$$

$$\Delta f_{v,bal} = \begin{cases} \max[\Delta f, \nu_v^f], & \nu > 0 \\ 0, & \text{else} \end{cases} \quad (56)$$

Here, the limits guarantee that (i) the balancing does not exceed the actual fractional sDACCCS cover change that is supposed to be realized within the current year (applies to forward and backward transitions) and (ii) that it does not exceed growth limits (forward transitions only). The lower bound for backward transitions is already included in the definition of Δf (see Equation (41)). Compensating the mismatches ν_b^f and ν_v^f thus only takes place if the sDACCCS area changes in the current annual step of land use transitions. If the sDACCCS area is constant for several years, no re-balancing between sDACCCS on vegetated and bare land will take place, avoiding repeated secondary transitions for CDR deployment. Here we assume that CDR facilities would not be relocated for re-balancing.

Finally, after accounting for the imbalance between vegetated and bare land, the sDACCCS deployment that remains to take place at relatively equal fractions on both land types is

$$\Delta f_{res} = \Delta f - \Delta f_{v,bal} - \Delta f_{b,bal} \quad (57)$$

Based on definitions (53) to (56), at most one of $\Delta f_{v,bal}$ and $\Delta f_{b,bal}$ is non-zero in a grid cell. Thus, the changes in cover fraction which have to be realized on bare and vegetated land, Δc^b and Δc^v are,

Case 1: Forward transition:

$$\Delta c^b = \min[f_{CDR,max}^b - f_{CDR}^b, \Delta f_{res} + \Delta f_{b,bal}] \cdot \frac{1}{1 - f_v} \quad (58)$$

$$\Delta c^v = \min[f_{CDR,max}^v - f_{CDR}^v, \Delta f_{res} + \Delta f_{v,bal}] \cdot \frac{1}{f_v} \quad (59)$$

Case 2: Backward transition:

$$\Delta c^b = \frac{\Delta f_{res} + \Delta f_{b,bal}}{1 - f_v} \quad (60)$$

$$\Delta c^v = -1 \cdot \frac{\Delta f_{res} + \Delta f_{v,bal}}{f_v} \quad (61)$$

The negative sign in Equation (61) reflects that entries in the transition matrices are always positive.

Second stage – translating anticipated changes in sDACCCS cover into land use transitions

On bare land, Δc^b directly translates into an updated implicit sDACCCS cover fraction on a daily time scale

$$c_{CDR,d+1}^b = \max[\min[c_{CDR,d}^b + \Delta c_b^{(d)}, c_{CDR,max}^b], c_\epsilon] \quad (62)$$

where $\Delta c_b^{(d)}$ is the linearly interpolated daily change in CDR cover fraction and the index d refers to the daily stepping. The purpose of the minimum cover fraction $c_\epsilon \ll 0$ and the limits employed in Equation (62) is a measure of JSBACH to ensure numerical stability.

On vegetated land, the deployment scheme takes two more steps to integrate into JSBACH's transition scheme [73, 74]. First, we determine anticipated transition matrix elements $T^{k \triangleright \text{CDR}}$ from other land cover types k to sDACCSS cover and elements $T^{\text{CDR} \triangleright k}$ for the opposite case. Exploiting the area conservation for all land cover types k, l , $\sum_{kl} T_{kl} = 1$, the anticipated matrix elements are

Case 1: Forward transition:

$$T^{k \triangleright \text{CDR}} = \min \left[\Delta c^v \cdot f_k^v / f_v, 1 - \sum_{k \neq l, \iota_l^{\text{CDR}} = \text{FALSE}} T^{k \triangleright l} \right] \quad (63)$$

$$T^{\text{CDR} \triangleright k} = 0 \quad (64)$$

Case 2: Backward transition:

$$T^{\text{CDR} \triangleright k} = \Delta c^v \cdot f_k^v / f_v \quad (65)$$

$$T^{k \triangleright \text{CDR}} = 0 \quad (66)$$

The mask ι_l^{CDR} excludes CDR land cover from the summation in Equation (68). With this summation, we prioritize land use transitions of the agricultural land use scenario over CDR deployment. Following Reick et al. [74]'s line of argument and their notation, we determine the realisable annual transition matrix elements $T^{k \triangleright l}$ from the potential ones $\tilde{T}^{k \triangleright l}$. Here, the $k, l \in \{\text{LCT}_{\text{veg}}\}$ denote the land cover types. The notation $k \triangleright l$ represents the matrix element converting from type k to l . For agricultural land use the $\tilde{T}^{k \triangleright l}$ stem from a pre-defined protocol [73, 74, 77]. However, the sDACCSS cover couples dynamically to a CDR target and the climatological state of irradiation. Thus, the $\tilde{T}^{k \triangleright l}$ with $\iota_k^{\text{CDR}} = \text{TRUE} \vee \iota_l^{\text{CDR}} = \text{TRUE}$ have to be computed annually, at the step of JSBACH's land cover change.

Exploiting the area conservation [74] $\sum_{ij} T_{ij} = 1$, the realisable transition elements $T^{k \triangleright l}$ for forward transitions are

Case 1: Forward transition:

$$\tilde{T}^{k \triangleright \text{CDR}} = \Delta c^v \cdot f_k^v / f_v \quad (67)$$

$$T^{k \triangleright \text{CDR}} = \min \left[\tilde{T}^{k \triangleright \text{CDR}}, 1 - \sum_{k \neq l, \iota_l^{\text{CDR}} = \text{FALSE}} T^{k \triangleright l} \right] \quad (68)$$

$$T^{\text{CDR} \triangleright k} = 0 \quad (69)$$

where Equation (68) gives priority to agricultural land use transitions. The backward transitions, do not require such limits on the sDACCSS cover to prioritize the agricultural land use protocol. Therefore, the matrix elements converting from CDR-covered to other land are

Case 2: Backward transition:

$$T^{\text{CDR} \triangleright k} = \tilde{T}^{\text{CDR} \triangleright k} = \Delta c^v \cdot f_k^v / f_v \quad (70)$$

$$T^{k \triangleright \text{CDR}} = 0 \quad (71)$$

Second stage – priority rules

As the final step, we expand JSBACH's prioritization rules 1–3 for land use transitions [73, 74]. These rules determine in which order natural land gets converted into agricultural land and vice versa. Again prioritizing the agricultural land use scenario, we add *rule 4* converting natural lands to sDACCSS cover and *rule 0* for the back-conversion. Here, natural lands consist of contributions by forests (F) and grasslands (G), agricultural lands comprise pastures (P) and croplands (C).

Rule 4: $F+G \rightarrow \text{CDR}$ (forward transition, shrinkage of natural lands for sDACCCS)
To establish CDR land cover, convert the remainder of G and F land *after* expanding agricultural lands based on *rules 1* to *3* at equal proportion.

Rule 0: $\text{CDR} \rightarrow F + G$ (backward transition, shrinkage of sDACCCS cover)
Convert CDR-used land into F and G land based on their relative abundance while respecting their potential natural extent.

In addition to *rules 4* and *0*, we amend the existing *rules 1* to *3* because reducing CDR cover for the benefit of natural land fills up a fraction of their potential natural extent. This share of potential extent cannot be used for re-converting agricultural lands back into natural ones, analogous to shrinking different types of agricultural lands as implemented by Reick et al. [74]. We derive the formal expressions implementing the new priority rules and the amendments to existing rules in the following. The amended rules culminate in daily transition matrix elements that are applied to every tile of every land cover class.

Analogous to (10.14) – (10.18) of Reick et al. [74], our CDR model implements priority *rule 4* with a scaling factor ρ . It scales $T_{N \triangleright \text{CDR}}$ in relation to the remaining natural land cover fraction after *rules 1* to *3* have been applied

$$\rho = T_{N \triangleright \text{CDR}} \cdot c_N \cdot [c_N - \Delta_{G \triangleright P} - \Delta_{F \triangleright P} - \Delta_{G \triangleright C} - \Delta_{F \triangleright C}]^{-1} \quad (72)$$

Here, the $\Delta_{K \triangleright L}$, $K \in \{G, F\}$, $L \in \{P, C\}$ stand for the shares in natural vegetation cover which have already been converted to agricultural lands in the current step. Then, *rule 4* comes down to

$$\begin{aligned} T_{G \triangleright \text{CDR}} &= \rho \cdot (1 - T_{G \triangleright P} - T_{G \triangleright C}) \\ T_{F \triangleright \text{CDR}} &= \rho \cdot (1 - T_{F \triangleright P} - T_{F \triangleright C}) \end{aligned} \quad (73)$$

The calculations materializing *Rule 0* follow the line of arguments set out by Reick et al. [74] on *rule 1* for shrinking agricultural lands. The conversion from sDACCCS cover to F and G lands takes place at the same general relative factor a

$$\begin{aligned} T_{\text{CDR} \triangleright G} c_{\text{CDR}}^v &= a (c_G^{\text{pot}} - c_G) \\ T_{\text{CDR} \triangleright F} c_{\text{CDR}}^v &= a (c_F^{\text{pot}} - c_F) \end{aligned} \quad (74)$$

with potential natural vegetation extents c_K^{pot} . These potentially available F and G lands also constrain the transition matrix elements for the conversion from sDACCCS cover as

$$\begin{aligned} T_{\text{CDR} \triangleright G} &\leq \frac{c_G^{\text{pot}} - c_G}{c_{\text{CDR}}^v} \\ T_{\text{CDR} \triangleright F} &\leq \frac{c_F^{\text{pot}} - c_F}{c_{\text{CDR}}^v} \end{aligned} \quad (75)$$

Together, Equations (74) and (75) result in

$$a \leq \frac{1}{c_{\text{CDR}}^v} \quad (76)$$

On the other hand,

$$\begin{aligned} T_{\text{CDR} \triangleright N} &= T_{\text{CDR} \triangleright G} + T_{\text{CDR} \triangleright F} \\ &= \frac{a}{c_{\text{CDR}}^v} (c_N^{\text{pot}} - c_N) \end{aligned} \quad (77)$$

Thus, in combination of Equations (74) and (77),

$$a = T_{\text{CDR} \triangleright N} \frac{c_{\text{CDR}}^v}{c_N^{\text{pot}} - c_N} \quad (78)$$

Combining conditions (76) and (78), the annual transition matrix elements for *rule 0* are

$$T_{\text{CDR} \triangleright G} = \min \left[\frac{1}{c_{\text{CDR}}}, \frac{T_{\text{CDR} \triangleright N}}{c_N^{\text{pot}} - c_N} \right] \cdot (c_G^{\text{pot}} - c_G) \quad (79)$$

$$T_{\text{CDR} \triangleright F} = \min \left[\frac{1}{c_{\text{CDR}}}, \frac{T_{\text{CDR} \triangleright N}}{c_N^{\text{pot}} - c_N} \right] \cdot (c_F^{\text{pot}} - c_F) \quad (80)$$

From analogous reasoning, follow the amended calculations for *rule 1* for shrinking agricultural land

$$\begin{aligned} T_{C \triangleright G} &= \min \left[\frac{1}{c_C}, \frac{T_{C \triangleright N}}{c_N^{\text{pot}} - c_N - T_{\text{CDR} \triangleright N} c_{\text{CDR}}^v} \right] \\ &\quad \cdot (c_G^{\text{pot}} - c_G - T_{\text{CDR} \triangleright G} c_{\text{CDR}}^v) \\ T_{C \triangleright F} &= \min \left[\frac{1}{c_C}, \frac{T_{C \triangleright N}}{c_N^{\text{pot}} - c_N - T_{\text{CDR} \triangleright N} c_{\text{CDR}}^v} \right] \\ &\quad \cdot (c_F^{\text{pot}} - c_F - T_{\text{CDR} \triangleright F} c_{\text{CDR}}^v) \end{aligned} \quad (81)$$

In addition to the default JSBACH model, *rule 1* now accounts for the fraction of potentially available natural lands which have already been “filled up” with re-converted CDR land due to *rule 0*. This fill-up is expressed by the terms $T_{\text{CDR} \triangleright \{N, G, F\}} c_{\text{CDR}}^v$ in equations (81). Similarly, the amendments to *rules 2* and *3* for shrinking agricultural land consist of corrections to the potential natural vegetation extent

$$T_{P \triangleright F} = \min \left[T_{P \triangleright N}, \frac{c_F^{\text{pot}} - (c_F + T_{C \triangleright F} c_C + T_{\text{CDR} \triangleright F} c_{\text{CDR}})}{c_P} \right] \quad (82)$$

$$T_{P \triangleright G} = \min \left[T_{P \triangleright N} - T_{P \triangleright F}, \frac{c_G^{\text{pot}} - (c_G + T_{C \triangleright G} c_C + T_{\text{CDR} \triangleright G} c_{\text{CDR}})}{c_P} \right] \quad (83)$$

Analogous to Reick et al. [74], the CDR model interpolates the realized land use transitions to daily resolution and converts them into tile contributions

$$T_{k_j \triangleright \text{CDR}_i}^{(d)} = \frac{T_{k \triangleright \text{CDR}}}{N_d} \quad (84)$$

$$T_{\text{CDR} \triangleright k_j}^{(d)} = \begin{cases} \frac{T_{\text{CDR} \triangleright k}}{N_d} \cdot \frac{c_{k_i}}{c_k}, & k \in \{P, C\} \\ \frac{T_{\text{CDR} \triangleright k}}{N_d} \cdot \frac{c_{k_i}^{\text{pot}} - c_{k_i}}{c_k}, & k \in \{F, G\} \end{cases} \quad (85)$$

Here, the k_j are different plant functional types of land cover class k . Following each step of land cover change, we recompute the box cover fraction of sDACCS as

$$f_{\text{CDR}} = \max \left[\min \left[c_{\text{CDR}}^v \cdot f_v + c_{\text{CDR}}^b \cdot (1 - f_v), 1 \right], 2c_\epsilon \right] \quad (86)$$

which enters again into the model for CO₂ sequestration.

Transitioning from no-CDR simulation spin-ups to experiments with sDACCCS representation

Integrating the components of our CDR model into ECHAM6.3 and JSBACH entails technical extensions to these models, including model restart files and support code. They spread across JSBACH's entire call tree (Supplementary Figure S S5) and into the land coupling variables of ECHAM6.3. Throughout a simulation, MPI-ESM writes restart files, typically at an interval of one simulation year. These files contain all necessary state variables to re-initialize the model from a previous simulation. Extending JSBACH with a land cover class for sDACCCS implicitly changes the format of restart files because the number of land cover types changes. To re-initialize from a spun-up simulation without sDACCCS representation, our CDR component comes with a transitioning mode. This mode runs for the first year of a simulation with CDR. During this year, no sDACCCS can deploy on the land surface, but the sDACCCS land cover type already exists in the model at a minimal technical fraction. This allows computing relevant restart variables for CDR land cover without impacting the simulated Earth system state. Only after this initial year of transition mode the CDR cover is allowed to change to non-negligible cover fractions. Our CDR extension further comes with tools for setting up CDR scenarios, pre-processing restart and input files, and post-processing CDR-specific output variables.

Zero-dimensional model for CDR through sDACCCS chains

Along seven steps, the zero-dimensional model follows the process chain from incident irradiation on a solar absorber to resulting CO₂ withdrawal (Figure S8).

(i) Absorption of solar irradiation JSBACH provides a visible and a near-infrared spectral band aggregated from the sixteen spectral bands of ECHAM6.3. We diagnose the effective absorption coefficient a_ξ , $\xi \in \{\text{vis}, \text{nir}\}$ of a tile

$$a_\xi = (1 - \alpha_{\text{CDR}, \xi})(1 - c_s) + (1 - \alpha_{s, \xi})c_s \quad (87)$$

with albedo $\alpha_{\text{CDR}, \xi}$ of the solar absorber in the spectral band ξ and snow cover fraction c_s . Thus, the radiative forcing includes the shading effect of snow cover, assuming that snow-covered solar absorbers can still operate with the fraction of irradiation that does not get reflected. The absorbed fraction of the incident irradiation I_{surface} follows as

$$I_{a, \xi} = a_\xi \cdot I_{\text{surface}} \left[\text{W/m}^2 \right] \quad (88)$$

(ii) Effective energy flux The absorbed energy flux is subject to losses in the solar absorber and along the process chain. We capture these losses with the system efficiency η_{sys} . In addition, the amount of energy available to reduce CO₂ depends on the spatial setup of solar absorbers. We incorporate this constraint with a space factor $\mu_{\text{space}} = 0.25$ which converts the area of solar absorbers to the land use footprint of sDACCCS. We choose μ_{space} in the order of typical space factors for photovoltaic devices [78, 75, 79], assuming that comparable spacing would also apply to CO₂ capturing facilities. Then, the effective irradiation flux available for reducing CO₂ molecules is

$$I_{e, \xi} = I_{a, \xi} \cdot \eta_{\text{sys}} \cdot \mu_{\text{space}} \left[\text{W/m}^2 \right] \quad (89)$$

(iii) Effective photon flux In a solar absorber, incident photons can be thought of as generating electron-hole pairs ($e^- + h^+$) based on the photoelectric effect. Subsequently, these electrons can be used to reduce CO₂ molecules in a catalytic reaction. The internal quantum efficiency $\eta_{\text{QE}}(\lambda)$ captures the yield efficiency for charge carriers resulting from the photoelectric effect in

response to incident photons of wavelength λ [80]. $\eta_{QE}(\lambda)$ differs, for example, between different materials and setups used for a solar absorber [80]. The photon flux Φ_ξ within a spectral band $[\lambda_1, \lambda_2]$ incorporates this electron yield efficiency

$$\Phi_\xi = \frac{1}{hc} \int_{\lambda_1}^{\lambda_2} d\lambda F(\lambda) \cdot \eta_{QE}(\lambda) \cdot \lambda \quad (90)$$

Here $F(\lambda)$ is the wavelength-dependent effective irradiation flux onto the solar absorber, c is the speed of light, and h the Planck constant. Given the simple spectral setup of JSBACH with two aggregated spectral bands and the uncertain technological details of sDACCCS, we assume $\eta_{QE}(\lambda)$ as constant over a spectral band, $\eta_{QE}(\lambda) \equiv \eta_{QE}$, and employ a normalization approach of the spectral irradiance (SI S1). Then, we obtain a scaling constant relating the integrated spectral power I_ξ to the photon flux in the respective spectral band

$$\mu_\xi = \Phi_\xi / I_\xi \left[1 / (\text{W} \cdot \text{s}) \right] \quad (91)$$

One can interpret μ_ξ as the number of electrons excited per unit of integrated irradiance in the spectral band ξ (SI S1).

(iv) Solar energy demand of sDACCCS process chains For the high efficiency (hE) process chain, μ_ξ would already correspond to the conversion efficiency from incident irradiation to CO_2 withdrawal flux if no further energy to capture atmospheric CO_2 would be required. However, the CO_2 reduction cannot consume all available electrons because they also need to drive the capturing process. For formate as a sink product, the DAC stage consumes about one out of four available electrons (SI S2), assuming reported energy demands of existing DAC facilities around 0.5 kWh per kilogram of captured CO_2 [81] and 32% yield efficiencies of future photoabsorbers [82]. We incorporate this efficiency discount by modifying the conversion efficiency, $\mu_{\text{CO}_2/e^-} \rightarrow \tilde{\mu}_{\text{CO}_2/e^-}^{\text{hE}}$ (SI S2). In addition to the solar energy needed for atmospheric CO_2 capture, the low efficiency (lE) process chain demands energy for electrolysis. Assuming 80% overpotential of an industrial-scale electrolysis cell in the order of CO_2 -to-carbon monoxide reduction [cf. 83] and silicate photovoltaic cells (25% yield efficiency [82]), this process stage demands 4.26 kWh per kilogram of CO_2 reduced to formate (SI S2). We incorporate this additional energy demand in $\tilde{\mu}_{\text{CO}_2/e^-}^{\text{lE}}$ (SI S2).

(v) CO_2 sequestration flux Then, drawing on Equation (91) and on the energy flux available to excite electron-hole pairs (Equation (89)), the CO_2 sequestration flux $F_{\text{CO}_2, \xi}$ is given by

$$F_{\text{CO}_2, \xi} = I_{e, \xi} \cdot \tilde{\mu}_\xi \cdot \mu_{\text{CO}_2/e^-}^i \cdot M_{\text{CO}_2} \cdot 1/N_A \cdot \mu_c \left[\text{kg}(\text{CO}_2) / (\text{m}^2 \cdot \text{s}) \right] \quad (92)$$

Here, μ_{CO_2/e^-}^i denotes the number of CO_2 molecules reduced per electron and $i \in \{\text{lE}, \text{hE}\}$. The factor μ_c calibrates sDACCCS' land footprint to theoretical values from May and Rehfeld [79] (SI S4). The molar mass of CO_2 , M_{CO_2} , and the Avogadro constant N_A convert the net count of CO_2 molecules into a mass flux. This mass flux constitutes the CDR forcing in the CO_2 balance of ECHAM6.3.

(vi) Carbon sink pool and potential withdrawal From the withdrawal fluxes of the two spectral bands, $F_{\text{CO}_2, \text{vis}}$ and $F_{\text{CO}_2, \text{nir}}$, we diagnose the net change in carbon sink product m_c (here, expressed in units of CO_2 , m_{CO_2}). Given the area occupied by sDACCCS at time t in a grid cell with area A_{cell}^t , $A_{\text{CDR}}^t = A_{\text{cell}}^t \cdot f_{\text{CDR}}^t$, the annual CO_2 withdrawal is

$$m_{\text{CO}_2} = \sum_{t=t_0}^{t_0+N_t} m_{\text{CO}_2}^t = 10^{-12} \cdot \sum_{t=t_0}^{t_0+N_t} (F_{\text{CO}_2, \text{nir}}^t + F_{\text{CO}_2, \text{vis}}^t) \cdot A_{\text{CDR}}^t \cdot \Delta t \left[\text{Gt}(\text{CO}_2) \right] \quad (93)$$

where t_0 denotes the first time step of a simulated year, N_t is the number of steps in that year, and Δt is a time step's length. Drawing on Equation (93), we also obtain the climatological CO_2 withdrawal potential ψ_{τ_i} at the first time step of year i , τ_i .

$$\psi_{\tau_i} = \frac{1}{N_{\text{clim}}} \sum_{\tau=\tau_i-N_{\text{clim}}}^{\tau_i} \sum_{t=\tau_i}^{\tau_i+N_t} m_{\text{CO}_2}^t \frac{A_{\text{CDR,max}}}{A_{\text{CDR}}^t} \quad (94)$$

Here, $A_{\text{CDR,max}}$ is the upper limit for the grid cell area occupied by sDACCCS, irrespective of land availability constraints. We choose an averaging interval of $N_{\text{clim}} = 15$ yr, still allowing for variability beyond that time scale. The climatological withdrawal potential translates a CDR target into changes in sDACCCS cover fraction when computing land use transitions (see below).

(vii) Thermal cooling from CO_2 fixation The sDACCCS process chain converts solar energy into energy stored in the chemical bonds of a carbon-rich sink product. Storing this product away in an integrated process chains as in the hE scenario corresponds to a cooling of the surface climate that is not captured in the energy balance of MPI-ESM. The ESM's radiative scheme would overestimate the long-wave surface forcing through thermalization of photons that get absorbed by solar absorbers, if this effect of energy storage is not corrected for. As a conservative estimate, we diagnose the heat flux due to CO_2 fixation from the minimum energy needed to drive the reduction of CO_2 to formate, that is its Gibbs free energy of formation $\Delta G_{\text{CO}_2 \rightarrow \text{HCOOH}} = 1.4 \text{ eV} = -135.08 \text{ kJ/mol}$ [84, 79]. We diagnose the thermal cooling from constructing chemical bonds as

$$H_{\text{bonds}} = \frac{F_{\text{CO}_2} \cdot \Delta G_{\text{CO}_2 \rightarrow \text{HCOOH}}}{10^{-3} \cdot M_{\text{CO}_2}} \left[\text{W/m}^2 \right] \quad (95)$$

and couple H_{bonds} into the surface energy balance of JSBACH

$$C \frac{\partial T_{\text{surf}}}{\partial t} = R_{\text{net}} + H_{\text{sensible}} + H_{\text{latent}} + H_{\text{ground}} + H_{\text{bonds}} \quad (96)$$

Here, C denotes the (dynamic) heat capacity of the surface soil layer, T_{surf} is the surface temperature, R_{net} the net radiation, and H_{sensible} , H_{latent} , and H_{ground} are sensible, latent, and ground heat fluxes, respectively [74].

Muting CDR at low ambient CO_2 concentrations

No chemical reaction removing CO_2 will occur efficiently if its concentration $[\text{CO}_2]$ is too low. Real-world reaction kinetics of direct air capture and (photo-)electrochemistry are complex and require dedicated modeling of catalysts and electrolytes based on real-world experimental data. This modeling based on first principles is different from the aim of our study, and an Earth system model would not be an ideal tool for this. Instead, we aim at storyline experiments to assess the feasibility of sDACCCS as a large-scale CDR approach in general. Therefore, a simple sigmoid response curve approximates the reaction kinetics at low CO_2 concentrations. Sigmoid response curves are a widely applied model for chemical reactions, mainly if the reaction rate depends (or is assumed to depend) on the concentration of a single educt [85]. We employ the logistic function

$$f_l = \frac{1}{1 + \exp(-\kappa([\text{CO}_2] - [\text{CO}_2]_H))} \quad (97)$$

with decay rate $\kappa = 0.05 \text{ mol(air)}/\mu\text{mol}(\text{CO}_2)$ and a concentration at the inflection point $[\text{CO}_2]_H = 160 \mu\text{mol}(\text{CO}_2)/\text{mol}(\text{air})$. The chosen parameters correspond to a CDR response ≥ 0.999 for $[\text{CO}_2] >$

299 $\mu\text{mol}/\text{mol}$ and ≥ 0.99 for $[\text{CO}_2] > 252 \mu\text{mol}/\text{mol}$. In the model, we set $[\text{CO}_2] < 300 \mu\text{mol}/\text{mol}$ as a threshold below which the response curve can affect CO_2 removal because of numerical reasons. If surface CO_2 concentrations in our scenarios were close to this threshold or within the range of the dampening curve, CO_2 removals would be sensitive to the parameters of the sigmoid. However, CO_2 concentrations in all of our study's experiments are far above the threshold.

As a consequence, the dampened CO_2 removal at low concentrations practically serves the purpose of numerical stability because it prevents local concentrations from dropping below unphysical levels if CO_2 concentrations are already low because of the variability of atmospheric mixing and CDR combined. This is a rare case in the model and typically would occur on time scales of single time steps (20 minutes). On the temporal resolutions of interest in our study, atmospheric mixing continuously readjusts CO_2 abundance for local CDR, even at high grid cell coverages (see Figure 3a of the updated manuscript). Future work should refine the parameters and shape of the response curve if it is relevant to the envisaged study.

Linear scaling of the photon flux

To accommodate (5) within JSBACH's simple spectral representation, we normalize the photon flux Φ_ξ by the integrated spectral power $I_\xi = \int_{\lambda_1}^{\lambda_2} d\lambda F(\lambda)$ of the AM1.5G reference spectrum [86, 87] using the YaSoFo tool for spectral integration [79]. Table 1 summarizes results of the spectral integrations. Utilizing the same reference spectrum globally in our model neglects non-linearities in the electron yield curve of the photoelectric effect, the local seasonality of solar insolation, and climatic effects on the solar spectrum. Thus, precisely estimating global CDR potential for a specific technological pathway requires dedicated spectral modeling. Still, we correct some of these shortcomings by model calibration (see below).

S2 Process chain efficiencies of sDACCS

To integrate energy harvest and process chain efficiencies of the hE and IE technology scenarios into the zero-dimensional sDACCS parametrization, we draw on modified conversion efficiencies. For the hE scenario, the conversion efficiency incorporates the solar energy harvest required to drive DAC. In the IE scenario, energy harvest for DAC and electrolysis are incorporated. The on-going development of sDACCS and DAC-type process chains limits available efficiency estimates. However, both technology scenarios have been successfully demonstrated for hydrogen production [80, 88, 89] and with a focus on carbon capture and utilization [90, 91], aiming at synthetic fuel production not at maximizing the CO_2 withdrawal potential of sink products.

hE technology scenario

We include the energy harvest for the hE scenario's CO_2 capturing stage into its conversion factor $\mu_{\text{CO}_2/e^-}^{\text{hE}}$. Therefore, we compute the module area of photovoltaic solar absorbers required to drive the DAC process delivering CO_2 as an input for photoelectrochemical (PEC) reduction. First, we obtain the CO_2 withdrawal flux F per PEC module area at a given insolation I from (7). Here, we utilize $\mu_{\text{CO}_2/e^-} = \eta_{\text{STC}}$, where η_{STC} is the solar-to-carbon conversion efficiency for the PEC reduction stage alone [79]. The CO_2 withdrawal corresponds to an energy demand $E_d = F \cdot 0.5 \text{ kWh}/\text{kg}(\text{CO}_2)$ of the DAC stage, based on reported values of DAC facilities [92, 81] and assuming that the sorbent of CO_2 can be used within the electrolyte. Then,

$$F' = F \cdot \left(1 - \frac{F \cdot E_d}{\eta_{\text{PV}} \cdot I}\right) \quad (98)$$

where η_{PV} denotes the efficiency of photovoltaic devices, assuming prospective perovskite-silicon tandem cells [82]. Now, solving (7) for the conversion factor, including 50% system loss, and utilizing the constants and parameters summarized in Table 3, we obtain $\mu_{CO_2/e^-}^{hE} = 0.071$. Integrating the energy harvest for DAC and associated efficiencies of the solar absorbers thus reduces the ideal conversion efficiency [79] by $\sim 24.1\%$.

IE technology scenario

In addition to the energy required to drive the DAC process, the IE scenario demands energy to drive the extraction of the CO_2 from the DAC's sorbent and for electrolysis. The minimum energy required to power the electrolytic reduction of CO_2 to formate is

$$E_{CO_2} = U_{cell} \cdot F \cdot n_{CO_2} \cdot n_e \quad (99)$$

with U_{cell} being the cell potential, F the Faraday constant, n_{CO_2} the number of moles of CO_2 consumed, and $n_e = 2$ the number of electrons consumed in the half-cell evolution reaction to formate. n_i is calculated as $n_i = m_i/M_i$, with m_i being the mass of the educt/product consumed/produced and M_i the respective molar mass. In real-world electrolysis, the activation of the electrochemical reaction and electrolyte resistance demand additional energy, leading to a so-called overpotential [93]. As a result, U_{cell} has to be higher than the reaction's thermodynamic limit, as given by its Gibbs free energy [93]. Therefore, we assume cell overpotentials of 80% in light of experimental data for the reduction of CO_2 to carbon monoxide [83]. Then, drawing on the parameters and constants as summarized in Table 4, we obtain an energy demand for the electrolysis stage of $E_{CO_2} = 3.045$ kWh per kg(CO_2) reduced, corresponding to $E_{HCOOH} = 1.456$ kWh per kg formate produced. We further assume a system efficiency $\eta_{el} = 0.5$ for the electrolysis setup as for the hE pathway. The energy demand of the DAC process is analogous to the hE scenario. On the energy supply side, we assume typical efficiencies of modern commercial crystalline silicate photovoltaic cells [82], applying a 1-2% discount on the most recent values to account for some lag in the rollout of newest technologies. Table 5 aggregates the assumend values for energy demands and supply of the IE scenario.

With the aggregated energy demand $E_d = \frac{E_{CO_2}}{\eta_{el}} + E_{DAC}$ per unit of CO_2 withdrawn from the atmosphere, we can deduce the associated withdrawal flux per module area of solar absorbers at a given insolation $I = 1000$ kWh/yr as $F_{CO_2} = 29.10$ kg(CO_2)/m²(module) · a where

$$F_{CO_2} = I \cdot \frac{\eta_{PV}}{E_d} \quad (100)$$

Then, we are able to compute an effective conversion efficiency for the IE process chain by inverting (7). Again, we draw on the AM1.5G reference spectrum to convert between the power-related efficiency η_{PV} and an efficiency relating to the photon flux

$$\mu_{CO_2/e^-}^{IE} = \frac{F_{CO_2}}{I \cdot \mu_{nir+vis}} \cdot \frac{N_A}{M_{CO_2}} \quad (101)$$

Here, we employ a scaling constant $\mu_{nir+vis}$ allocating the combined irradiation I to both spectral windows of JSBACH by their respective contribution to the overall spectral power

$$\mu_{nir+vis} = \frac{\Phi_{nir} + \Phi_{vis}}{I_{nir} + I_{vis}} \quad (102)$$

where individual contributions are assumed to be

$$I_{\xi} = \frac{\Phi_{\xi}}{I_{\xi}} \frac{I_{\xi}}{I_{nir} + I_{vis}} \cdot I \quad (103)$$

Drawing on the parameters in Table 1 and 50% system loss, we obtain $\mu_{CO_2/e^-}^{IE} = 0.0347$.

S3 Spatiotemporal sDACCS targets and compatible emission forcings

One of the distinguishing features of our CDR extension to MPI-ESM is the ability to model CDR explicitly compared to the implicit representation of typical scenario simulations. However, to still obtain an effective emission forcing that is compatible between simulations and with the SSP framework, we modify the SSP emission forcing. Then, the explicit CO₂ removal and the modified forcing combine to SSP1-2.6 again. As a first step, we interpolate global emission scenarios linearly from their native five-yearly temporal resolution [94] to the CDR target's annual resolution. Due to the shape of SSP scenarios, a piece-wise linear interpolation is preferable to higher order interpolation to avoid a systematic bias in the effective emission forcing. In case of the max scenarios, the difference in net emission forcing $\Delta E = E_{\text{SSP3-7.0}} + E_{\text{CDR}_{\text{max}}} - E_{\text{SSP1-2.6}} = \frac{E_{\text{SSP3-7.0}} - E_{\text{SSP1-2.6}}}{2} > 0$. For min scenarios, $\Delta E = E_{\text{SSP1-2.6}} + E_{\text{CDR}_{\text{min}}} - E_{\text{SSP1-2.6}} = E_{\text{CDR}_{\text{min}}} < 0$. Then, we re-scale all emitters in the spatial emission scenario as

$$E_{ij} = E_{ij} + \Delta E \cdot \frac{E_{ij} A_{ij} t_{ij}^E}{\sum_{ij} E_{ij} A_{ij} t_{ij}^E} \quad (104)$$

where the mask

$$t_{ij}^E = (E_{ij} > 0 \wedge |\phi_{ij}| < 88^\circ) \quad (105)$$

The deployment scheme uses contribution weights w_{ij}^c to split the global target change into contributions of individual grid cells (Section S1). The w_{ij}^c have to fulfil

$$\sum_{i,j} w_{ij}^c / w_{ij}^a = 1 \quad (106)$$

with area weights w_{ij}^a . In the Eql scenario, all grid cells within a latitudinal band from ϕ_S to ϕ_N contribute a relatively equal share to the overall sDACCS cover based on their area. We limit deployment to this latitudinal range to account for the sparse year-round sunlight in high latitudes, reducing the cost-efficiency of solar absorbers. The contribution mask for a grid cell $(i, j) \in \{(1, 1), (1, 2), (2, 1), \dots, (N_{\text{lon}}, N_{\text{lat}})\}$ is

$$t_{ij}^{\text{Eql}} \equiv (t_{ij}^{\text{land}} = \text{TRUE} \wedge |\phi_{ij}| < 60^\circ) \quad (107)$$

with ϕ_{ij} indicating the cell's latitude and t_{ij}^{land} the land-sea mask (returning TRUE for land grid cells). Then, the global normalization of contribution weights is

$$\mathcal{N}^{\text{Eql}} = \sum_{i,j \in I} w_{ij}^a \quad (108)$$

with area weights w_{ij}^a and $I = \{(i, j) : t_{ij}^{\text{Eql}} = \text{TRUE}\}$. The contribution weights result as

$$w_{ij}^c = \begin{cases} w_{ij}^a / \mathcal{N}^{\text{Eql}}, & t_{ij}^{\text{Eql}} = \text{TRUE} \\ 0, & \text{else} \end{cases} \quad (109)$$

For the Prop scenario, we draw on a CDR burden sharing paradigm by Fyson et al. [95], which follows a "polluter pays principle" on the country level. Fyson et al. allocate responsibility for CDR deployment to those countries that exceed their "fair share" of global CO₂ emissions, taking emissions in 1990 as a baseline. To spread the countries' burdens across the grid space, we first compute gridded country masks t_{ij}^k from political boundaries k and JS-BACH's land-sea mask. For that purpose, we clip the land-sea mask to country boundaries

and interpolate missing values. This approach ensures that no t_{ij}^k overlap, with contributions below the grid's resolution being neglected. Then, the contribution of each cell is

$$w_{ij}^c = \sum_k \frac{b^k w_{ij}^a t_{ij}^k}{\sum_{ij} w_{ij}^a t_{ij}^k} \quad (110)$$

where b^k denotes the emission burden of country k . Again, we normalize the w_{ij}^c as for the EqI scenario to fulfill Equation (106).

As a separate spatial constraint, we limit CDR cover on land that is (partially) mountainous, protected, urban, or covered by water (Figure 1c). Thus, we exclude area fractions that would likely not be used for CDR built-up. To constrain the fraction of urban settlements within each area, we draw on Hurtt et al. [77]. For all remaining constraints, we refer to ESMAP [96].

S4 Validating the extended MPI-ESM model

Effective emission forcing

We validate the physical consistency of the combined forcing of anthropogenic emissions and CO₂ removal by comparing global removal targets with simulated CDR and the atmospheric CO₂ response between CDR experiments and the pathway control experiment. Annual and cumulative CDR deployment follows targets precisely until ~2150 and we find good agreement between the CO₂ responses (Figure 2 a–d). Thus, the explicit and interactive CDR deployment scheme behaves accurately. Furthermore, these results demonstrate that CDR and the emission scenario combine accurately to an effective emission forcing. After 2150 the model exhibits some difficulties in scaling CDR down. A possible explanation is an insufficient amount of potential natural vegetation that could occupy the previously sDACCS-covered land. The fact that the model still follows declining CDR targets for a couple of years before partially leveling off supports this hypothesis. Nonetheless, since the drift off the CDR targets occurs well outside of our time windows of interest, it is not relevant for our study's results. However, for investigating the long-term reversibility of CDR implications into the next centuries with our explicit CDR representation, this shortcoming would still have to be rectified.

Carbon conservation

A consistent response of the modeled carbon cycle is crucial for evaluating the implications of land conversions for sDACCS on carbon stocks. Here, Figure S7 validates the consistency of the extended model's carbon cycle. We conduct test simulations (α – ϵ) differing by the global CDR target ($\alpha \leftrightarrow \beta$, γ , $\delta \leftrightarrow \epsilon$; Figure S7 b) and the resulting emission forcing (Figure S7 c), as well as the spatial sDACCS deployment under the same effective emission pathway (β –spread-out, γ –semi-localized, δ –localized). Test experiments span 2015 to 2100. We observe a slight global drift in the global carbon budget, but it is minor compared to absolute global, marine, terrestrial, and atmospheric carbon stocks as well as their respective changes over the course of the simulations. Crucially, representing sDACCS explicitly does not significantly alter this response, justifying our comparison between simulation experiments.

Calibrating the land footprint of sDACCS chains

The land use efficiency of a CDR approach co-determines its environmental implications. Here, we seek to represent the land footprint of sDACCS chains as suggested by May and Rehfeld [79, 97]. Because our zero-dimensional parametrization and JSBACH's coarse resolution of the solar spectrum strongly approximate CO₂ capturing and electrochemical processing

[79, 98], we calibrate the modeled sDACCS land footprint to match theoretical calculations. This ensures compatible results between different studies. Given that in the zero-dimensional parametrization CO_2 removal responds linearly to irradiation, we can conduct this calibration at any pair of irradiation and removal as long as system efficiencies correspond. As an example, May and Rehfeld [79] compute that $135,000 \text{ km}^2$ of land would be needed for integrated photoelectrochemical devices to deliver a CO_2 withdrawal of $10 \text{ Gt CO}_2/\text{yr}$ assuming irradiance conditions of the Sahara desert. This theoretical calculation assumes a total system loss of 50 % and includes the footprint of the required infrastructure. However, land use for harvesting energy to drive CO_2 capture is not included.

We conduct the calibration only for the hE process chain and prior to determining the effective conversion factors μ_{hE} and μ_{IE} , which incorporate the effect on land use of energy harvest for DAC and industrial electrolysis into the technology scenarios. This approach is motivated by the fact that both scenarios can be phrased in terms of an effective theoretical conversion efficiency from solar irradiation to CO_2 removal.

Three steps make up the calibration procedure (Figure S6). Initially, we conduct a one-year test simulation with the uncalibrated sDACCS model (blue in Figure S6), that is with a calibration factor $\mu_{\text{C}} = 1$ and without accounting for the reduced conversion efficiency due to energy harvest ($\mu_{\text{hE}} = 1$). Based on the simulated CO_2 removal potential ψ (Equation (9)) on all grid cells with $\psi > 0$, we match the simulated, uncalibrated response to the zero-dimensional model when calculated offline (dashed line in Figure S6). This step is necessary to again account for the two simulated spectral windows in the MPI-ESM model. Finally, we utilize the calibrated offline response (dashed in Figure S6) to determine the calibration factor $\mu_{\text{C}} = 1.702$ for matching theoretical expectation (solid line in Figure S6) with the simulations (green in Figure S6).

Table 1 | Integrated properties of the reference spectrum [86, 87] used for scaling the electron yield of solar absorbers with insolation.

Parameter	Description	Value	Unit
$\Phi_{\lambda_1, \lambda_2}^{vis}$	photon flux (vis)	0.01074	$10^{23} \text{ photons}/(\text{m}^2 \cdot \text{s})$
$\Phi_{\lambda_1, \lambda_2}^{nir}$	photon flux (nir)	0.01235	$10^{23} \text{ photons}/(\text{m}^2 \cdot \text{s})$
$I_{\lambda_1, \lambda_2}^{vis}$	spectral power (vis)	467.3872	W/m^2
$I_{\lambda_1, \lambda_2}^{nir}$	spectral power (nir)	257.0784	W/m^2

Table 2 | Process stage efficiencies for energy harvest, direct air capture, and electrolysis as assumed for the hE technology scenario.

Process stage	Energy demand (+)/supply (-)
PV	$-I \cdot \eta_{PV} \text{ kWh}(\text{m}^2 \cdot \text{a})$
DAC	0.5 kWh/kg CO ₂ [92] (no thermalization required)
PEC	parameterized in the zero-dimensional sDACCES model

Table 3 | Efficiencies employed to compute the hE chain's conversion efficiency $\mu_{\text{CO}_2/e}^{\text{hE}}$.

Parameter	Description	Value
η_{PV}	PV efficiency	0.32 [82] (perovskite-silicon tandem cells)
η_{STC}	solar-to-carbon efficiency formate (dual-junction solar absorber)	0.19 [79]
η_{sys}	system efficiency	0.5 [79]
μ_{space}	space factor of PV and solar absorbers	0.25

Table 4 | Constants and parameters employed to compute the IE chain's conversion efficiency μ_{IE} .

Parameter	Description	Value	Unit
U_{cell}	cell potential	2.5 (80% overpotential [83])	V
F	Faraday constant	96485	C/mol
$\Delta G_{\text{CO}_2 \rightarrow \text{HCOOH}}$	Gibbs free energy of CO ₂ reduction to formate	1.4	eV
m_F	mass of formate produced	1	kg
M_F	molar mass of formate	46.03	g/mol
m_{CO_2}	mass of CO ₂ reactant	1	kg
M_{CO_2}	molar mass of CO ₂	44.01	g/mol
I	irradiation	location-dependent	$\text{kWh}/(\text{m}^2 \cdot \text{a})$
η_{PV}	solar energy conversion efficiency of PV (silicon) [82]	0.25	-
η_{el}	system efficiency electrolysis	0.5	-
μ_{space}	space factor of PV	0.25	-

Table 5 | Energy supply and demand for the process stages of the IE technology scenario.

Process stage	Energy demand (+)/supply (-)	Unit
PV	$-I \cdot \eta$	$\text{kWh}/(\text{m}^2 \cdot \text{a})$
DAC	0.5 + 2.0 [92]	$\text{kWh}/\text{kg}(\text{CO}_2)$
Electrolysis	3.045	$\text{kWh}/\text{kg}(\text{CO}_2)$

Table 6 | Aggregated IPCC reference regions [99] that are highlighted in the main text.

Abbreviation	IPCC region(s)	Name(s) of the (aggregated) IPCC region(s)
CNA	WNA, CNA, ENA	Western, central, and eastern North America
NSA	NSA, SAM	Northern South America and South American Monsoon
NCE	NEU, WCE	Northern, western, and central Europe
SAH	SAH	Sahara
ARP	ARP	Arabian Peninsula
EAS	EAS	Eastern Asia

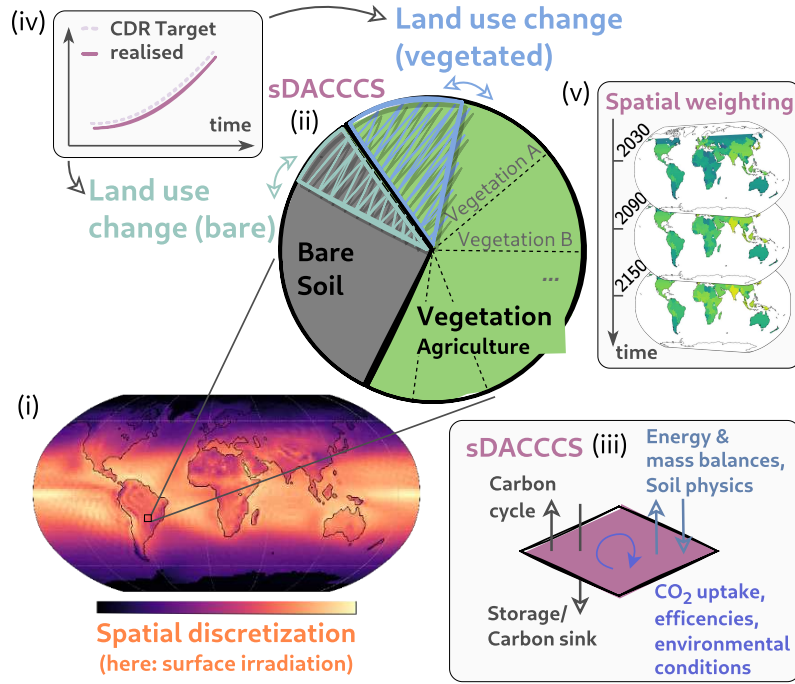


Figure S1 | Schematic overview of representing sDACCCS as an interactive and dynamic land surface type in MPI-ESM/JSBACH. Within JSBACH's spatial discretization (i) and tiling scheme (ii), we describe sDACCCS separately on vegetated and bare land (ii). In the model, sDACCCS interacts with its environment through surface balances and the carbon cycle and its CDR chain gets driven by solar irradiation (iii). In response to targeted and realised global CDR (iv), the model changes sDACCCS cover interactively while taking a spatial deployment scenario into account (v).

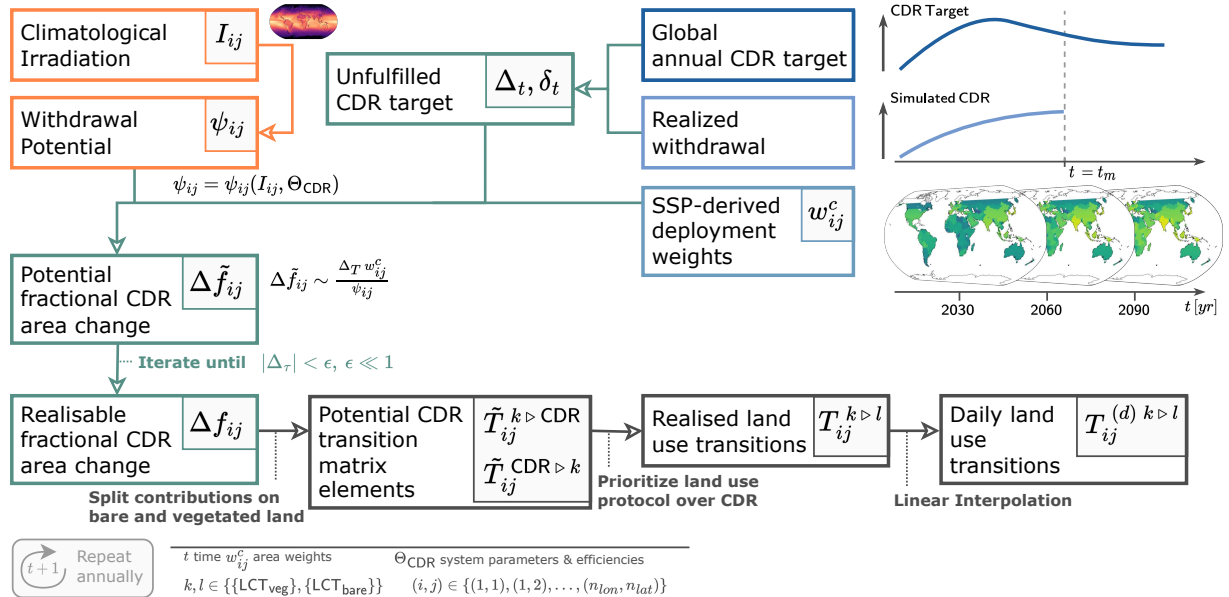


Figure S2 | Process steps and key variables for calculating the sDACCCS deployment target and land use transitions. A first stage covers the computations of the global CDR target (blue). The second stage transfers this target into anticipated fractional area changes of sDACCCS within grid cells, taking the withdrawal within the CDR tile (orange) into account. Finally, the model translates anticipated area changes into actual land cover changes (dark grey) in extension of JSBACH's land cover dynamics.

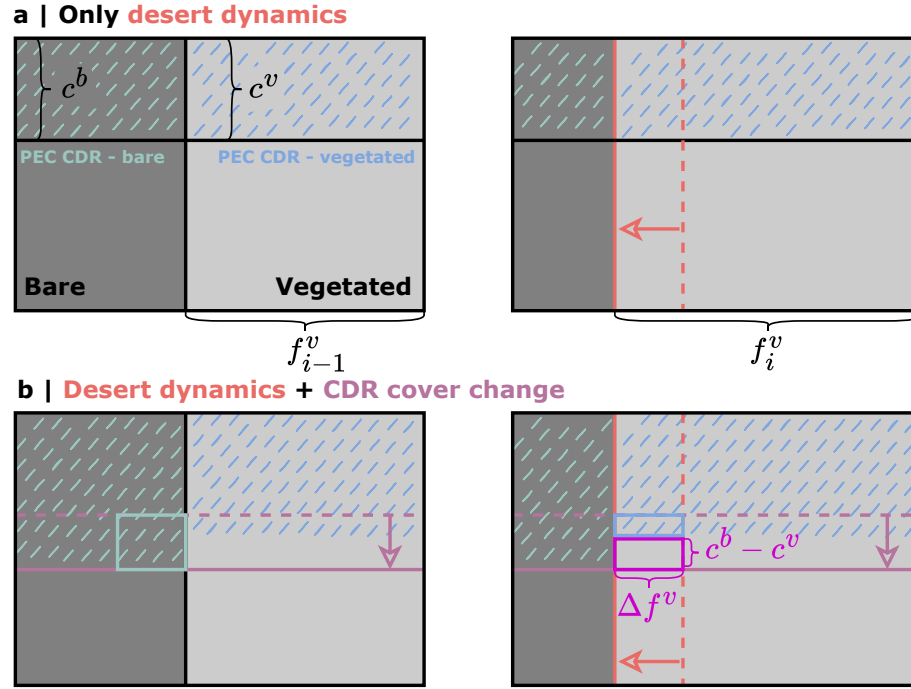


Figure S3 | Combining variations in natural vegetation extent (a) with CDR land cover change can lead to an imbalance between sDACCS cover fractions on bare and vegetated land (b). Unbalanced cover fractions (magenta) result from unfulfilled CDR land use transitions (violet) on vegetated land if the extent of natural vegetation changes at the same time (red). The subscript CDR of cover fractions is dropped for readability.

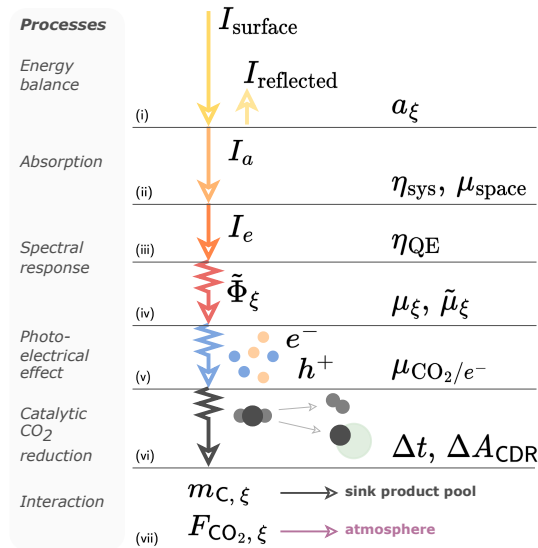
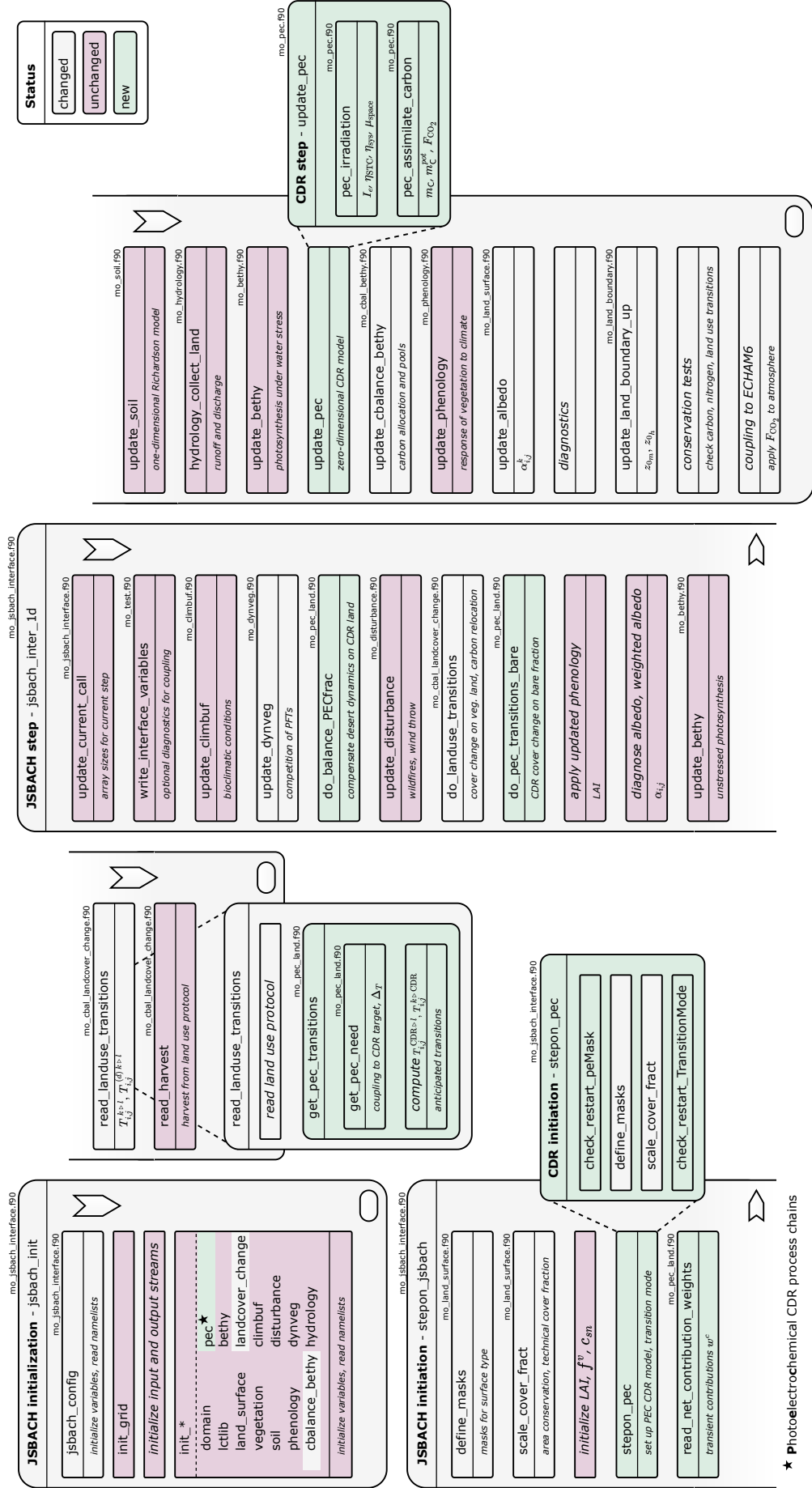


Figure S4 | Zero-dimensional parametrization of sDACCS with idealized process steps (i) to (vii). Saw-toothed arrows indicate unit conversions through process steps.



★ Photoelectrochemical CDR process chains

Figure S5 | Implementation of the CDR component in JSBACH's call tree. Initialization and initiation get called at the beginning of a simulation or after a restart. Land use transitions and harvest are read (vegetation)/computed (CDR) once per simulation year. Colors indicate routines and modules involved in representing the sDACCs chains. Arrows indicate the order of calls.

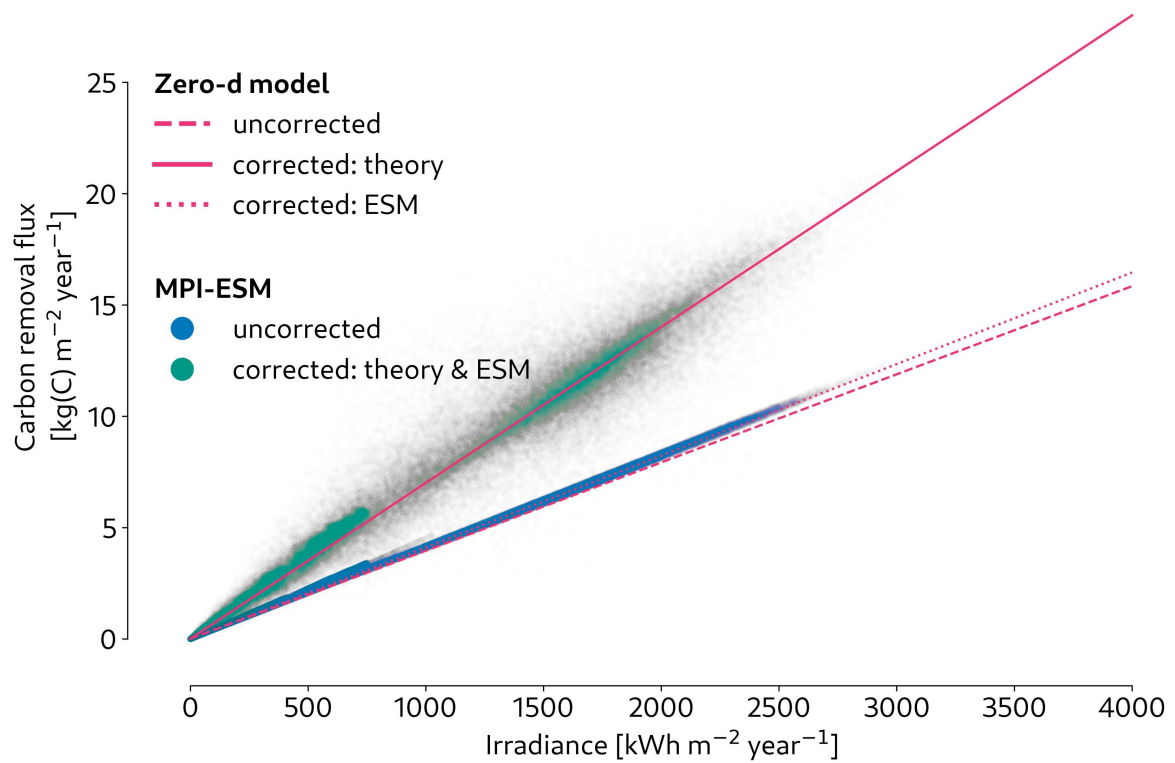


Figure S6 | Initial calibration of the sDACCS footprint in the zero-dimensional model. First, the theoretically expected carbon removal (dashed line) is corrected for the ESM's response (blue dots). Then, based on this model (dotted line), we compute a calibration factor which causes the ESM's CO₂ removal (green dots) to conform with the theoretical footprint (solid line) deduced by May and Rehfeld [79]. Note that the depicted carbon removal fluxes already comprise the spacing factor converting between the module area of solar absorbers and the sDACCS land footprint.

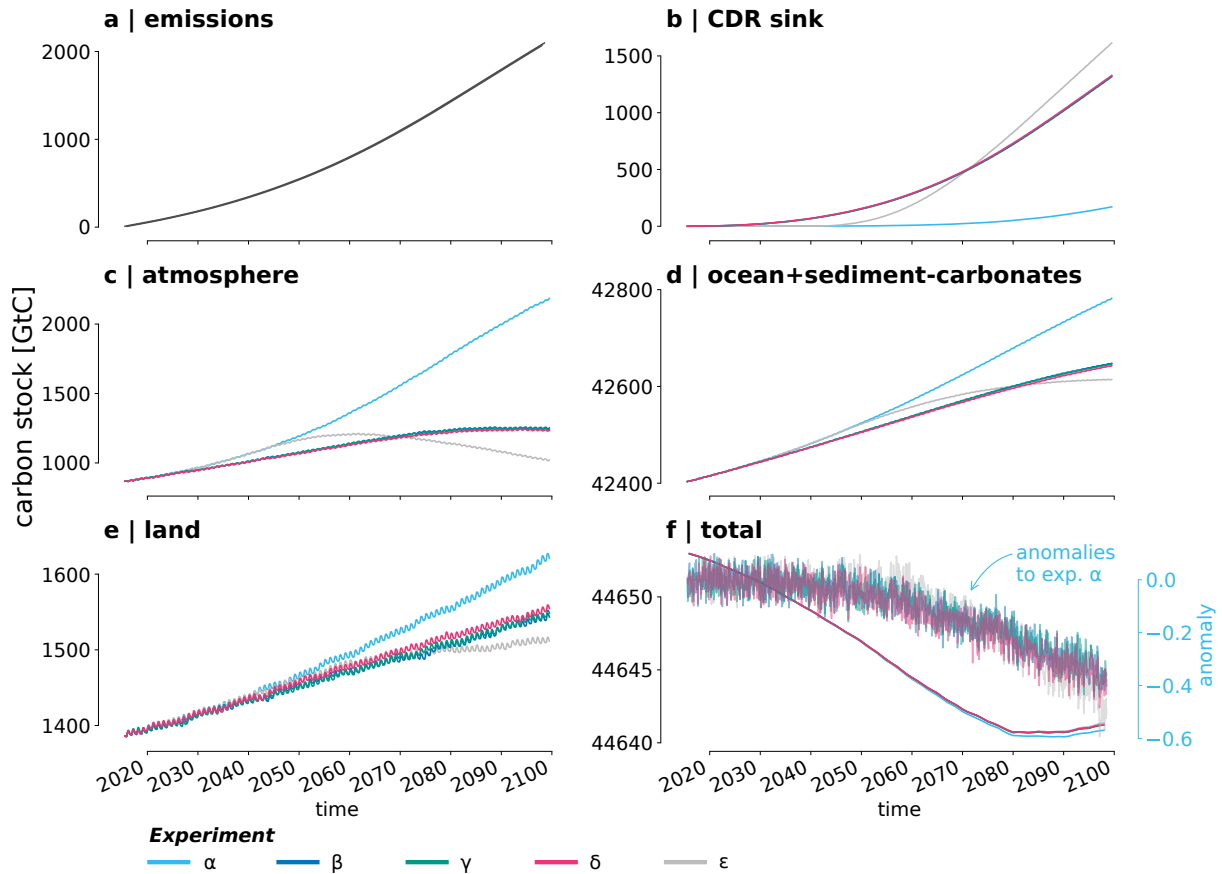


Figure S7 | Global carbon stocks and carbon conservation in simulations with sDACCS CDR in test simulations spanning a range of CDR pathways under the same emission scenario. To compensate the residual CO_2 forcing of cumulative emissions (a) and CO_2 removal (b), atmospheric (c), marine (d), and terrestrial (e) carbon stocks accumulate carbon. Still, the total carbon budget (f) should be closed and constant. The model does not perfectly reflect this conservation. However, anomalies between different CDR experiments (second scale in f) are $< 0.03\%$ of the cumulative emission forcing over 85 simulated years and make up $< 5\%$ of the model's total drift. In (a), the emission forcing references the starting point of simulations as zero. The initial model state still includes past anthropogenic forcing.

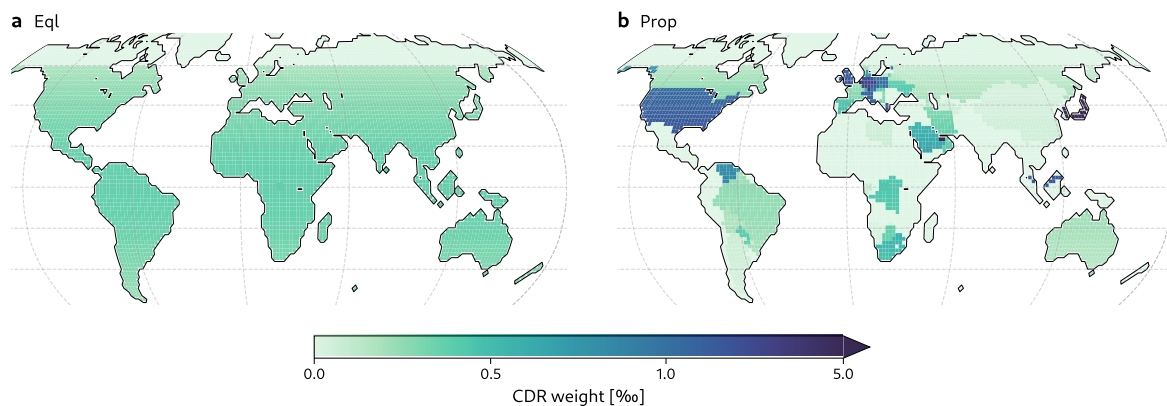


Figure S8 | CDR deployments weights of the Prop (a) and Eql (b) scenarios. Weights are derived from historic emissions (a) and relatively equal contributions (b) while accounting for cell area and permitting sDACCS deployment only within 60°S and 60°N . In addition to the spatial scenario, CDR deployment is subject to land availability constraints (Figure 2).

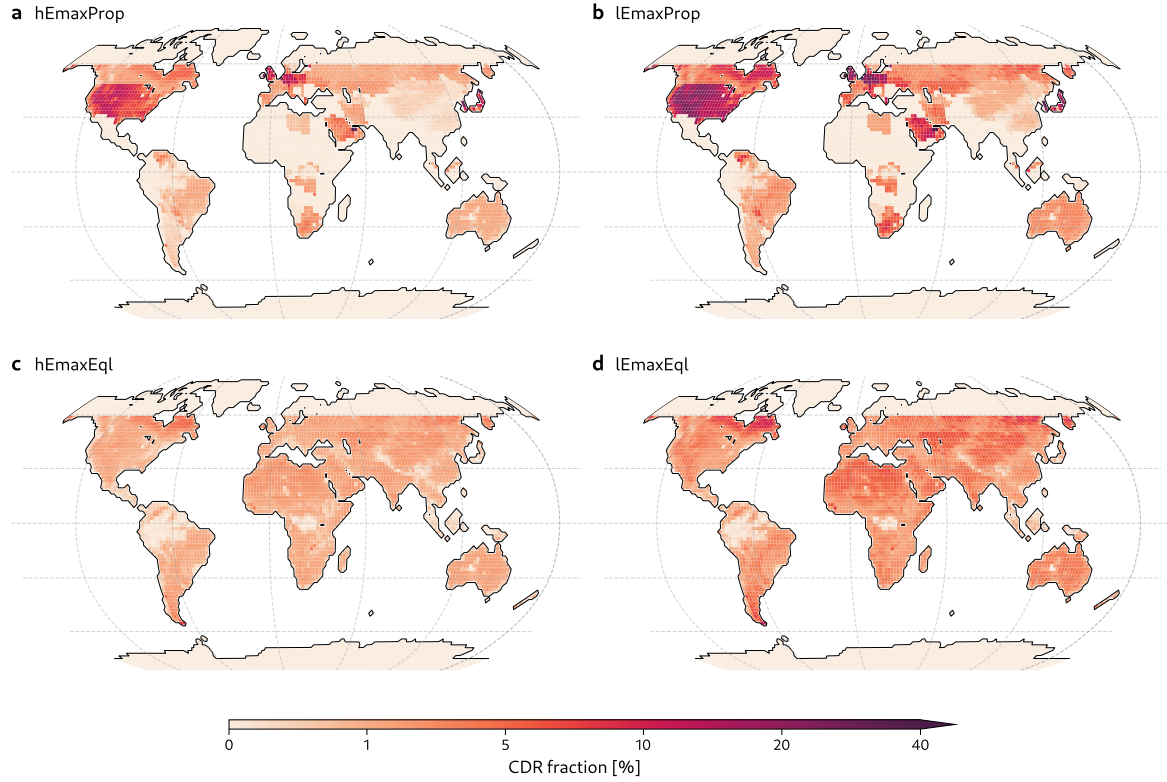


Figure S9 | Mean sDACCS realized in maxProp (a, b) and maxEql (c, d) experiments during 2110-2139, supplementing Figures 4b, c.

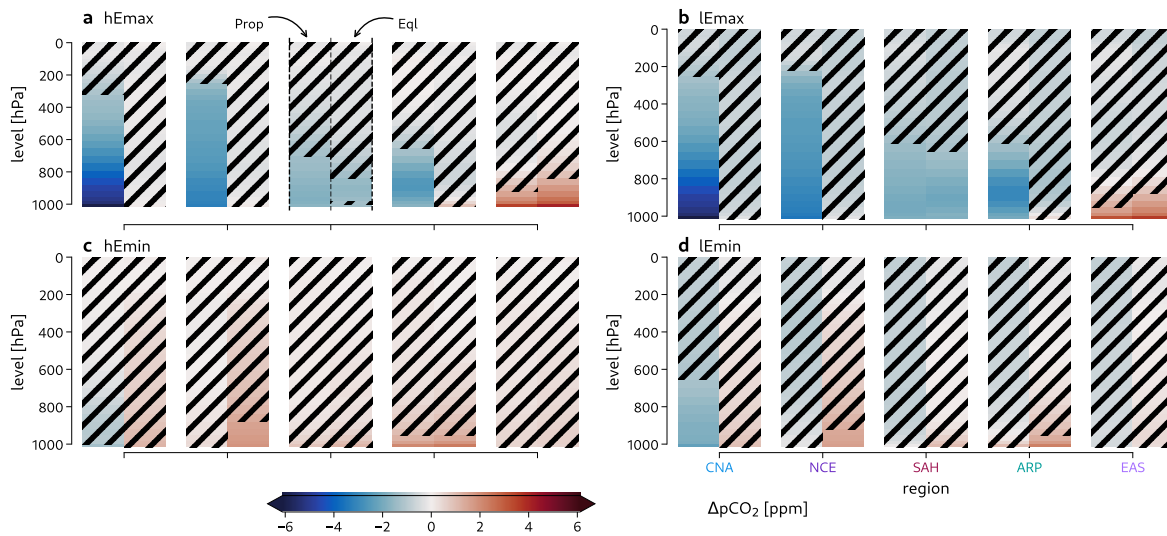


Figure S10 | Mean anomalies of CO₂ concentration along the atmospheric column in selected regions for hEmax (a), lEmax (b), hEmin (c), and lEmin (d) during 2110-2139, supplementing Figure 4d.

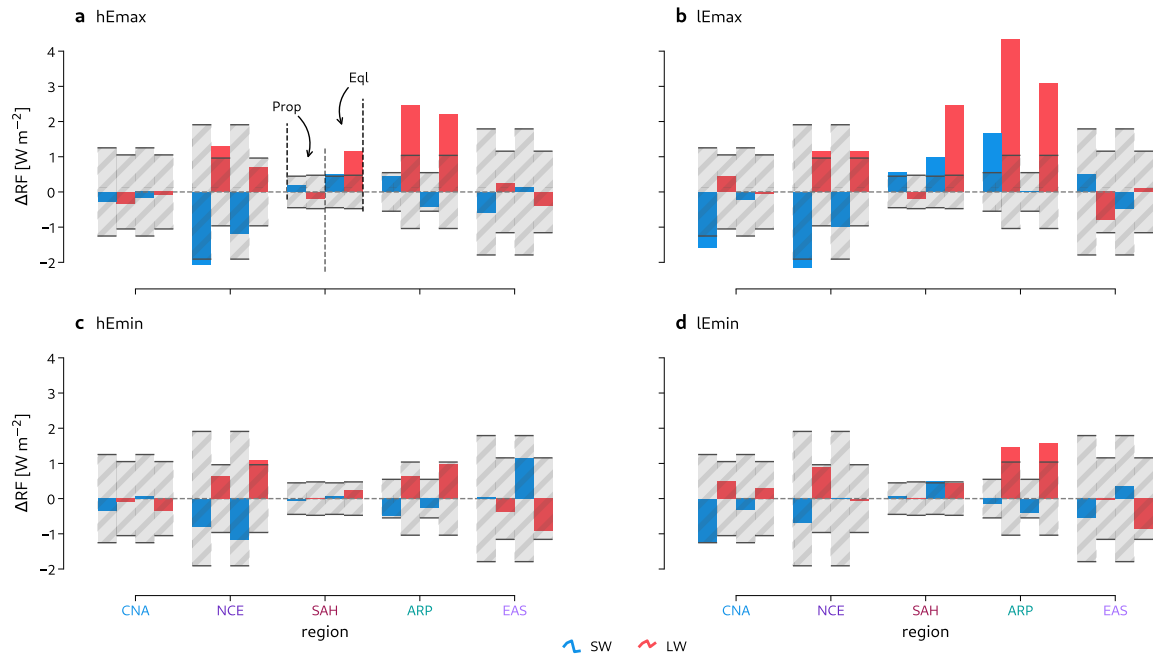


Figure S11 | Mean anomaly of short- (SW) and longwave (LW) radiative forcing at surface in selected regions analogous to Figure S10, supplementing Figure 4e.

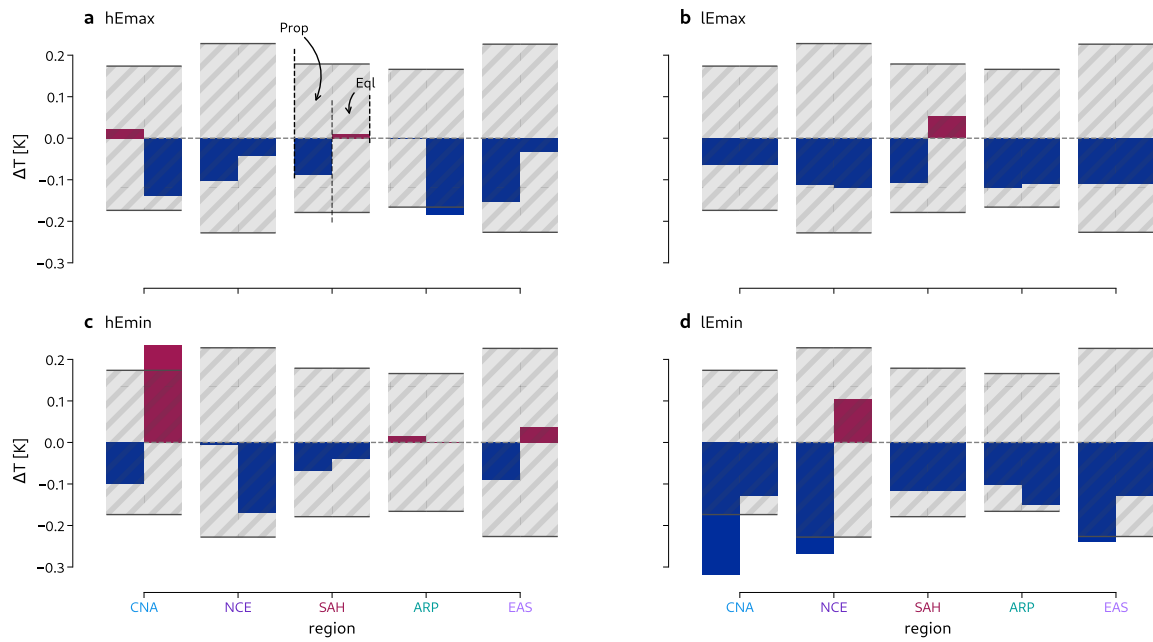


Figure S12 | Mean surface air temperature anomaly in selected regions analogous to Figure S10, supplementing Figure 4f.

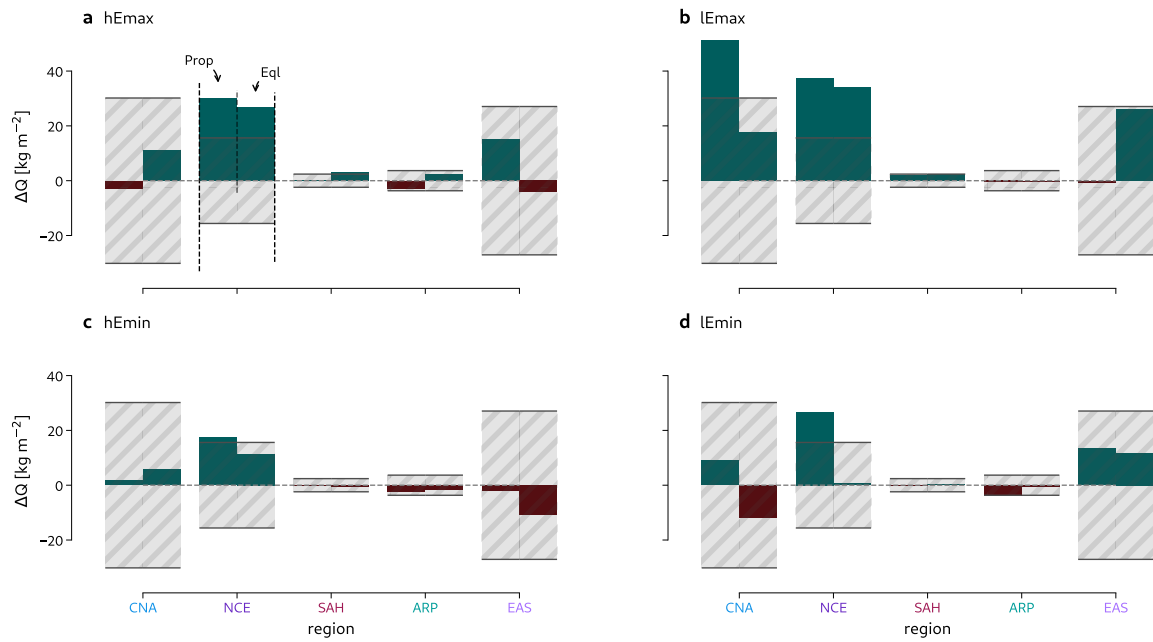


Figure S13 | Mean soil moisture anomaly in selected regions analogous to Figure S10, supplementing Figure 4g.

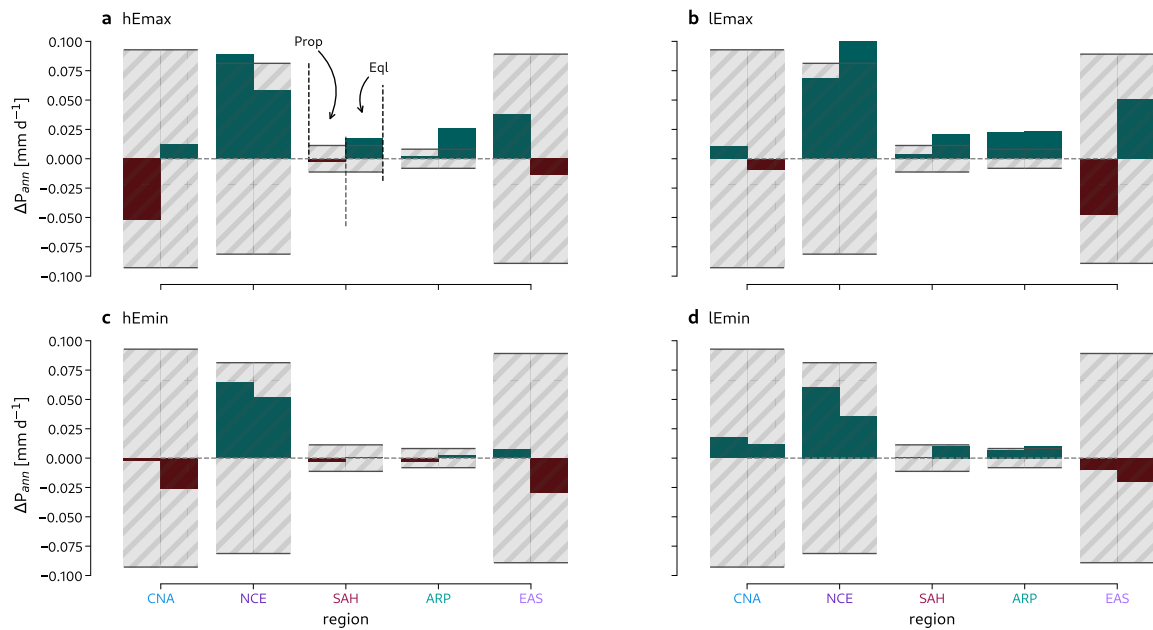


Figure S14 | Mean annual precipitation anomaly in selected regions analogous to Figure S10.

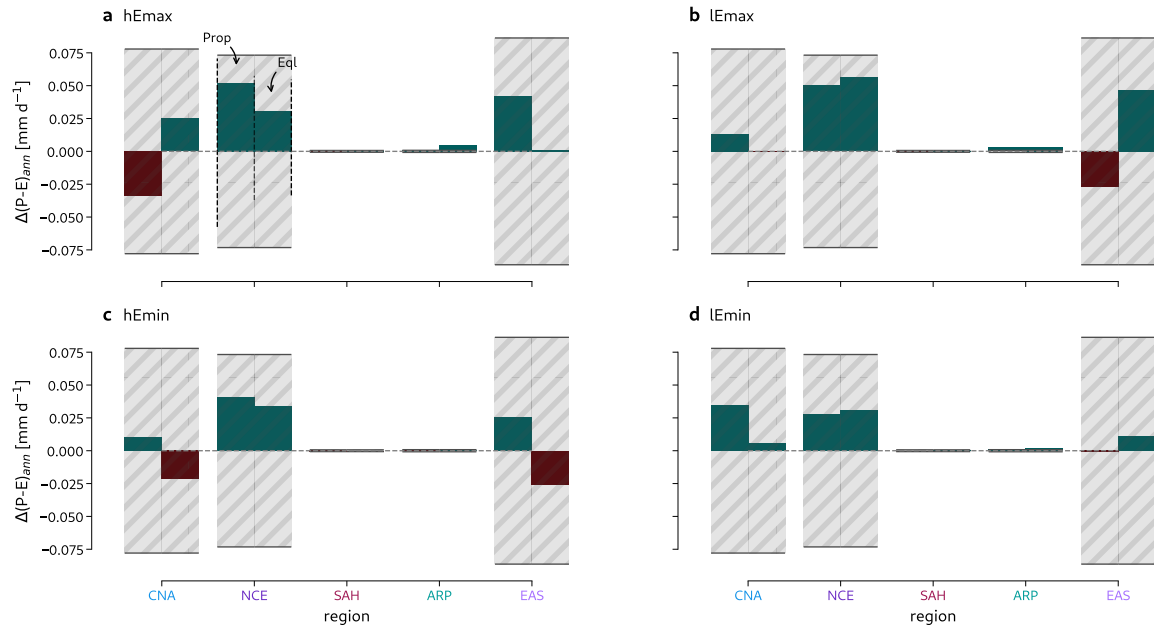


Figure S15 | Mean annual anomaly in moisture availability (precipitation minus evaporation) within selected regions analogous to Figure S10.

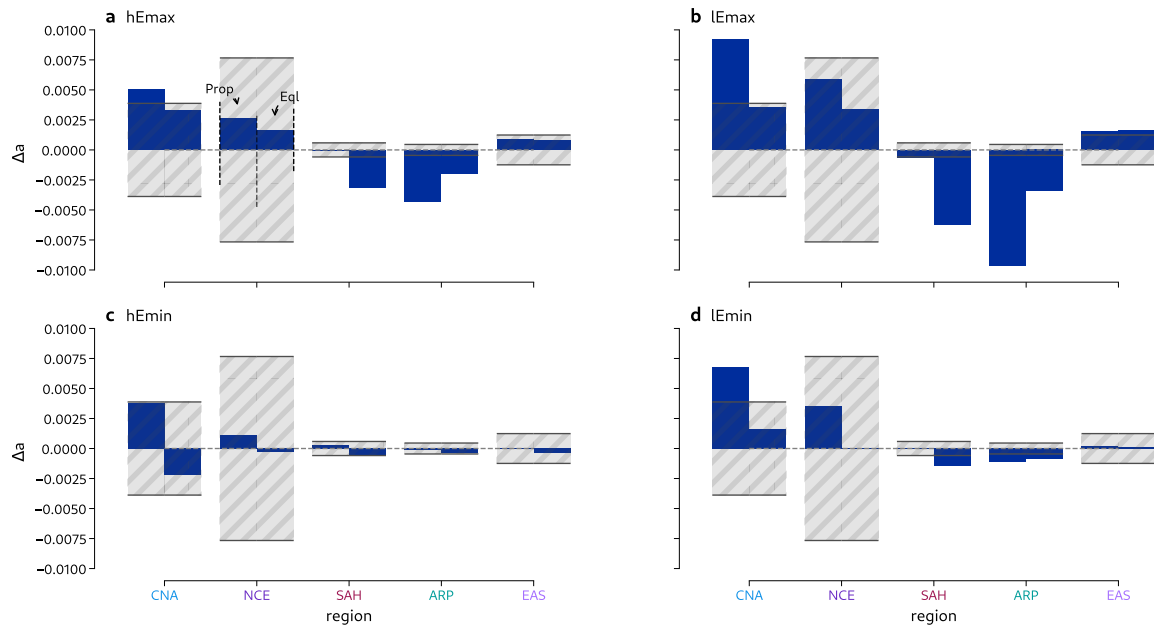


Figure S16 | Mean albedo anomaly in selected regions analogous to Figure S10.

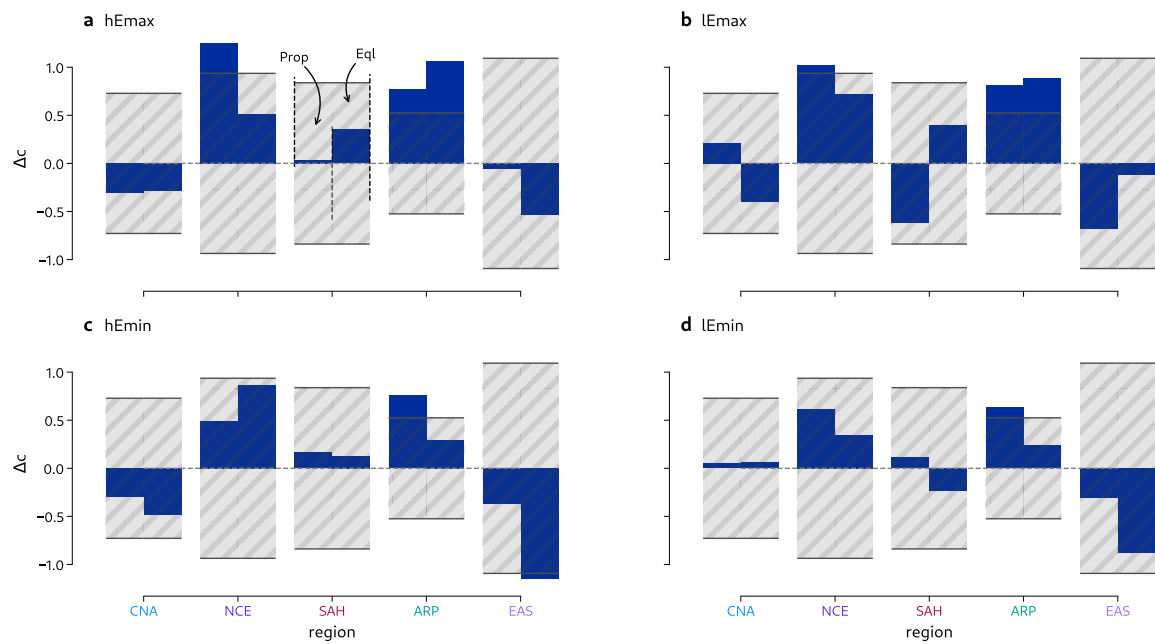


Figure S17 | Mean cloud cover anomaly in selected regions analogous to Figure S10.

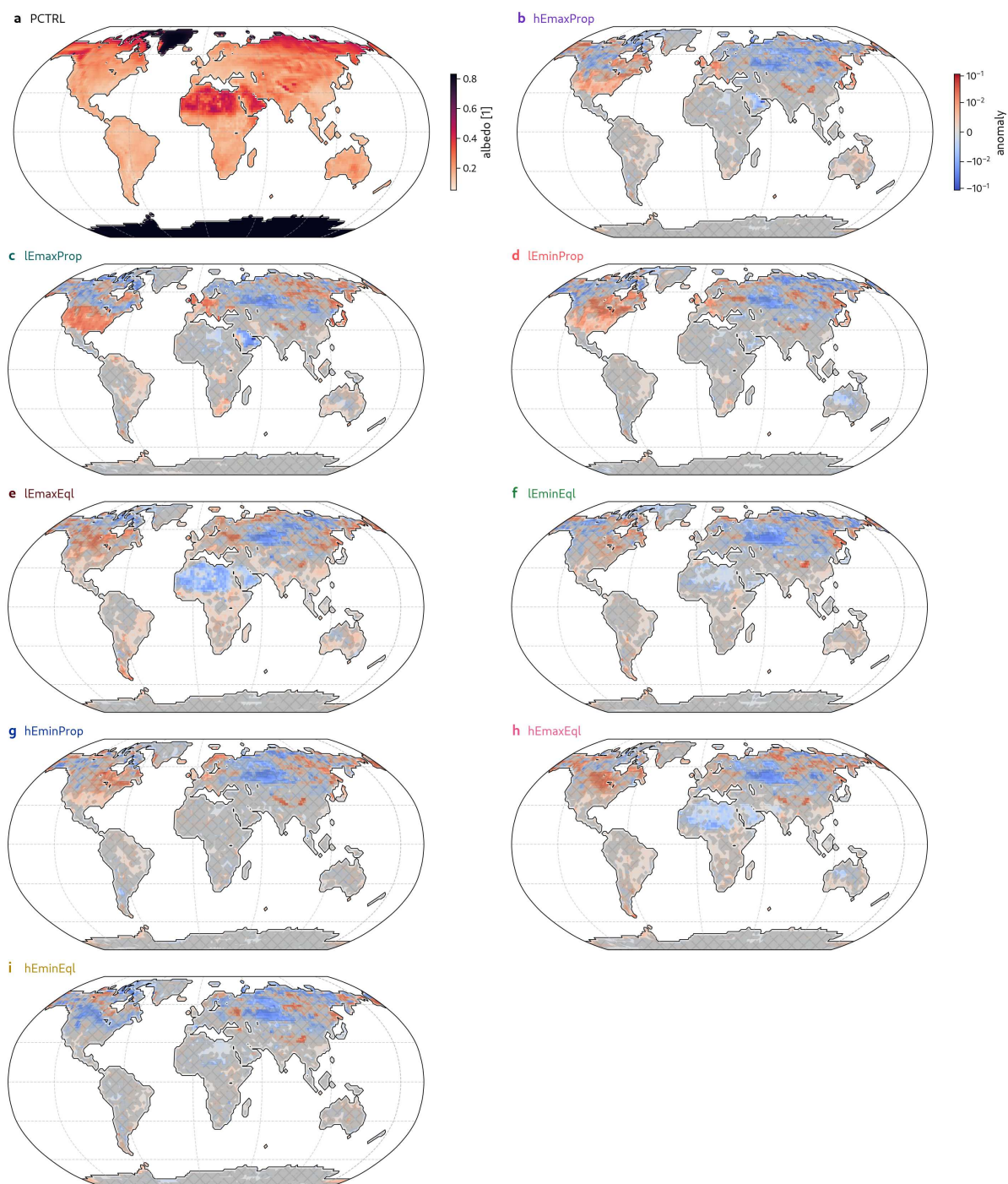


Figure S18 | Climatological anomalies in mean annual surface albedo in reference to the pathway control experiment (PCTRL, **a**) for all sDACCS experiments (**b–i**) averaged over the reference period for constant CDR (2110–2139). Hatchings indicate insignificant data with respect to the 95th percentile from subsequent 30-year climatologies of the equilibrium control simulation (CTRL).

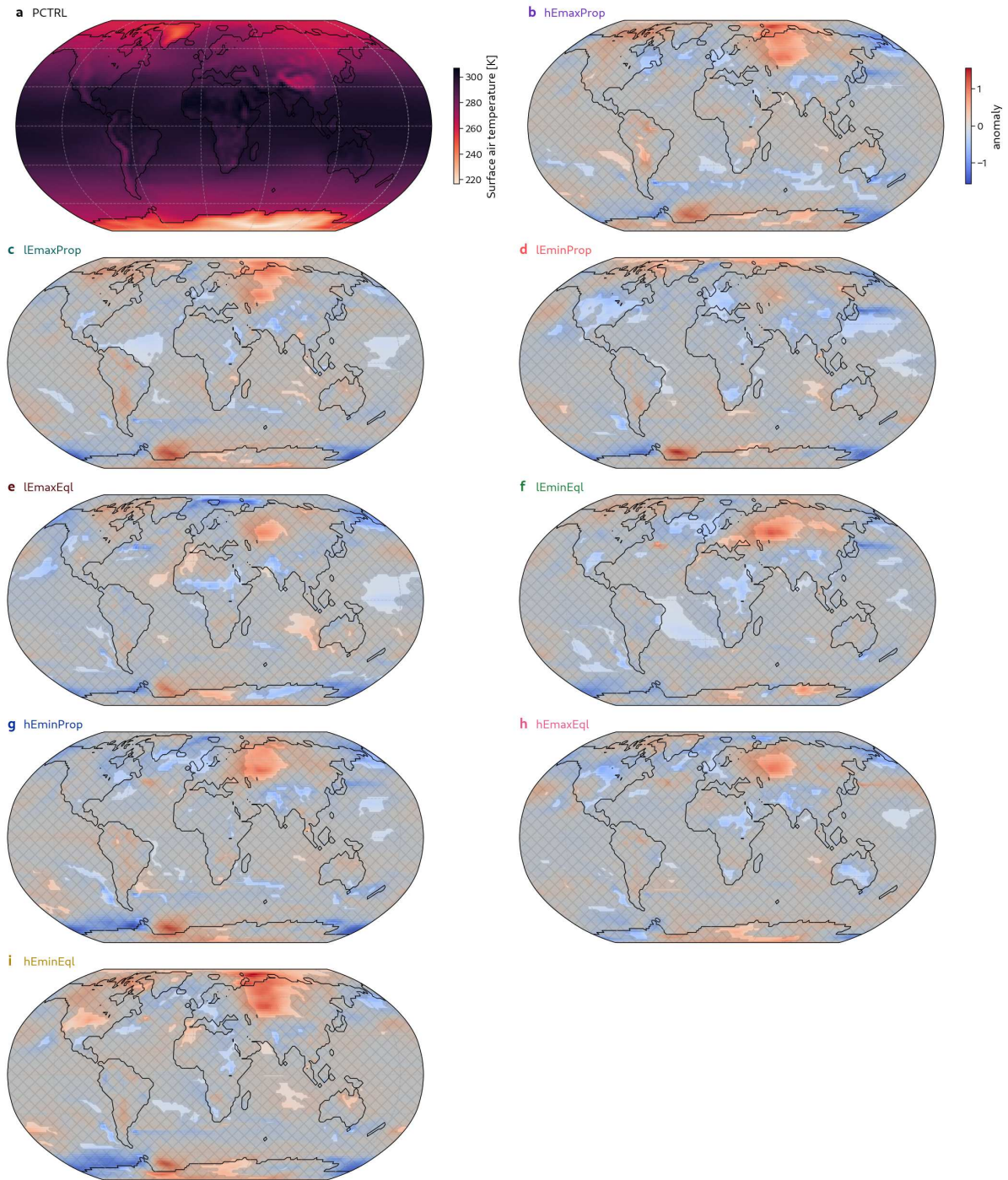


Figure S19 | Climatological anomalies in mean annual surface air temperature analogous to Figure S18.

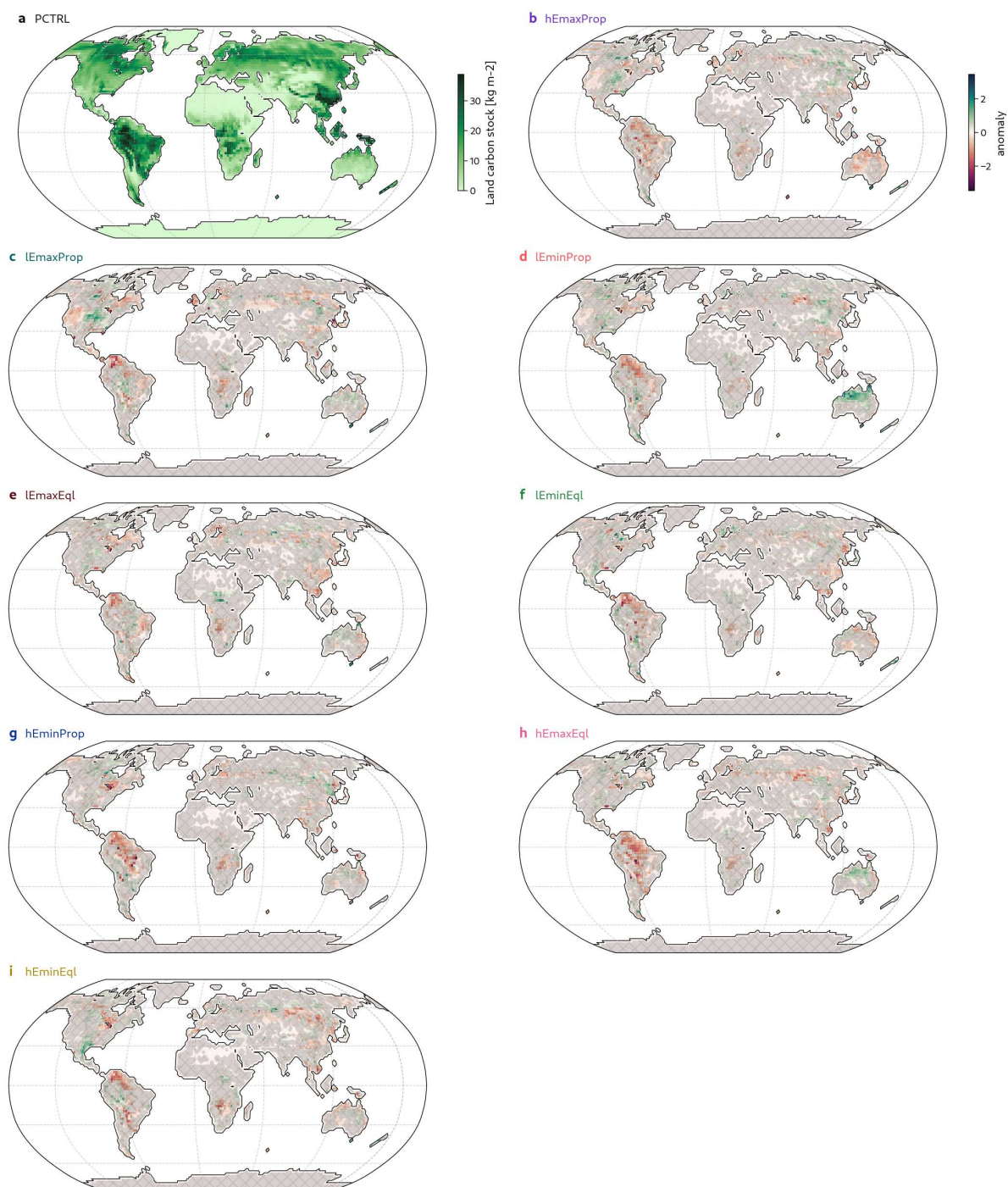


Figure S20 | Climatological anomalies in total land carbon stocks analogous to Figure S18.

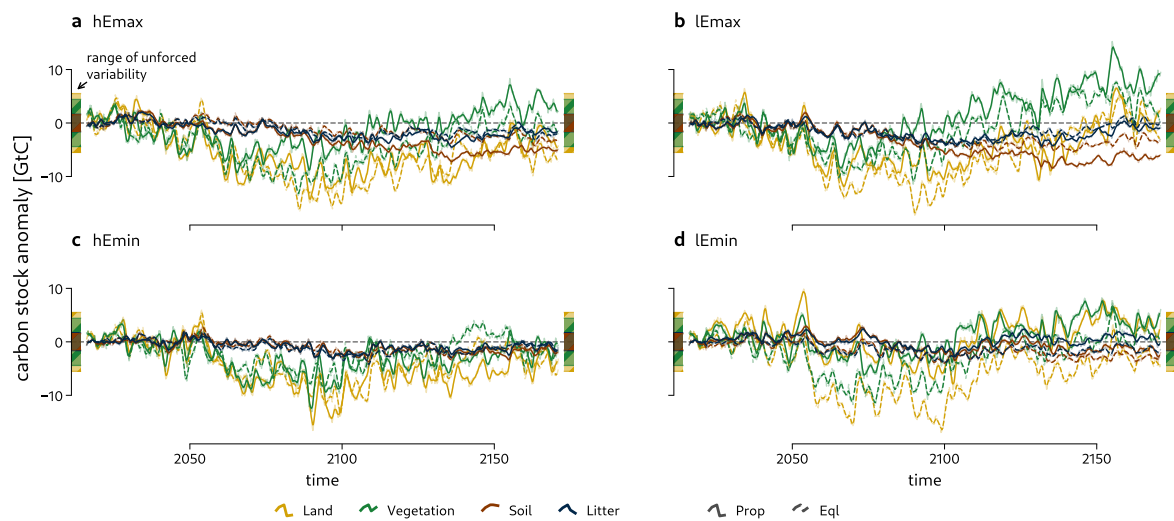


Figure S21 | Global carbon stock response in hEmax (a), and lEmax (b), hEmin (c), and lEmin (d) experiments, supplementing Figure 5a, b.

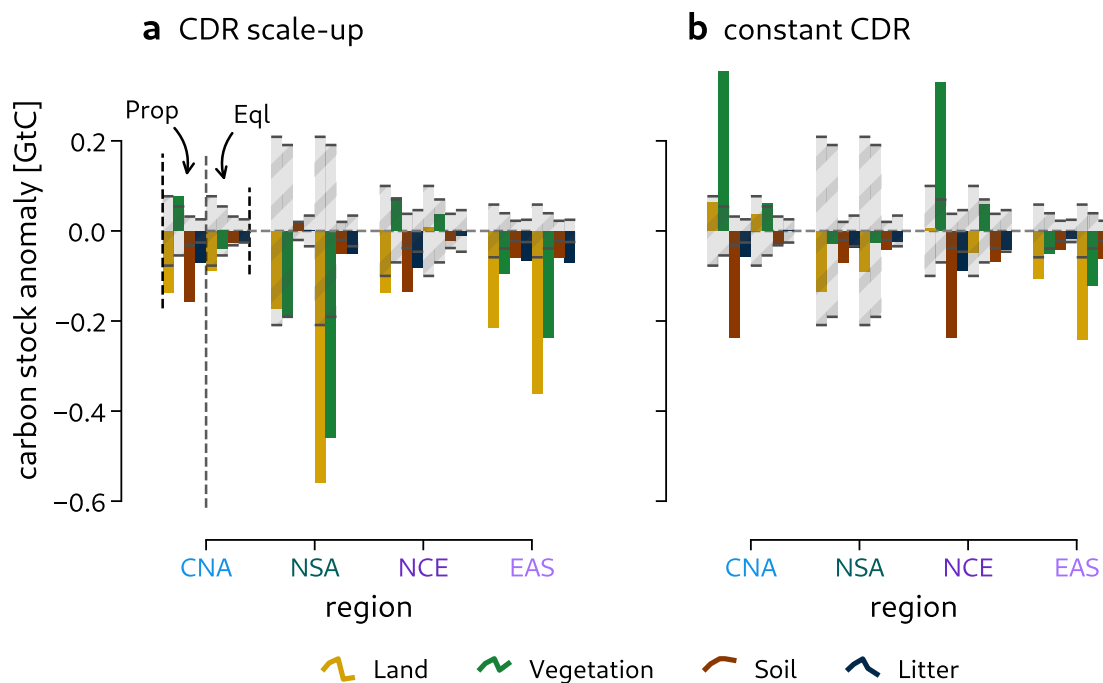


Figure S22 | Total carbon stock anomaly in selected regions within lEmin experiments during the periods of CDR scale-up (a) and constant CDR (b), supplementing Figure 5c, d.

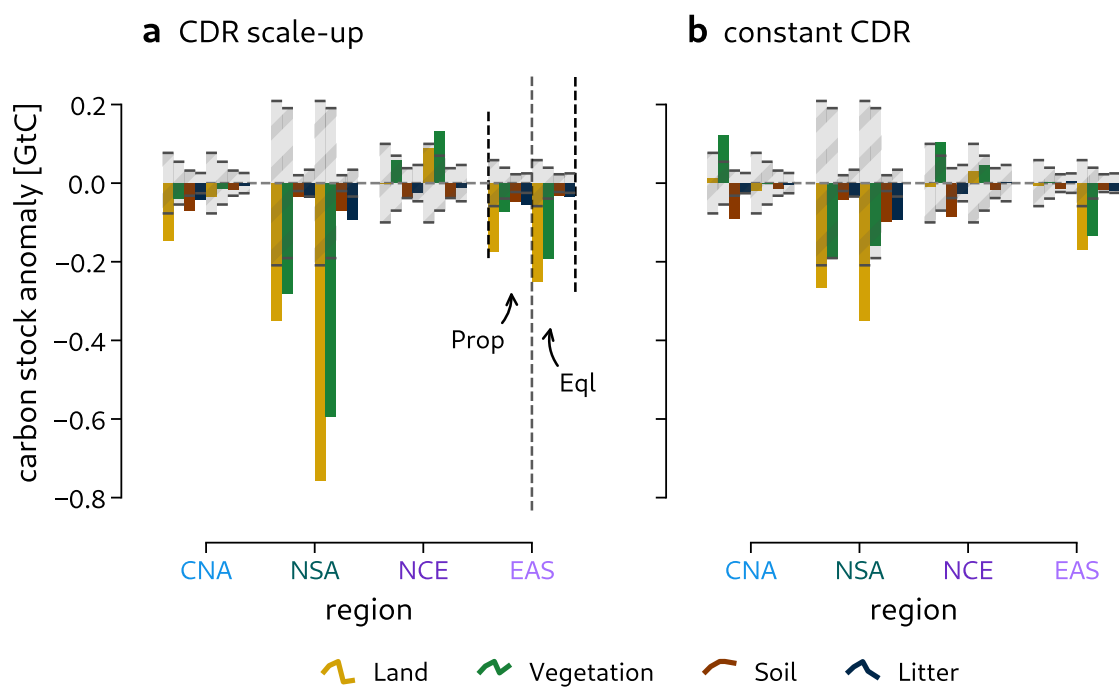


Figure S23 | Total carbon stock anomaly as in Figure S22 but for IEmin experiments.

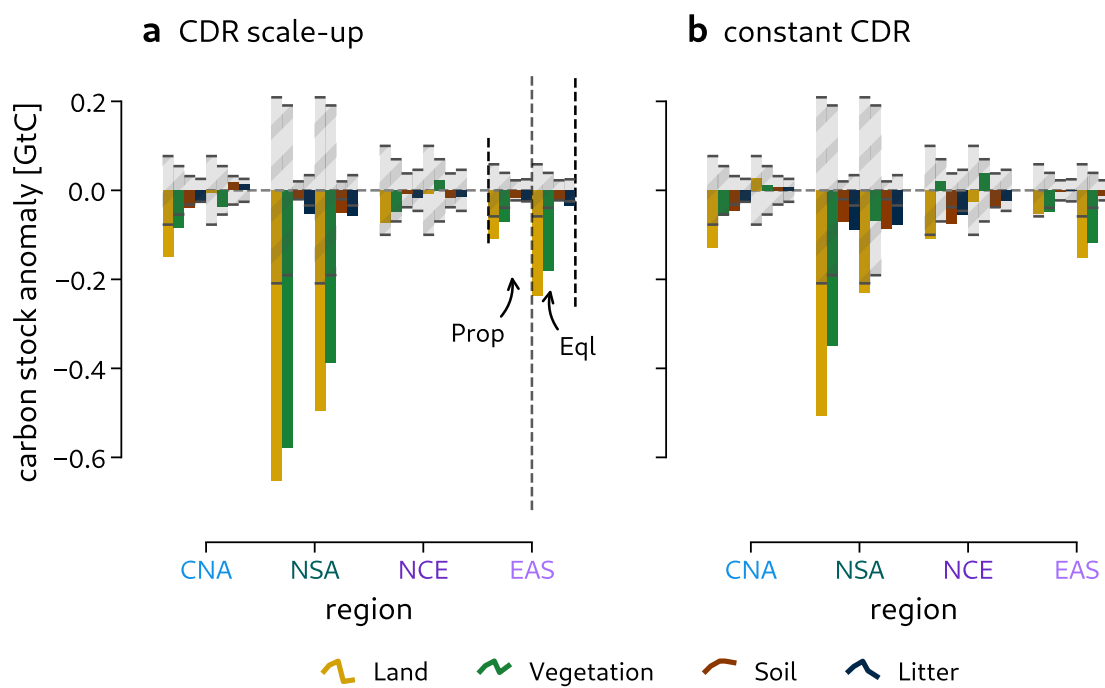


Figure S24 | Total carbon stock anomaly as in Figure S22 but for hEmin experiments.

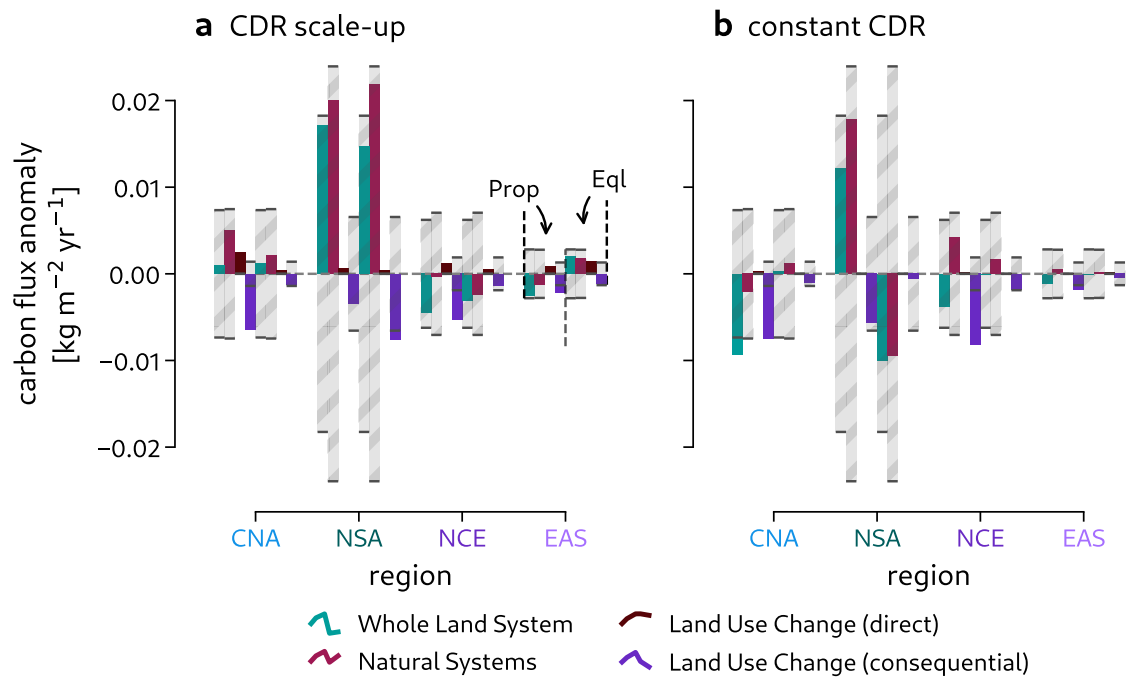


Figure S25 | Mean carbon flux anomaly in selected regions within IEmax experiments during the periods of CDR scale-up (a) and constant CDR (b), supplementing Figure 5e, f.

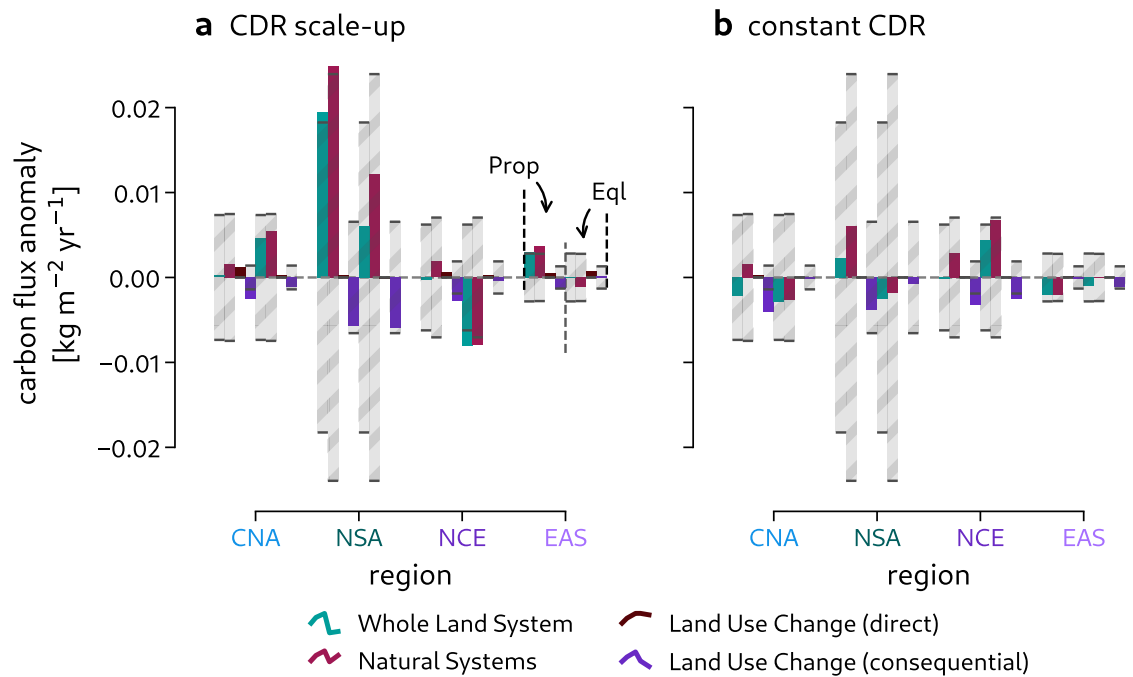


Figure S26 | Mean carbon flux anomaly as in Figure S25 but for IEmin experiments.

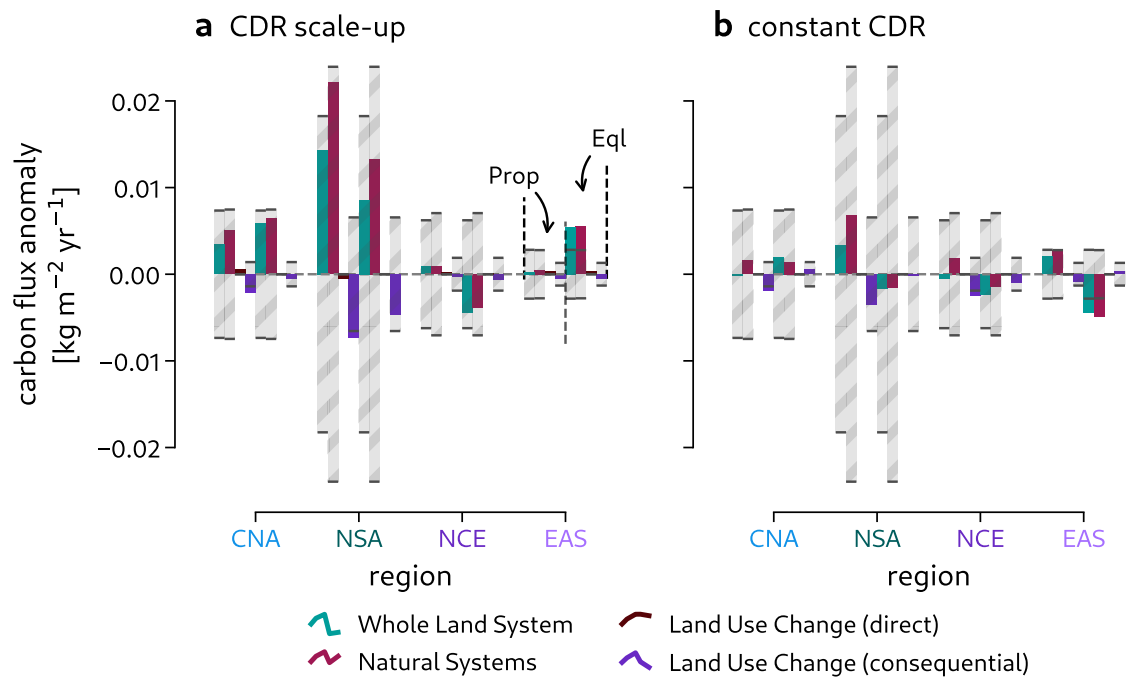


Figure S27 | Mean carbon flux anomaly as in Figure S25 but for hEmin experiments.

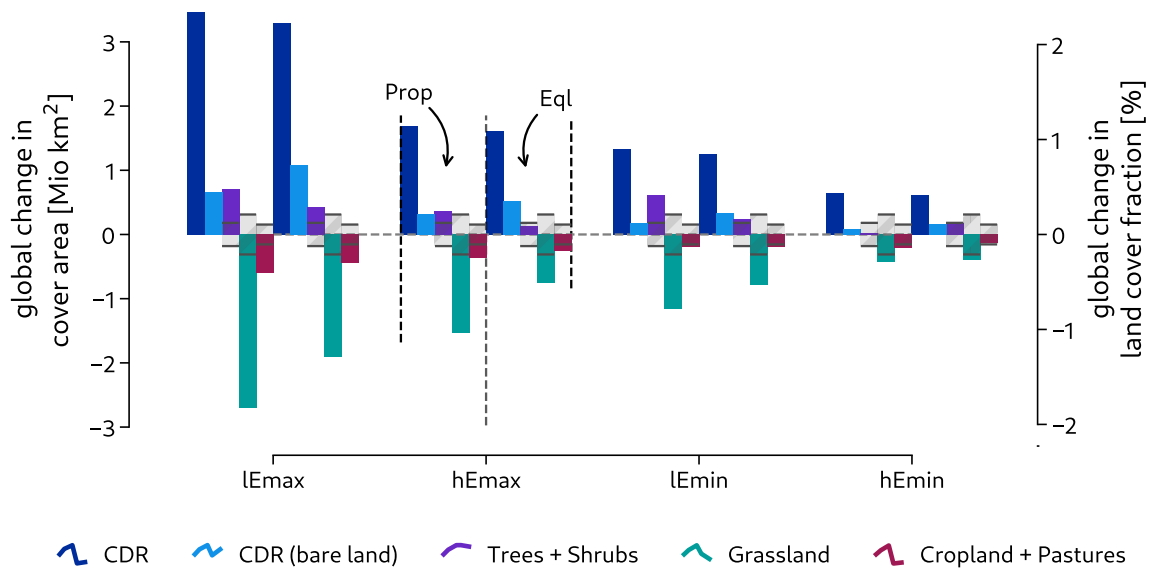


Figure S28 | Mean global changes in area and land cover fraction in the period of constant CDR in sDACCS experiments compared to PCTRL, supplementing Figure 6a. The total CDR cover also includes the displayed CDR cover on bare land.

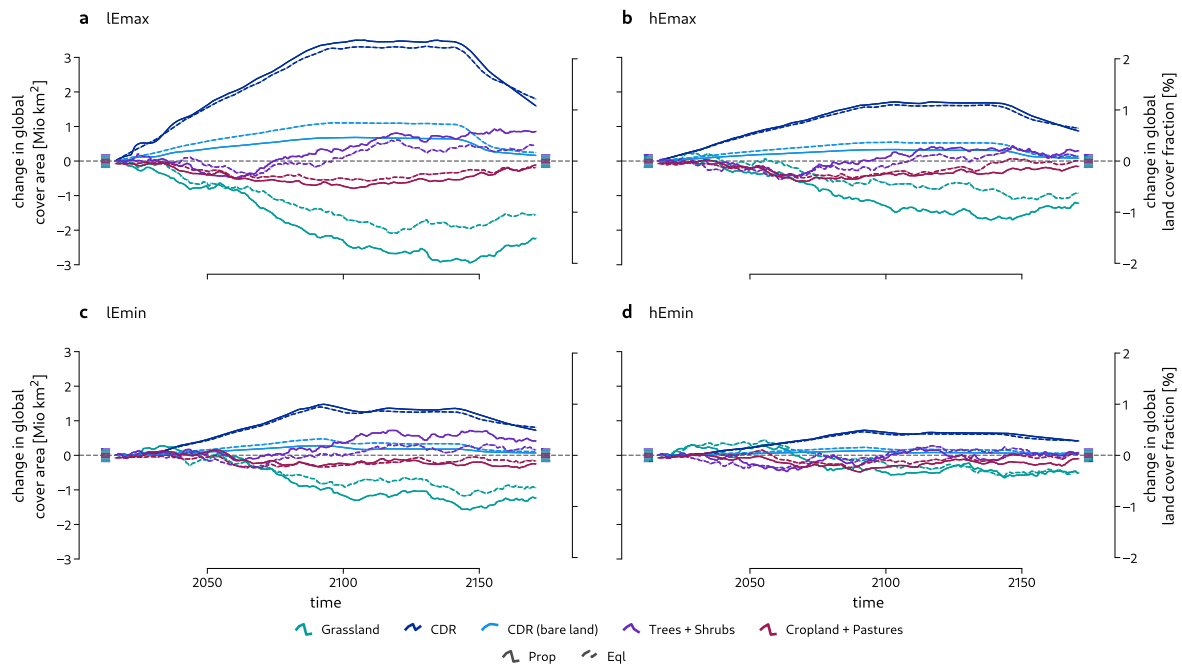


Figure S29 | Global changes in area and land cover fraction over time in IEmax (a), hEmax (b), IEmin (c), and hEmin (d) experiments compared to PCTRL. The total CDR cover also includes the displayed CDR cover on bare land.

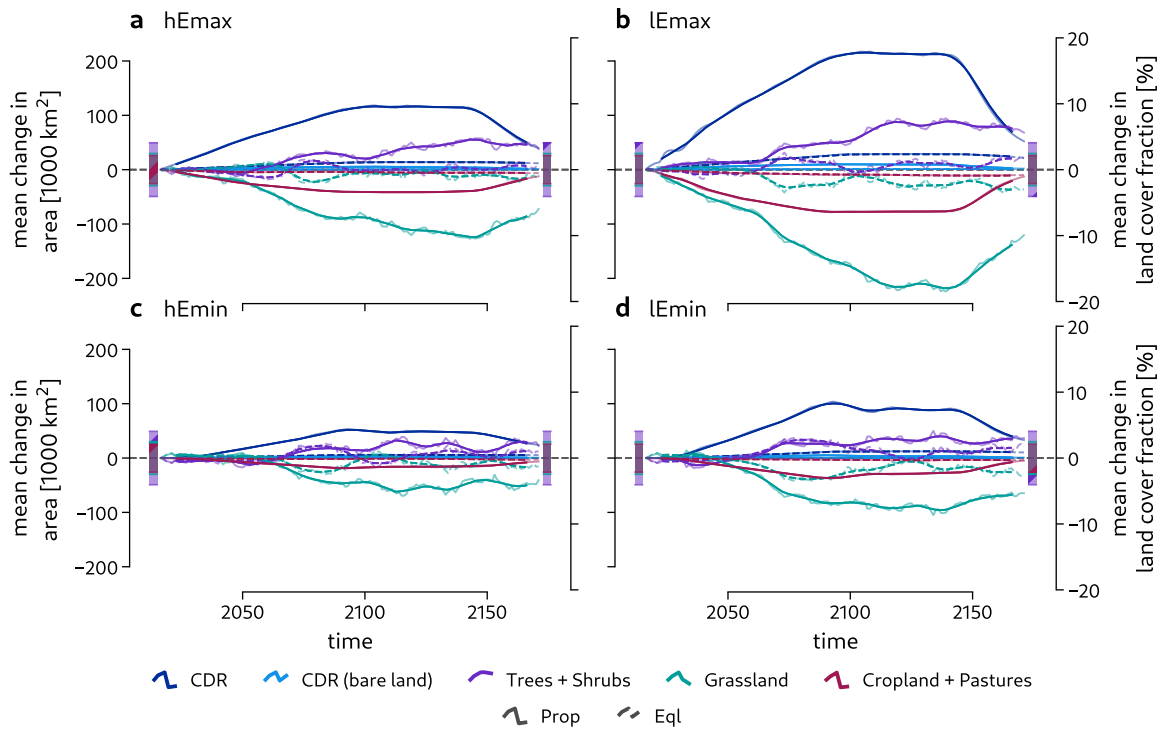
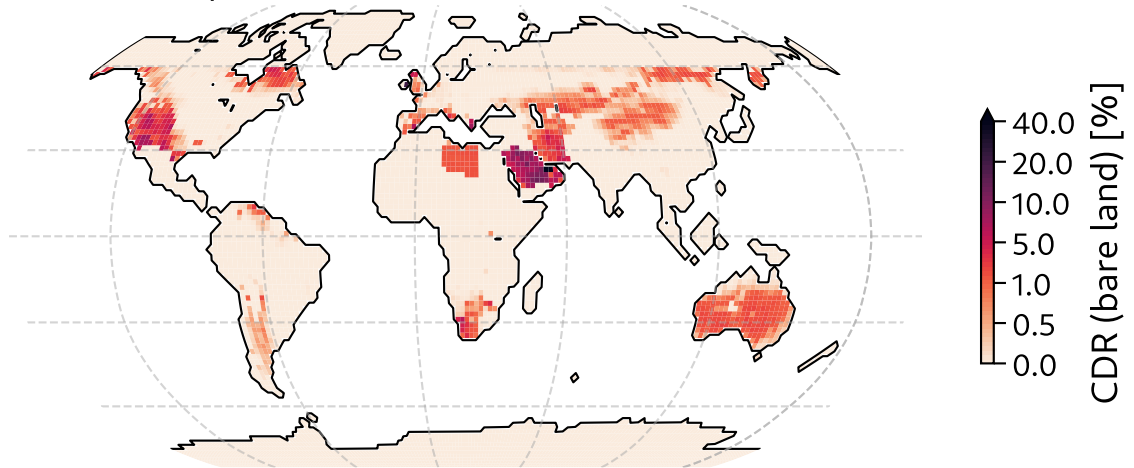


Figure S30 | Land conversions over time in the NCE* region when comparing hEmax (a), hEmin (b), and IEmin (c) experiments to PCTRL, supplementing Figure 6b.

a lEmaxProp



b hEmaxProp - lEmaxProp

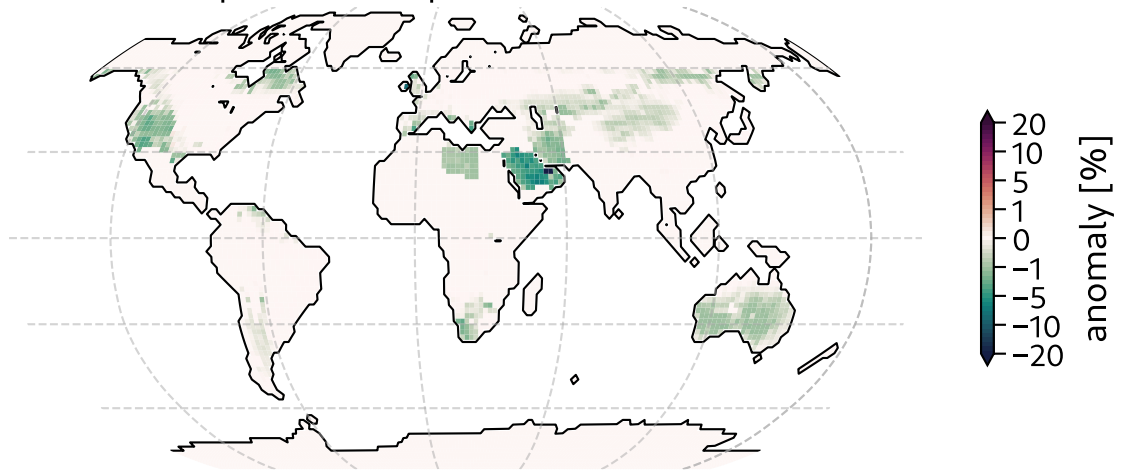


Figure S31 | Total land cover change on the bare fraction of land in lEmaxProp (a) and reduced land conversion in hEmaxProp (b), supplementing Figure 6c, d.

References – Supplementary Information

- [73] C. H. Reick et al. “Representation of natural and anthropogenic land cover change in MPI-ESM”. *Journal of Advances in Modeling Earth Systems* 5.3 (2013), 459–482. DOI: 10.1002/jame.20022.
- [74] C. H. Reick et al. *JSBACH 3: The land component of the MPI Earth System Model - Documentation of version 3.2*. Reports on Earth System Science / Max Planck Institute for Meteorology. Max Planck Institute for Meteorology, 2021. DOI: 10.17617/2.3279802.
- [75] Z. Lu et al. “Impacts of Large-Scale Sahara Solar Farms on Global Climate and Vegetation Cover”. *Geophysical Research Letters* 48.2 (2021), 1–10. DOI: 10.1029/2020gl090789.
- [76] M. Claussen. “Flux aggregation at large scales: on the limits of validity of the concept of blending height”. *Journal of Hydrology* 166.3-4 (1995), 371–382. DOI: 10.1016/0022-1694(94)05098-i.
- [77] G. C. Hurtt et al. “Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6”. *Geoscientific Model Development* 13.11 (2020), 5425–5464. DOI: 10.5194/gmd-13-5425-2020.
- [78] Y. Li et al. “Climate model shows large-scale wind and solar farms in the Sahara increase rain and vegetation”. *Science* 361.6406 (2018), 1019–1022. DOI: 10.1126/science.aar5629.
- [79] M. M. May and K. Rehfeld. “ESD Ideas: Photoelectrochemical carbon removal as negative emission technology”. *Earth System Dynamics* 10.1 (2019), 1–7. DOI: 10.5194/esd-10-1-2019.
- [80] M. M. May et al. “On the benchmarking of multi-junction photoelectrochemical fuel generating devices”. *Sustainable Energy & Fuels* 1.3 (2017), 492–503. DOI: 10.1039/c6se00083e.
- [81] D. W. Keith et al. “A Process for Capturing CO₂ from the Atmosphere”. *Joule* 2.8 (2018), 1573–1594. DOI: 10.1016/j.joule.2018.05.006.
- [82] M. A. Green et al. “Solar cell efficiency tables (Version 61)”. *Progress in Photovoltaics: Research and Applications* 31.1 (2023), 3–16. DOI: 10.1002/pip.3646.
- [83] M. Schreier et al. “Efficient photosynthesis of carbon monoxide from CO₂ using perovskite photovoltaics”. *Nature Communications* 6.1 (2015), 7326. DOI: 10.1038/ncomms8326.
- [84] J. Hong et al. “Photocatalytic reduction of CO₂: a brief review on product analysis and systematic methods”. *Analytical Methods* 5.5 (2012), 1086–1097. DOI: 10.1039/c2ay26270c.
- [85] W. W. Focke et al. “Kinetic interpretation of log-logistic dose-time response curves”. *Scientific Reports* 7.1 (2017), 2234. DOI: 10.1038/s41598-017-02474-w.
- [86] United States National Renewable Energy Laboratory. *Reference Air Mass 1.5 Spectra*. 2003. URL: <https://www.nrel.gov/grid/solar-resource/spectra-am1.5.html>.
- [87] C. A. Gueymard. “The sun’s total and spectral irradiance for solar energy applications and solar radiation models”. *Solar Energy* 76.4 (2004), 423–453. DOI: 10.1016/j.solener.2003.08.039.
- [88] M. Schreier et al. “Solar conversion of CO₂ to CO using Earth-abundant electrocatalysts prepared by atomic layer modification of CuO”. *Nature Energy* 2.7 (2017), 17087. DOI: 10.1038/nenergy.2017.87.
- [89] Y. Xiao et al. “An artificial photosynthetic system with CO₂-reducing solar-to-fuel efficiency exceeding 20%”. *Journal of Materials Chemistry A* 8.35 (2020), 18310–18317. DOI: 10.1039/d0ta06714h.
- [90] W. Gao et al. “Industrial carbon dioxide capture and utilization: state of the art and future challenges”. *Chemical Society Reviews* 49.23 (2020), 8584–8686. DOI: 10.1039/d0cs00025f.

- [91] A. Francis et al. "A review on recent developments in solar photoreactors for carbon dioxide conversion to fuels". *Journal of CO2 Utilization* 47 (2021), 101515. DOI: 10.1016/j.jcou.2021.101515.
- [92] M. Ozkan et al. "Current status and pillars of direct air capture technologies". *iScience* 25.4 (2022), 103990. DOI: 10.1016/j.isci.2022.103990.
- [93] A. J. Bard and L. R. Faulkner. "Electrochemical Methods: Fundamentals and Applications" (2001).
- [94] K. Riahi et al. "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview". *Global Environmental Change* 42 (2017), 153–168. DOI: 10.1016/j.gloenvcha.2016.05.009.
- [95] C. L. Fyson et al. "Fair-share carbon dioxide removal increases major emitter responsibility". *Nature Climate Change* 10.9 (2020), 836–841. DOI: 10.1038/s41558-020-0857-2.
- [96] ESMAP. *Global Photovoltaic Power Potential by Country*. 2020. URL: <https://globalsolaratlas.info/global-pv-potential-study> (visited on 01/27/2023).
- [97] M. M. May and K. Rehfeld. "Negative Emissions as the New Frontier of Photoelectrochemical CO2 Reduction". *Advanced Energy Materials* (2022), 2103801. DOI: 10.1002/aenm.202103801.
- [98] D. Esrafilzadeh et al. "Room temperature CO2 reduction to solid carbon species on liquid metals featuring atomically thin ceria interfaces". *Nature Communications* 10.1 (2019), 865. DOI: 10.1038/s41467-019-08824-8.
- [99] M. Iturbide et al. "An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets". *Earth System Science Data* 12.4 (2020), 2959–2970. DOI: 10.5194/essd-12-2959-2020.

Manuscript 2 — Supplementary Material | B

Supplementary Material to:

M. Adam, T. Schürmann, and K. Rehfeld (2026b). “Future volcanic eruptions shift the timing of net-zero emissions”. *EarthArXiv [preprint, accepted: PLOS Climate]*. DOI: [10.31223/X5946V](https://doi.org/10.31223/X5946V)

Refer to Chapt. 7 for a declaration on author contributions.

Supplementary Information to “Future volcanic eruptions shift the timing of net-zero emissions” by M. Adam et al.

In this Supplementary Information (SI), we describe climatological mean and variability responses to intermittent volcanic forcing in our ESM simulations (Sect. S1). We also discuss sensitivities of emulated temperature uncertainty to forcing characteristics (Sect. S2) and of internal surface climate variability to land–vegetation–atmosphere feedbacks (Sect. S3). In addition, we provide supplementary information on the forcing ensemble (Fig. S1), emulator design and fitting (Table 1, Fig. S2–S4), testing the emulator’s sensitivity and convergence (Fig. S5–S6), mean and variability responses (Fig. S7–S8), shared variances and inferred CO₂ flux uncertainties (Fig. S9–S13), and land–vegetation–atmosphere feedbacks (Fig. S14–S17).

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S1 Climatic responses to volcanic forcing

Surface cooling arises as a near-global air temperature response to volcanic forcing in the MPI-ESM simulations (Fig. 1c). The mean hydroclimate response is more heterogeneous, however. This becomes evident when comparing annual precipitation with the time-integrating signal of soil moisture. Our simulations exhibit a weakening of the equatorial precipitation systems in response to cooling, accompanied by a strengthening in the southern Indian Ocean and North Atlantic (Fig. 1e), suggesting some dynamical changes. Spatial patterns in soil moisture anomalies conform with changes in precipitation (Fig. 1f). Significant changes are nevertheless more localized in equatorial Africa, northwestern South America, and parts of the Northern Hemisphere's mid-latitudes. Similarly, significant anomalies in vegetation productivity and natural net carbon uptake are spatially well confined (Fig. S7b, c), showing a substantial overlap that significantly impacts the moisture budget (Fig. 1f). Although vegetation productivity significantly decreases in equatorial Africa in response to changes in radiative and climatic drivers, net carbon uptake into natural sinks increases within this region. This effect is due to the slowing decomposition of soil organic matter under cooler, less humid climatic conditions (Fig. S7d). In contrast, intermittent volcanic forcing significantly reduces natural carbon uptake in mid-latitudes, including southern Africa, central North America, and parts of central Eurasia. Here, the regional surplus in precipitation stimulates organic matter decomposition, which is not outweighed by an increase in vegetation productivity (Fig. S7c).

Intermittent forcing significantly amplifies the multi-annual to multi-decadal variability of the Earth's global radiative imbalance and surface air temperature (Fig. 1a, b). The ensemble mean spectrum of global mean surface air temperature (Fig. 1b, S8) prominently reflects this variability increase through a significantly higher power spectral density and an increased spectral scaling on timescales of 5–50 years. As a consequence of the supplementary variability, the 95 % confidence empirical spread between ensemble members increases by time-averaged factors of 6.2 for the radiative budget and 4.4 for surface air temperature when compared to a control ensemble (Fig. 1a). This increase in ensemble spread results from temporary differences in forcing between simulations with momentarily higher and lower event magnitudes. The enhanced ensemble spread does not exhibit a considerable dependency on the CO₂ state. However, individual large volcanic events at peak CO₂ concentration, as well as during level-off and stabilization, notably increase the spread due to the ensemble size (Section 2.2). This leads to variations in the relative increase of the surface air temperature's ensemble spread between time segments of up to -34 % and +172 % of the time-averaged mean.

S2 Probing the sensitivity of uncertainty estimates on ensemble size and forcing characteristics

Our assessment suggests the time-averaged uncertainty estimate of the global mean surface air temperature pathway to converge at 0.67 K (0.32 K increase compared to internal variability), when intermittent volcanic forcing is included (Section 2.2). Here, we quantify the convergence behavior in more detail and explore the effect of forcing load and intermittency on the global uncertainty estimate. To assess the convergence characteristics, we compare the median uncertainty and ensemble spread of the global mean temperature pathway between the simulated ensemble, the 300-member emulation ensemble, and a reduced emulation ensemble with 100 members (Fig. S5a). The empirical 95 % ensemble spread of the temperature pathway's time-averaged uncertainty is large for the simulated ensemble, spanning from 0.20 K to 1.36 K. The spread gets reduced by a third for the 100-member ensemble (0.42 K to 1.15 K) and halved for the full emulation ensemble (0.44 K to 0.95 K). At the same time, the simulation ensemble underestimates the median uncertainty by 0.20 K compared to the 300-member

ensemble, which is equivalent to 57 % of the internal variability. In contrast, the 100-member ensemble's offset to the 300-member reference is only 0.02 K, suggesting the uncertainty estimate to converge at approximately this ensemble size. A more granular analysis confirms that the median uncertainty and ensemble spread stabilize between 180 and 200 members (Fig. S5).

Clustering the emulated ensemble by total aerosol load confirms that differences in the time-aggregated magnitude of volcanic eruptions have a substantial effect on the estimate of global mean surface air temperature uncertainty (Fig. S5b). On the one hand, the median temperature uncertainty drawing on the fifth to 40th quartile of aerosol loads in the forcing dataset (ensemble size 105 members) reaches 0.51 K, which is 24 % lower than the estimate based on the full ensemble. On the other hand, for the 60th to 95th quartile of aerosol loads (equally 105 members), the uncertainty estimate reaches 0.83 K, which lies 24 % above the full ensemble's median.

In contrast to this strong effect of the aggregated aerosol load, differentiating by event count has no substantial effect. Regardless of whether the analysis is confined to those ensemble members with the 20 % fewest events or the 25 % most eruptions (excluding the 5 % lowest and highest aerosol loads), the respective temperature uncertainty estimates of 0.63 K and 0.61 K are virtually the same (Fig. S5c). However, the event count is relatively homogeneous in the forcing ensemble, with 7.3 events on average in the lowest 20 % and 10.5 in the upper 25 %. Therefore, we conduct a second sensitivity experiment with a reference subset from the forcing ensemble and an additive combination of selected members of the forcing ensemble. Compared to the reference subset (54 members), this modified forcing ensemble (55 members) decreases intermittency (average time between events) by 11 %, with an event occurring every 12.5 years on average versus 14 years in the reference subset. We select the members for additive stacking from the original forcing ensemble in such a way that the resulting ensemble, with decreased intermittency, has an average load distribution that is similar to that of the reference subset (not shown). This design isolates the effects of intermittency from those of the aggregated aerosol load. Compared to the reference ensemble with higher intermittency (lower event count), the ensemble with stacked forcing time series results in a lower temperature uncertainty estimate at 0.66 K (Fig. S5d), compared to 0.79 K for the reference ensemble, indicating that the forced response has only a short-term memory of intermittent volcanic forcing (Discussion, Section S3).

S3 Destabilizing land–atmosphere feedbacks enhance internal temperature variability without affecting the forced response

Our results indicate that the additional biosphere flux uncertainty due to intermittent volcanic forcing is still small compared to the strong variability increase in the climate variables (Section 2). This raises the question of whether different parametrizations of atmosphere–vegetation feedbacks could reduce the simulated biosphere's resilience to sporadic forcing and modulate the climate variability influenced by these feedbacks. Therefore, we conduct two ESM sensitivity experiments to explore the coupled system's stability with altered feedbacks. We leverage the emulator to separate forced from internal variability. The first sensitivity experiment turns off effects of climate change on vegetation. This setup results in lower biosphere productivity because vegetation does not experience the CO₂ fertilization effect. In addition, no shift in vegetation zones occurs, particularly no northward expansion of boreal forests. The second sensitivity experiment induces slightly more localized changes by lowering the albedo of C4 grasses situated in the (sub-)tropics to the value of tropical deciduous trees. This experimental change is intended to enhance local evaporation and increase sensible

heat release, both of which destabilize the regional climate and vegetation.

Anomalies in mean climatologies confirm the intention of the sensitivity experiments. Lowering the C4 grass albedo reduces surface albedo by up to 20 % in tropical to subtropical grasslands and savannas (Fig. S14a). In addition, vegetation–climate feedbacks also lead to a subtle albedo increase in Northern Europe. As a result of the induced changes in latent and sensible heat release (Fig. S14d, e), shifting circulation patterns stimulate precipitation particularly along the Atlantic inner-tropical convergence zone and the Northern Sahara. This occurs especially during the overshoot scenario’s initial phase (Fig. S14b). At the same time, precipitation gets reduced in the Eastern Pacific Ocean, Southern Indian Ocean, and over the Arabian Peninsula and Central Asia. Cooling of up to -1 K occurs along the Western coast of North America, Northern Eurasia and at the core of the Amazon rainforest, Eastern Asia, subtropical Africa, the Caribbean, and the Southern Ocean experience warming (Fig. S14c). In later stages of the overshoot scenario, some regional cooling effects are smaller or reversed, while dominant changes in circulation patterns persist (not shown).

Similar to the sensitivity experiment with lower C4 grass albedo, disabling the climate change feedback on vegetation yields a spatially heterogeneous mean response (Fig. S15). While albedo changes in the low latitudes are a lot smaller than in the experiment with lowered C4 albedo (Fig. S15a), disabling climate change–vegetation feedbacks results in a similar increase in high-latitude surface albedo in Eurasia, and a decrease over parts of North America. In return, anomalies in surface air temperature overlap substantially between the sensitivity experiments (Fig. S15c). This overlap also applies to precipitation increases along the Atlantic inner-tropical convergence zone, albeit with a negative anomaly in the Western Sahara, which does not occur in the experiment with lowered C4 albedo (Fig. S15b). In addition, the disabled climate change–vegetation feedbacks lead to a pronounced precipitation increase in the Equatorial Pacific where there is a substantial decrease in the experiment with lowered C4 grass albedo. Spatial mean changes are to some extent state-dependent (not shown), as are impacts on in multi-annual to multi-decadal temperature variability.

Altering vegetation feedbacks increases internal variability of global mean surface air temperature significantly in both sensitivity experiments, by factors of 2.6 and 2.1 on multi-annual time scales (Fig. S16). This variability increase is less pronounced in the experiment with lowered C4 grass albedo. This experiment exhibits a second significant increase, slightly below 30 years, which is absent in the experiment with a disabled climate change effect on vegetation. In return, disregarding the effect of climate change on vegetation causes a slight but significant decrease in variability on a time scale of approximately 20 years. Contrasting these significant changes in internal variability, the response to intermittent forcing remains unaffected by changes in vegetation–atmosphere feedbacks in both sensitivity experiments (Fig. S16). Shifting vegetation–atmosphere feedbacks also significantly destabilize global carbon fluxes on multi-annual time scales when neglecting the climate change effect on vegetation, reflected by an approximate doubling of the respective variance ratios (Fig. S17). At the same time, decadal to bi-decadal variability of net carbon uptake and vegetation productivity gets significantly reduced (Fig. S17). There are signs of decreased stability of the global GPP flux and increased stability of net carbon uptake on multi-annual time scales when lowering the C4 grass albedo. However, these induced changes are mostly insignificant given that the sensitivity experiments are built on single simulations, not comprehensive ensembles.

Supplementary Tables

Table 1 | Prior ranges for EBM fitting. This table reports only parameters that differ from the default *experimental* configuration of the ClimBayes package. Refer to Schillinger et al. [1] for a comprehensive documentation.

Parameter	Prior bounds
λ_1	[0.2, 25.0]
λ_2	[0.005, 1.5]
F_0	[-3.0, 3.0]
C (capacity)	[5.0, 100.0]

Supplementary Figures

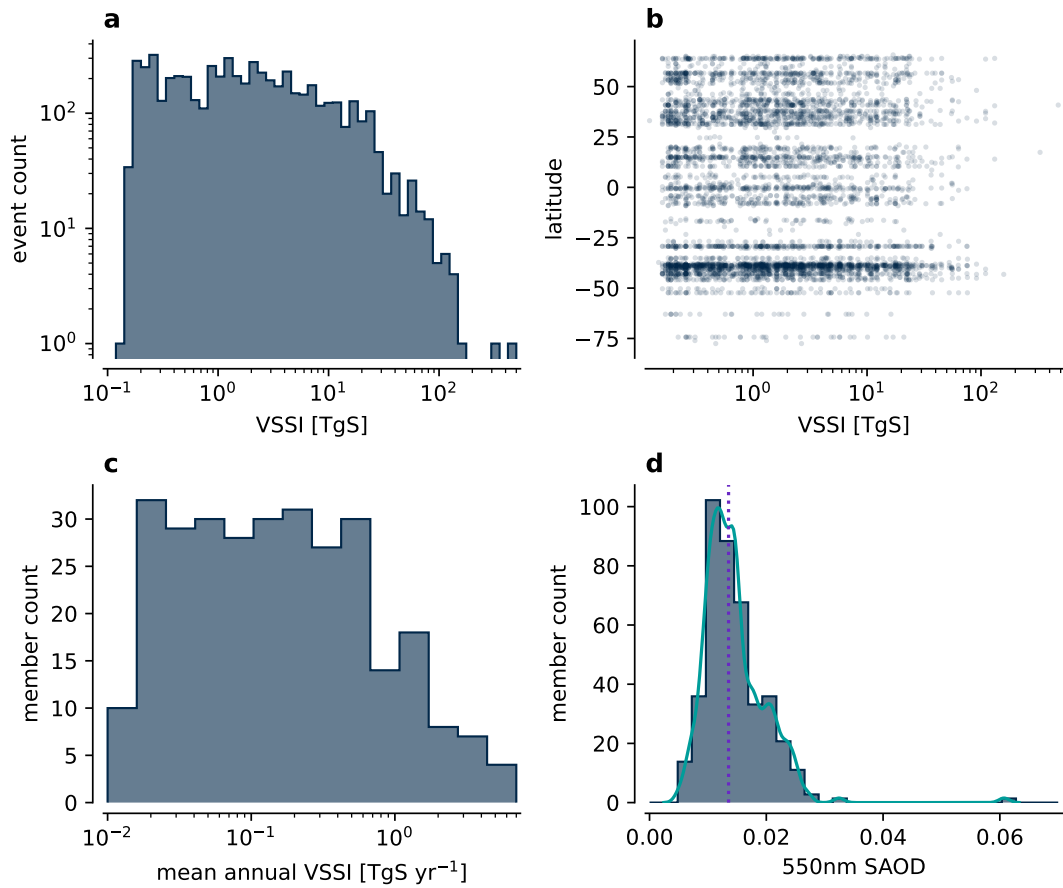


Figure S1 | Statistics of the volcanic forcing ensemble. (a) Event size distribution of volcanic stratospheric sulfur injections (VSSI) expressed as teragrams sulfur (TgS) across all 300 members of the forcing ensemble. (b) Latitudinal distribution of the same dataset. (c) Distribution of mean annual VSSI across the 300 members. (d) Distribution and kernel density estimate of the time-averaged stratospheric aerosol optical depth (SAOD) at 550 nm across the 300 members. The dotted vertical line indicates the median of the distribution (0.014).

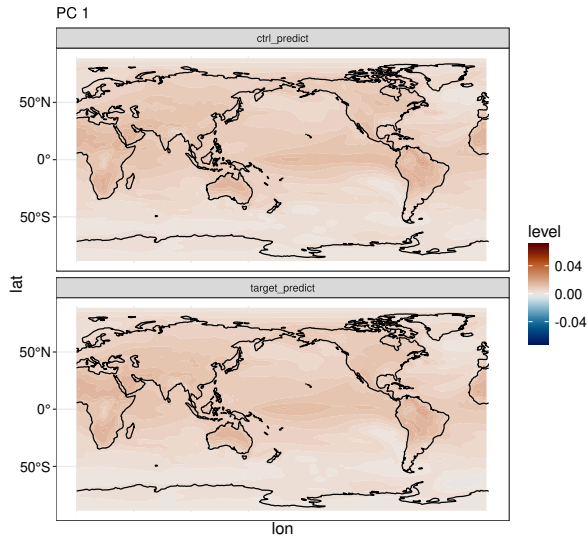
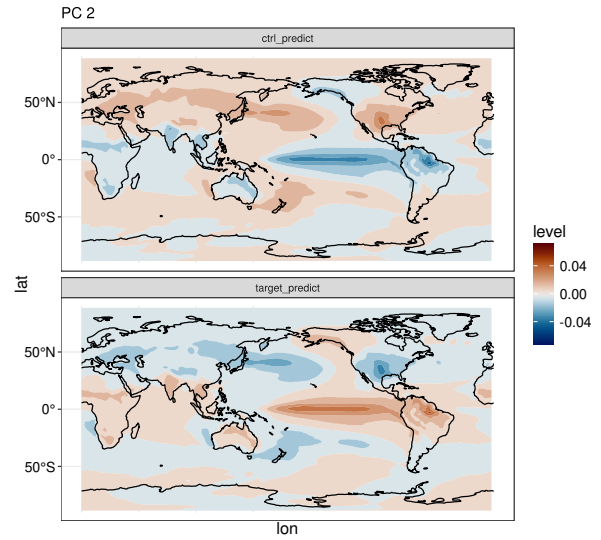
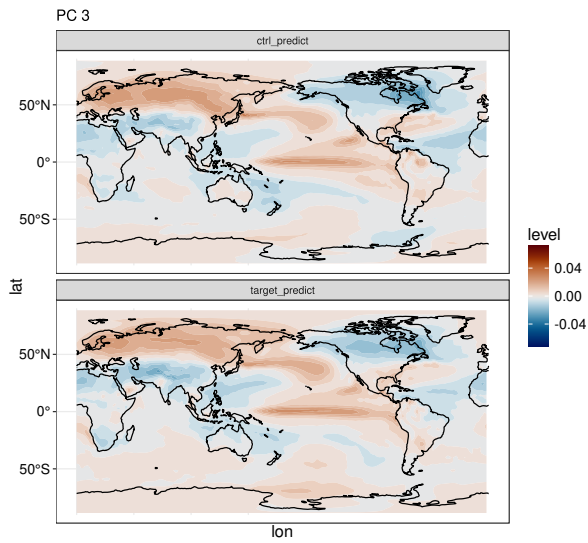
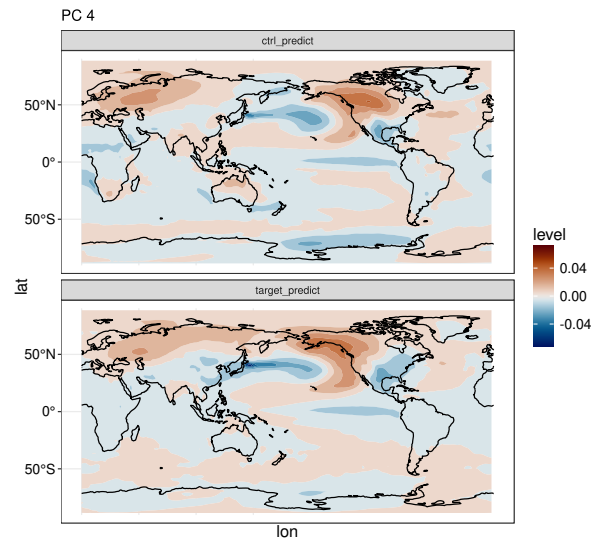
a**b****c****d**

Figure S2 | The first four spatial modes obtained from EOFs (a–d) for the control ensemble (top panels) and the ensemble with intermittent volcanic forcing (bottom panels). Note that the signs of the EOFs do not necessarily align. This is expected and accounted for when fitting the two-box EBM to the principal component time series. Coastlines from [naturalearthdata.com/downloads/110m-physical-vectors/110m-coastline](https://www.naturalearthdata.com/downloads/110m-physical-vectors/110m-coastline).

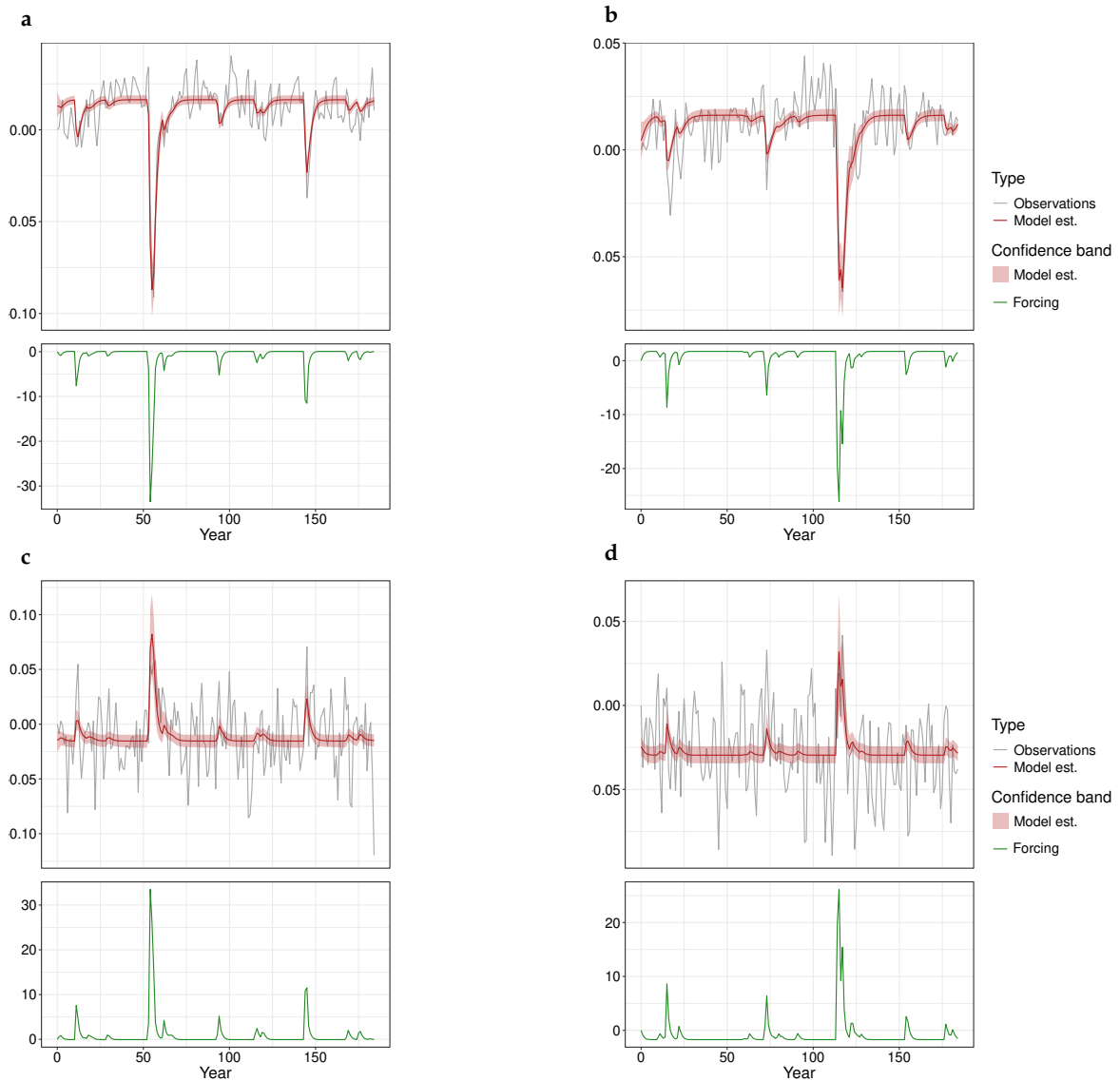


Figure S3 | Exemplary fits of the EBM to principal components. Fits are of the first (a, b) and third principal component (c, d) of ensemble members four and eight. Top subpanels show the full principle component time series with CO₂ trend removed (“Observation”) along with the fitted EBM estimate (“Model estimate” + 95 % confidence interval). Bottom subpanels depict the intermittent forcing, with time starting in 2015 CE (“Year 0”). Note that units are normalized and signs are not meaningful. Plots draw on built-in visualizations of the ClimBayes package [1].

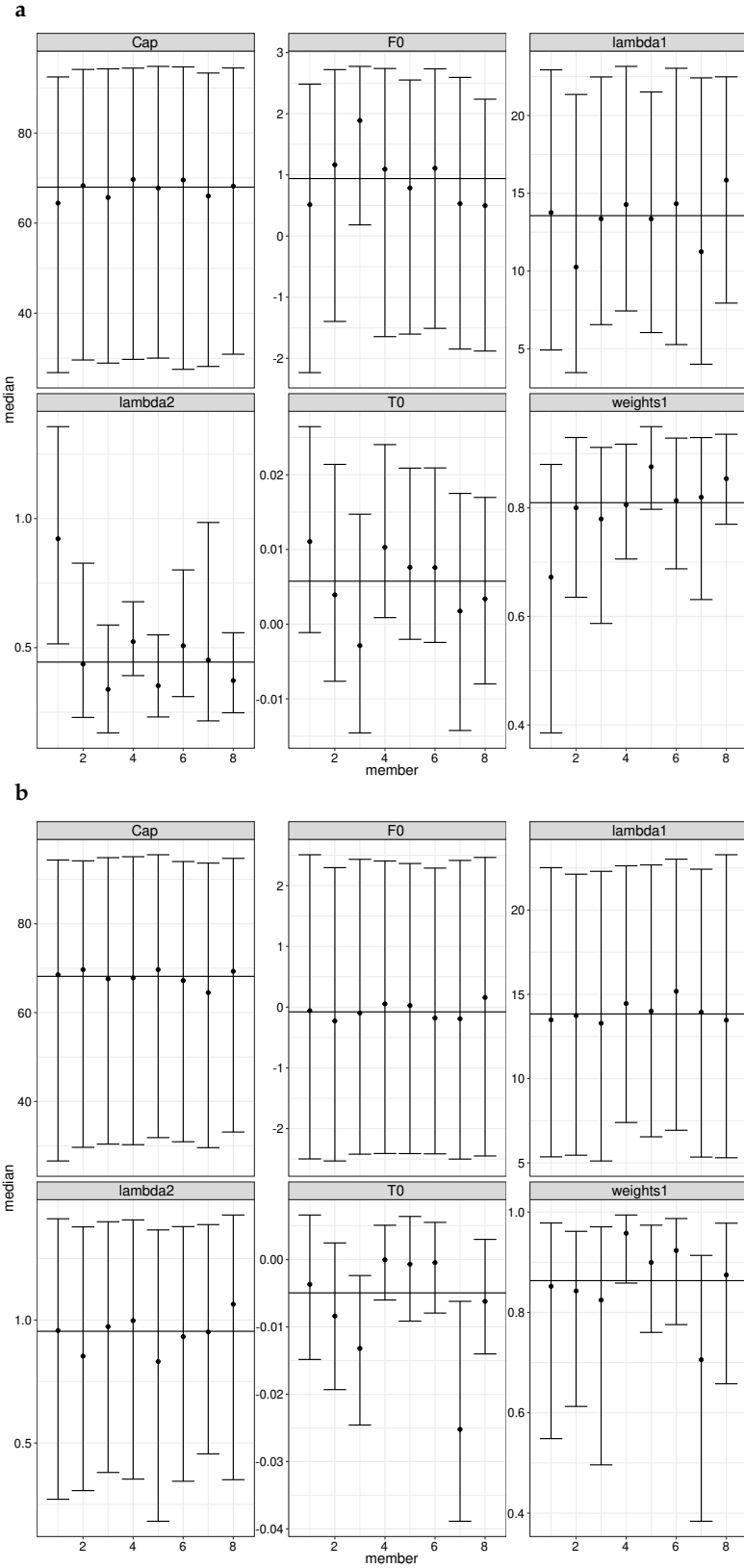


Figure S4 | Exemplary EBM parameters obtained for the first two principal components of all simulations with intermittent volcanic forcing. Errorbars represent 95% parameter confidence ranges inferred through Markov Chain Monte Carlo sampling. Horizontal lines indicate median parameter values, which are used when inverting the emulator. Refer to Schillinger et al. [1] for detailed model and parameter descriptions.

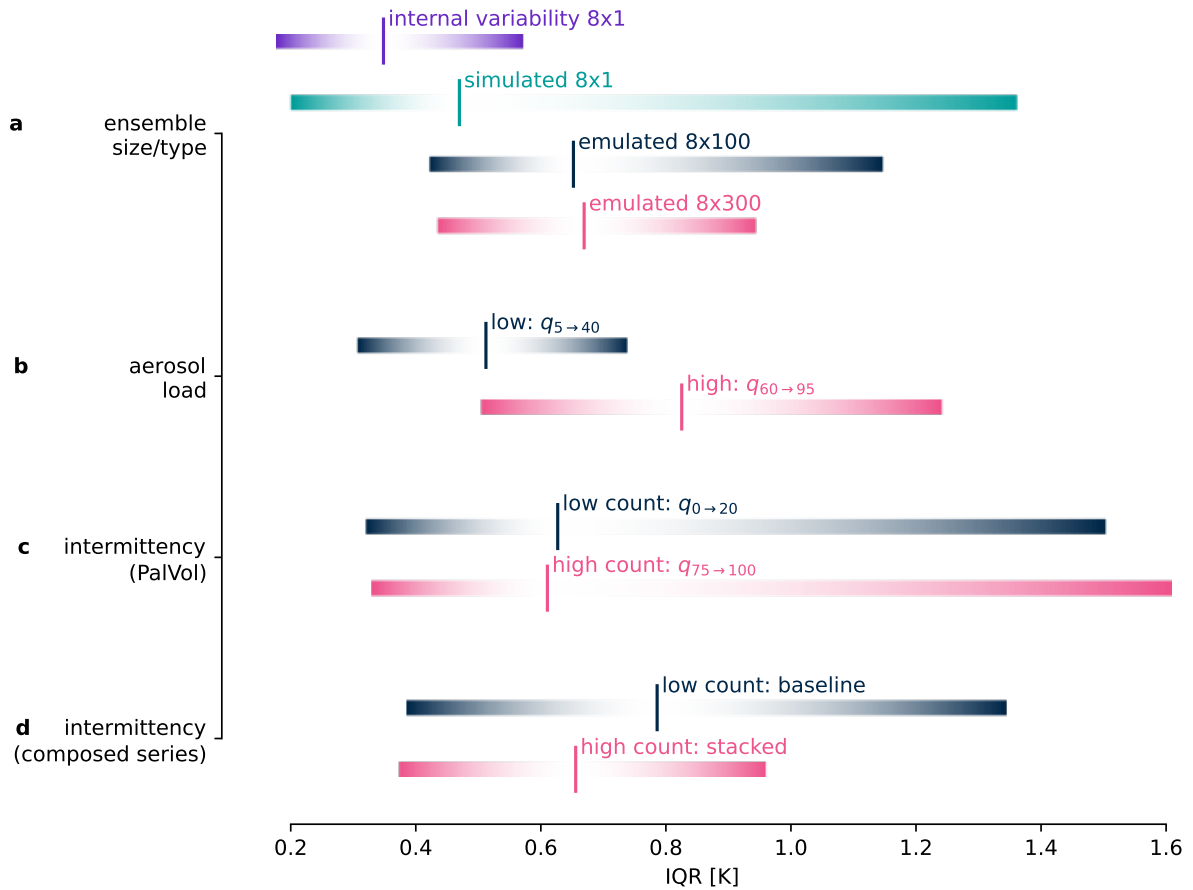


Figure S5 | Sensitivity of the predicted temperature uncertainty range to characteristics of the forcing ensemble. Vertical lines indicate the median 2.5–to–97.5 % inter-quartile range of global mean surface air temperature and shaded intervals span the range from the 2.5th to the 97.5th percentile. All sensitivity tests are conducted for the emulated 8x300 ensemble, except for the test on ensemble size and type in (a) which utilizes the ensembles as indicated. (b) The test of the inter-quartile range’s sensitivity to the total aerosol load from 2015 to 2200 compares the upper 60 to 95 % of injection loads to the lower 5 to 40 %. (c) Analogously, the intermittency tests on the PalVol dataset utilizes those forcing realizations with events occurring at least as often as in 75 % of all forcing realizations (high count, low intermittency) and those 20 % of realizations with the lowest event occurrence (low count, high intermittency). (d) The second test of inter-quartile range sensitivity to forcing intermittency compares a subset of the PalVol forcing with a similarly sized set of merged forcing time series (Sect. S2). The combined forcing dataset decreases intermittency by 11 % with respect to the baseline, while ensuring a comparable aerosol load distribution.

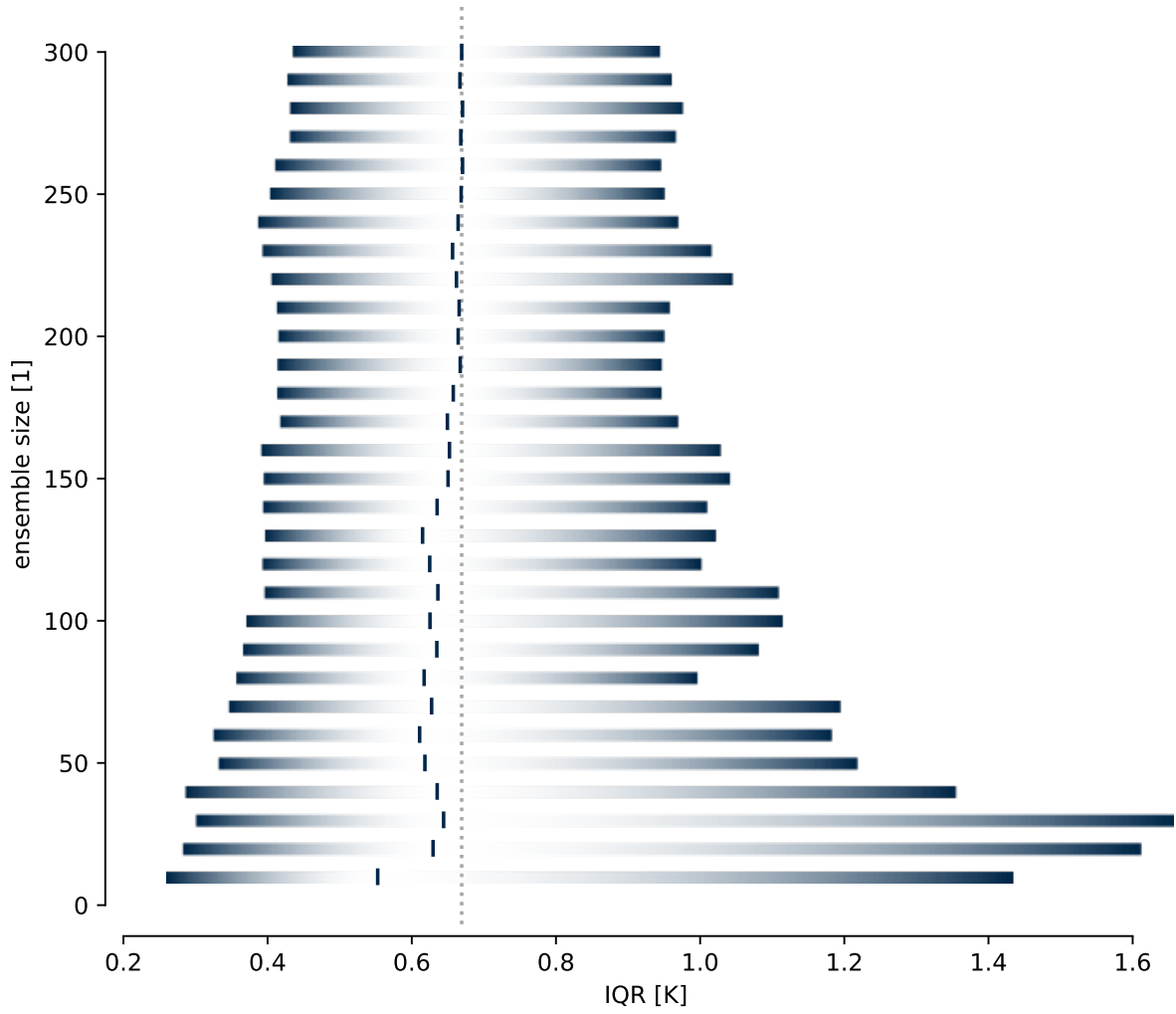


Figure S6 | Convergence of temperature uncertainty estimates with the emulated ensemble's size. The vertical dashed line indicates the 300-member ensemble median. Other description is analogous to Fig. S5.

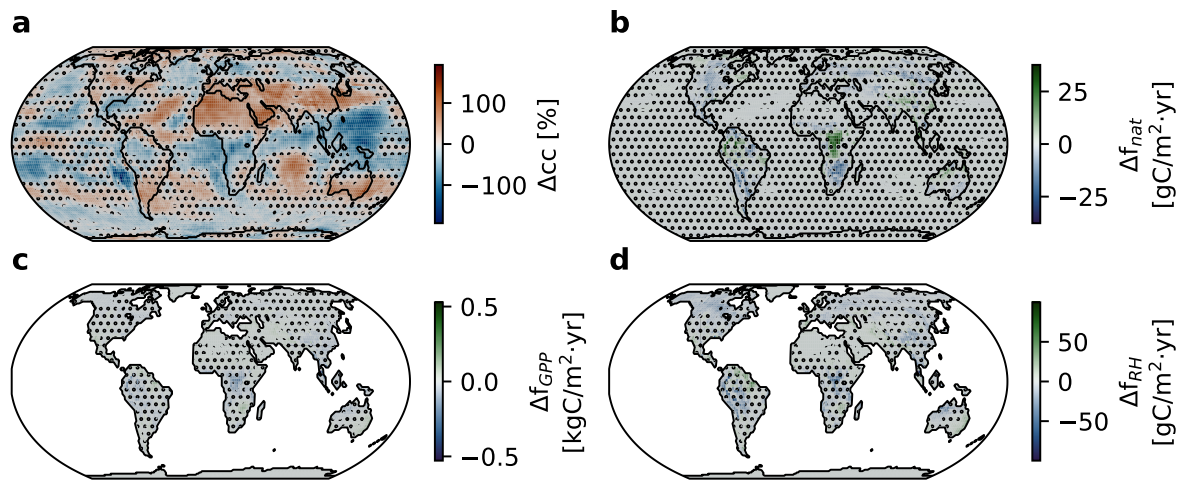


Figure S7 | Mean responses of simulations with intermittent volcanic forcing to the strongest 30 % of volcanic events. Panels show anomalies in (a) cloud cover, (b) net annual carbon uptake, (c) annual GPP flux, and (d) heterotrophic respiration. Further description is analogous to Fig. 1c–f.

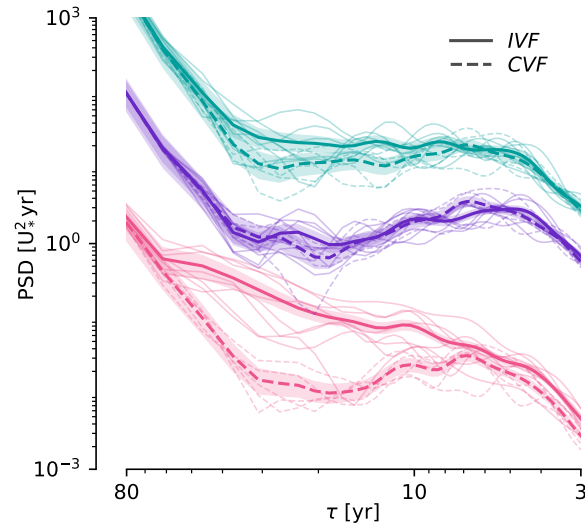


Figure S8 | Global mean power spectral density (PSD) across time scales τ for all members of the two simulation ensembles. Thin lines indicate individual ensemble members and thick lines the ensemble mean. Besides, the description is analogous to Fig. 1b.

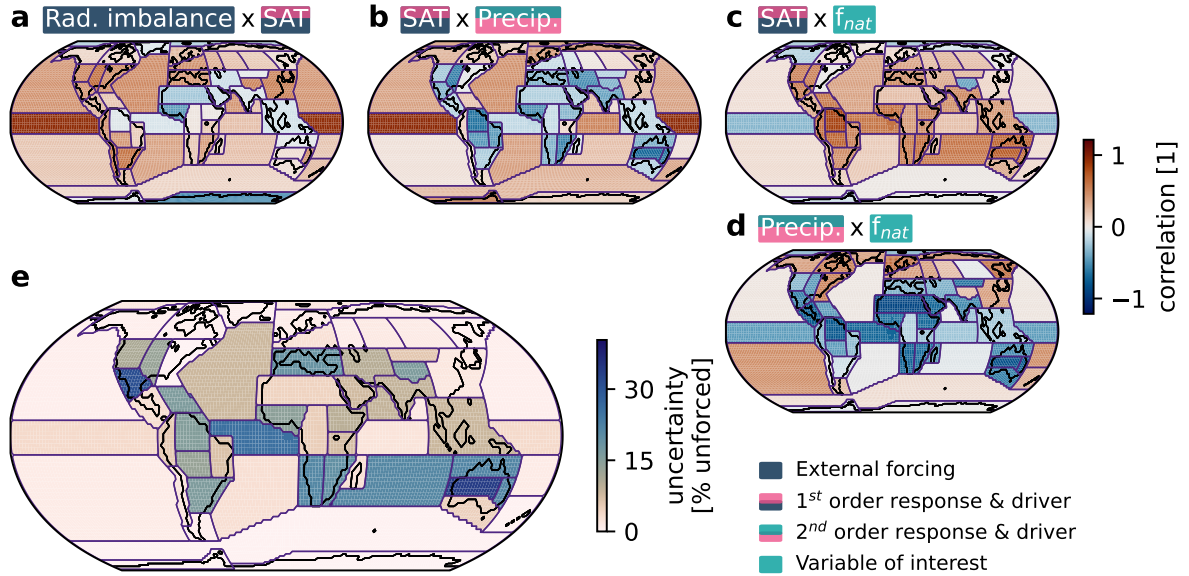


Figure S9 | (a–d) Shared variances between temperature and precipitation as climatic drivers and f_{nat} in response, with the resulting supplementary regional f_{nat} uncertainty from intermittent volcanic forcing (e). The description is analogous to Fig. 2. Note that this figure defines f_{nat} as Carbon flux *into* the atmosphere, in contrast to the conventions for f_{GPP} and for f_{nat} elsewhere.

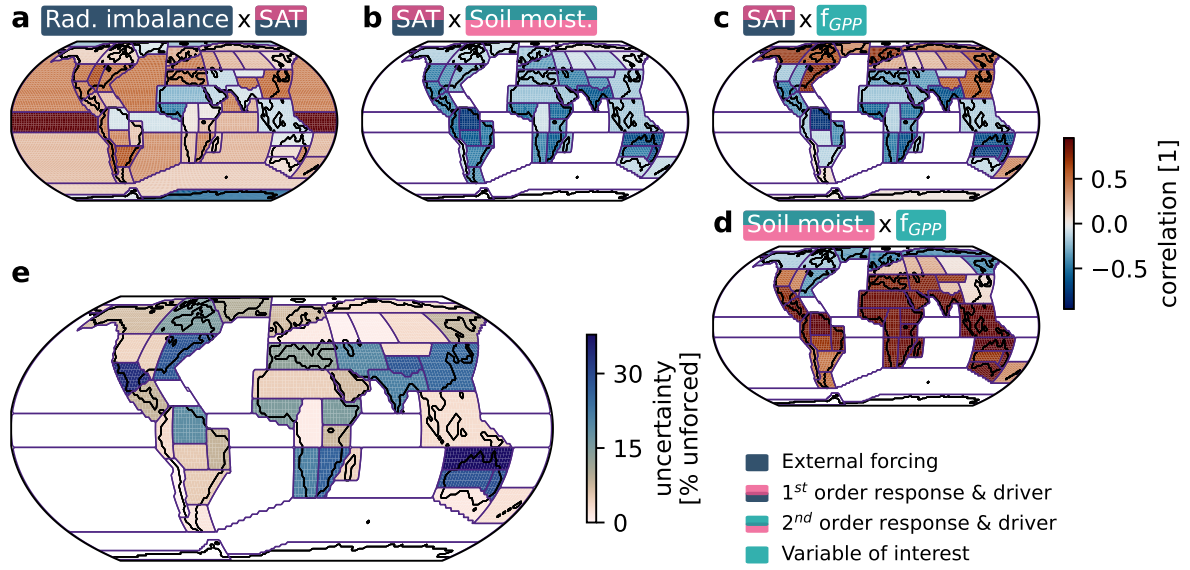


Figure S10 | (a–d) Shared variances between temperature and soil moisture as climatic drivers and f_{GPP} in response, with the resulting supplementary regional f_{GPP} uncertainty from intermittent volcanic forcing (e). The description is analogous to Fig. 2.

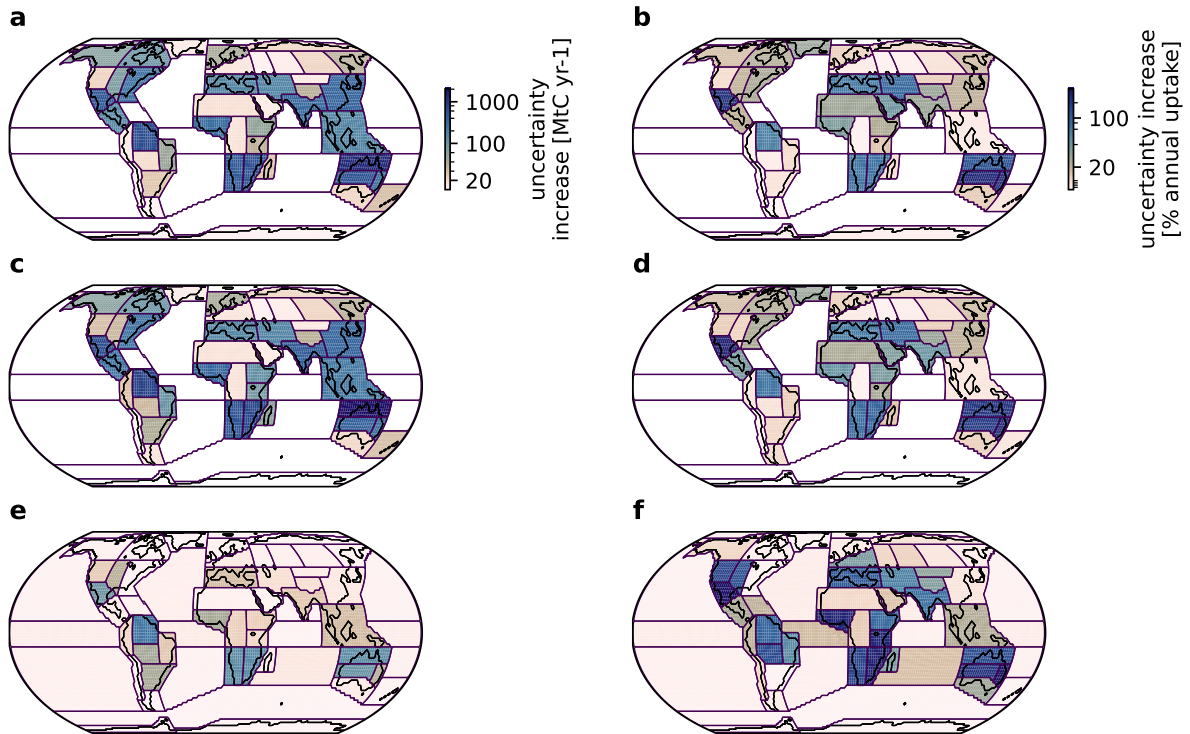


Figure S11 | Regional uncertainty increase of f_{GPP} and f_{nat} in response to intermittent volcanic forcing. Columns report absolute uncertainty increase (first column) and relative increase with respect to annual uptake (second column), averaged over the scenario's CO_2 rise, peak, and decline periods (Fig. 1). Panels show results for f_{GPP} with temperature and precipitation as climatic drivers (top row), with temperature and soil moisture as drivers (middle row), and for f_{nat} with temperature and precipitation as drivers (bottom row).

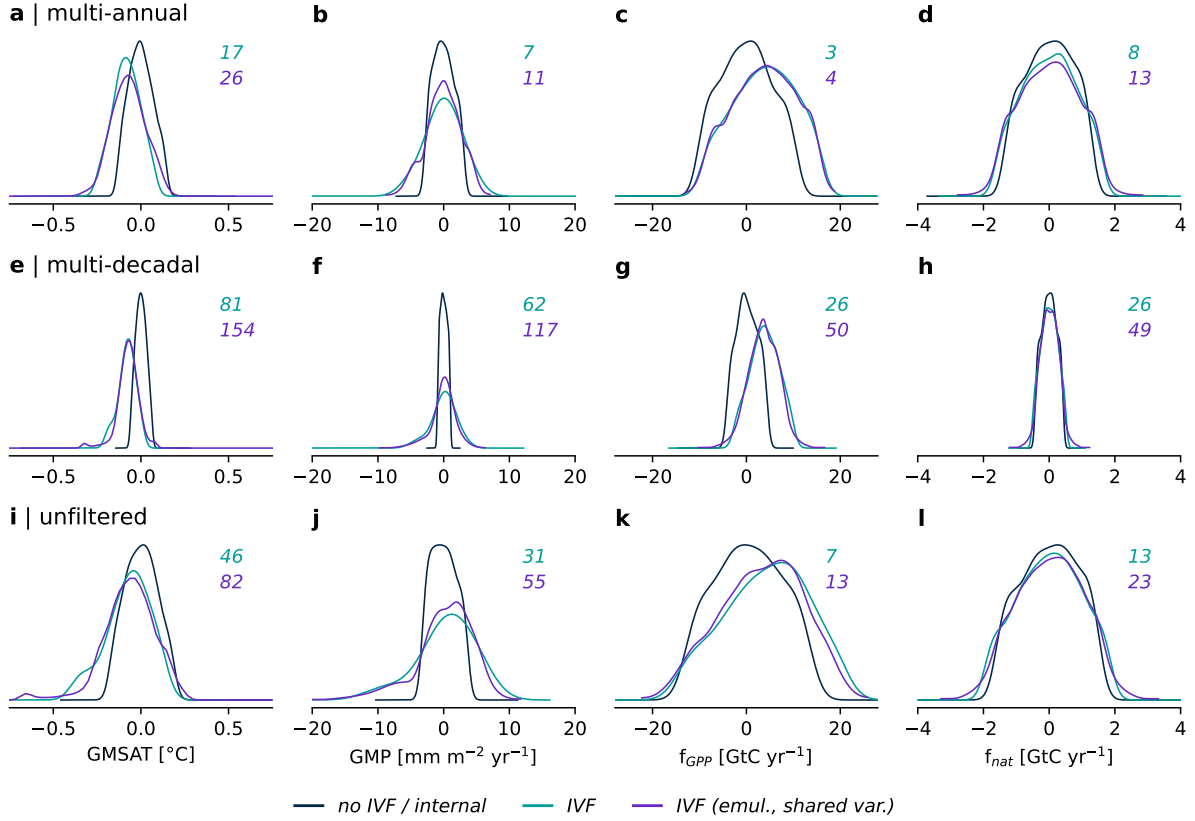


Figure S12 | Widened uncertainty distributions due to intermittent volcanic forcing used to augment SSP simulations of the MPI-ESM Grand Ensemble [2] with the varying forcing's effect. We use the modeled global mean surface air temperature data (first column; a, e, i) to calibrate empirical quantile transformations on the relation between modeled internal variability ("internal") and emulated internal+forced variability estimates ("IVF (emul.)"; Data & Methods). Subsequently, we propagate supplementary uncertainty with the shared variance approach ("IVF (shared var.)") onto the unforced distributions ("no IVF") to include effects of intermittent volcanic forcing on global precipitation (second column; b, f, k), GPP (third column; c, g, k), and net carbon uptake (last column; d, h, l). The forced simulations are shown for comparison ("IVF"). Rows depict variability on multi-annual (1–10 years; a–d) and multi-decadal time scales (10–30 years; e–h), as well as the unfiltered signal (i–l). Each distribution of internal variability is centered and corresponding forced distributions are shifted relative to this distribution by including the mean effect of additional volcanic forcing. Annotations report scaling factors in % for propagating the supplementary 95 % inter-quartile range uncertainty with the calibrated empirical quantile transformation. These scaling factors align closely with the simpler uncertainty propagation (Data & Methods).

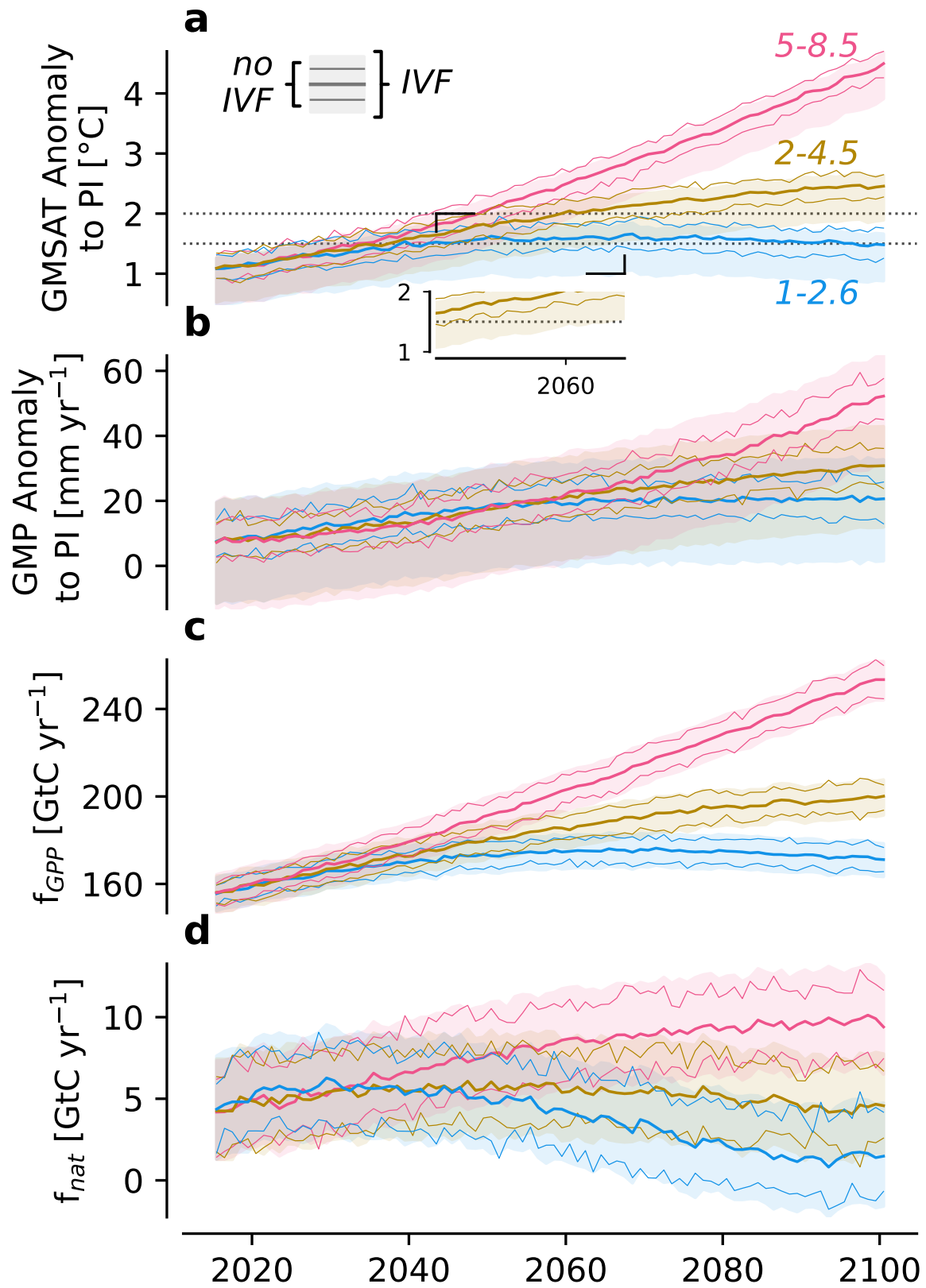


Figure S13 | Increased variability along future climate and carbon cycle pathways for the unsmoothed signal. Description is analogous to Fig. 5.

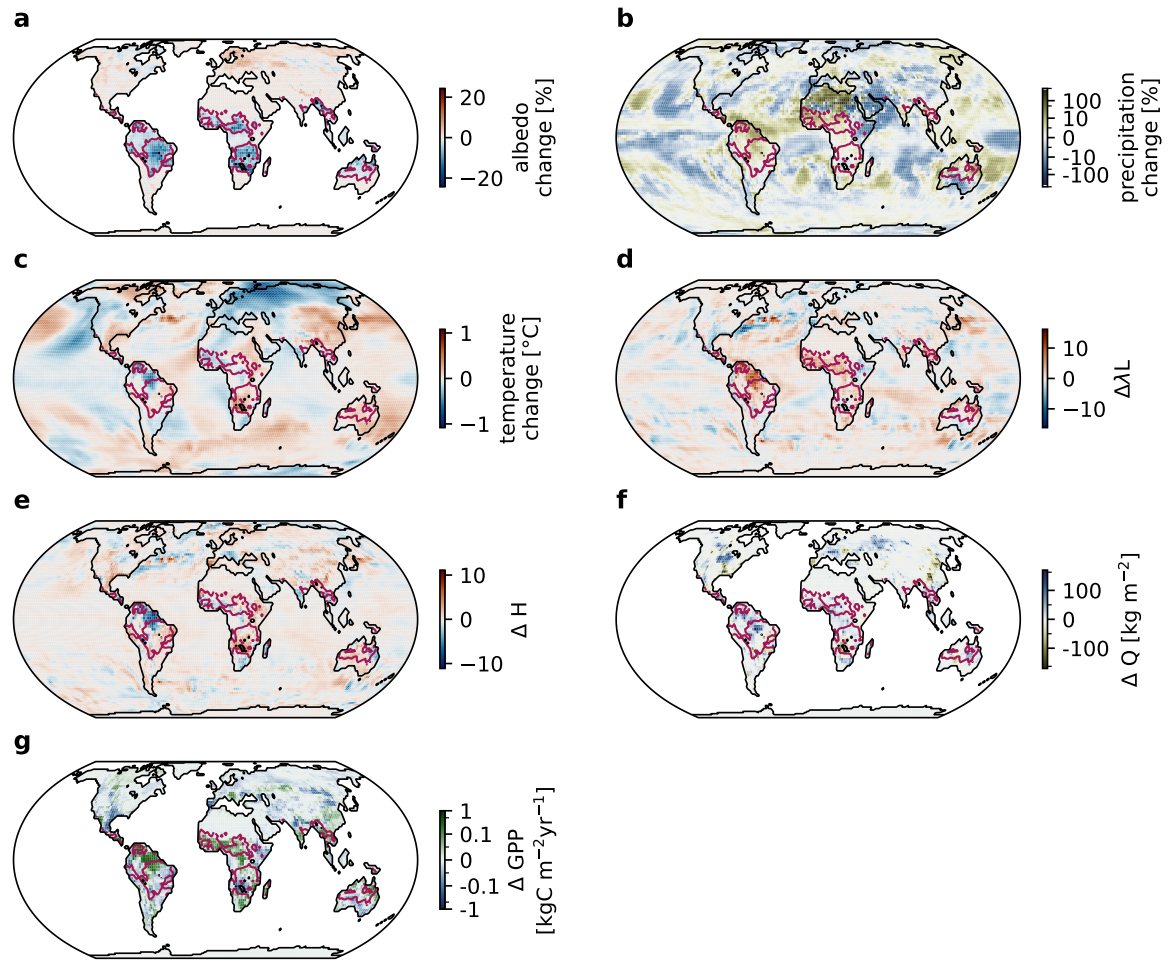


Figure S14 | Relative climatological mean anomalies of the sensitivity experiment with lowered C4 grass albedo to a control simulation. Panels depict anomalies in albedo (a), precipitation (b), surface air temperature (c), latent heat flux (d), sensible heat flux (e), full-column soil moisture content (f), and f_{GPP} . Contours outline the areas with a minimum of 10 % of C4 grass cover, providing an indication of the regions affected by the albedo change.

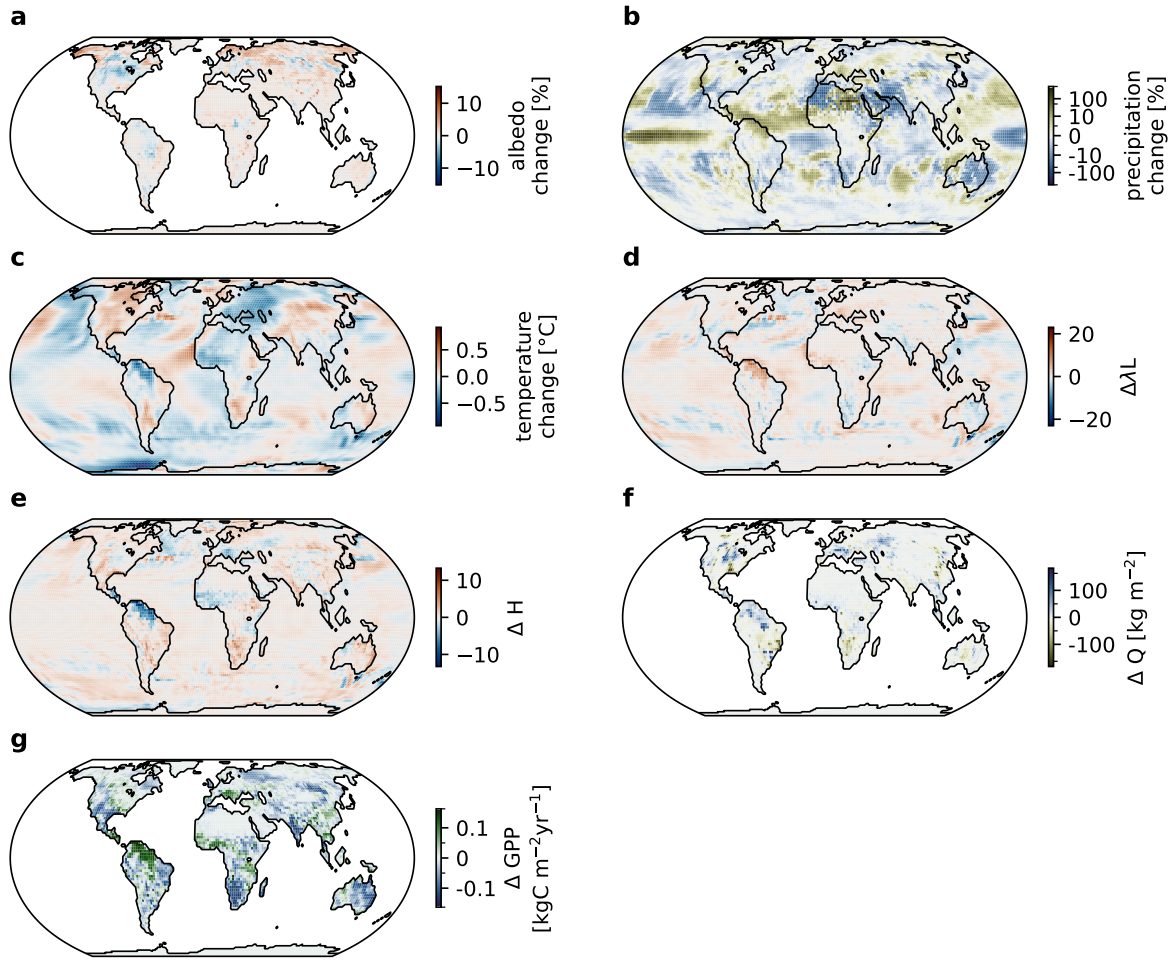


Figure S15 | Relative climatological mean anomalies of the sensitivity experiment with disabled climate change feedback on vegetation to a control simulations. Panel description analogous to Fig. S14.

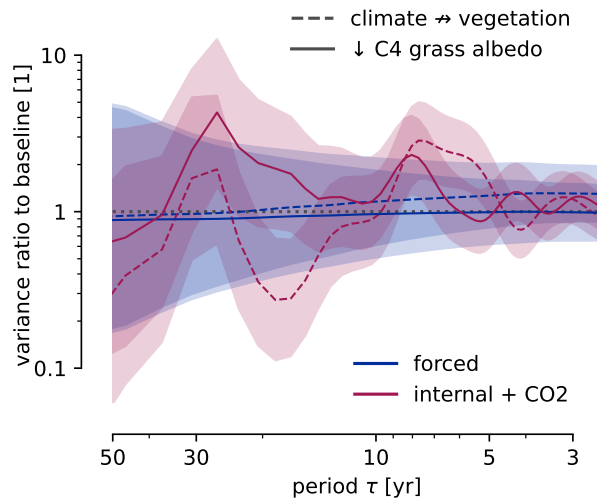


Figure S16 | Effect of vegetation feedbacks on internal variability and forced response of global surface air temperature. Variance ratio of the forced response and internal variability of global mean surface air temperature to control experiments in sensitivity experiments with the influence of climate change on vegetation disabled ($\rightarrow$) and with lowered C4 grass albedo ($\downarrow$). Both the sensitivity and control experiments include the same realization of varying volcanic forcing. The 95 % confidence intervals are based on the degrees of freedom of the spectrum of the sensitivity experiment and the control simulation, and on propagating the resulting uncertainty into the variance ratios (Data & Methods).

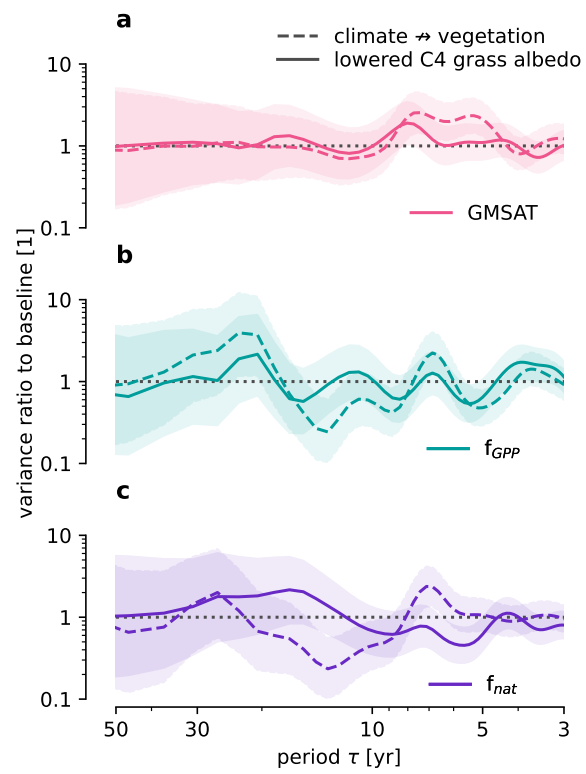


Figure S17 | Effect of vegetation feedbacks on the internal variability of GMSAT (a), f_{GPP} (b), and f_{nat} (c). The description is analogous to Fig. S16.

References – Supplementary Information

- [1] M. Schillinger et al. “Separating internal and externally forced contributions to global temperature variability using a Bayesian stochastic energy balance framework”. *Chaos: An Interdisciplinary Journal of Nonlinear Science* 32.11 (2022), 113146. DOI: 10.1063/5.0106123. eprint: 2206.14573.
- [2] D. Olonscheck et al. “The New Max Planck Institute Grand Ensemble With CMIP6 Forcing and High-Frequency Model Output”. *Journal of Advances in Modeling Earth Systems* 15.10 (2023). DOI: 10.1029/2023ms003790.

Manuscript 3 — Supplementary Material | C

Supplementary Material to:

M. Adam, E. Ziegler, B. Gonzalez, N. Weitzel, and K. Rehfeld (2026a). “Earth system models might overestimate the local plant productivity response to temperature–moisture extremes”. *EGUsphere* [preprint, under review]. DOI: [10.5194/egusphere-2026-626](https://doi.org/10.5194/egusphere-2026-626)

Refer to Chapt. 8 for a declaration on author contributions.

Supplementary Information to “Earth system models overestimate the local plant productivity response to temperature–moisture extremes” by M. Adam et al.

In this Supplementary Information (SI), we provide additional figures on the nullmodel’s convergence (Sect. S1), significance patterns that overlap between the datasets (Sect. S2), the assignment of IPCC regions to climatic zones (Sect. S3), statistical coupling strength and peak timing (Sect. S4), mechanistic responses (Sect. S5), and mean GPP biases (Sect. S6).

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S1 Convergence of the null model

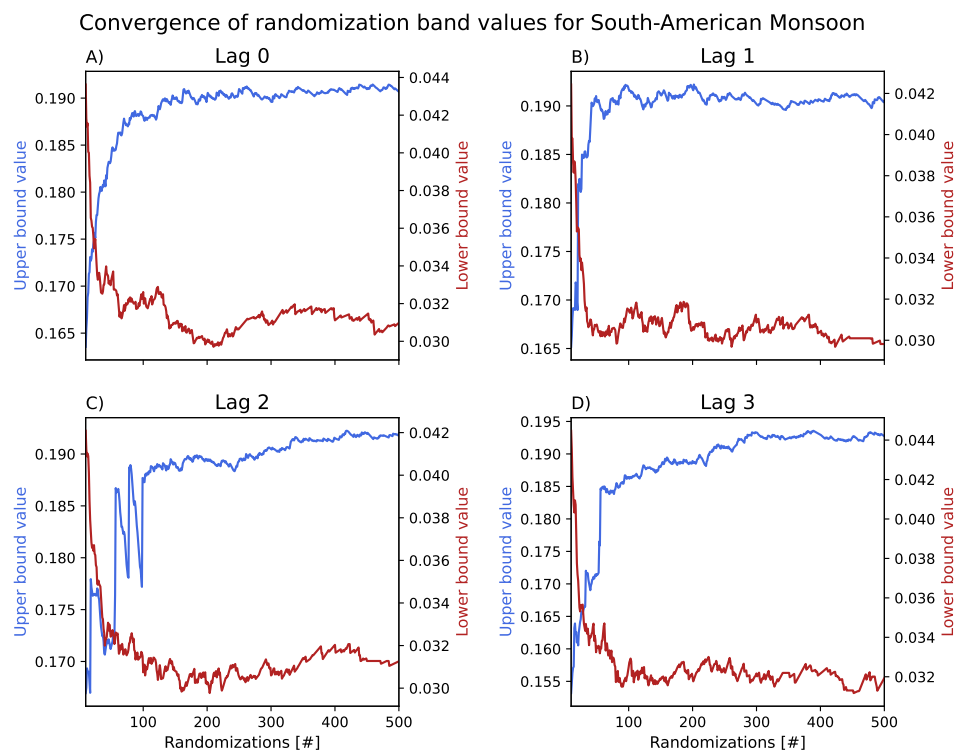


Figure S1 | Nullmodel convergence at different lags between temperature–moisture and GPP extremes. This example covers the South-American Monsoon (see Iturbide et al. (2020)) and reports the 95% range of the nullmodel ensemble as upper and lower bounds in units $^{[COR]}/_{100}$.

S2 Significance patterns and share of significant cells

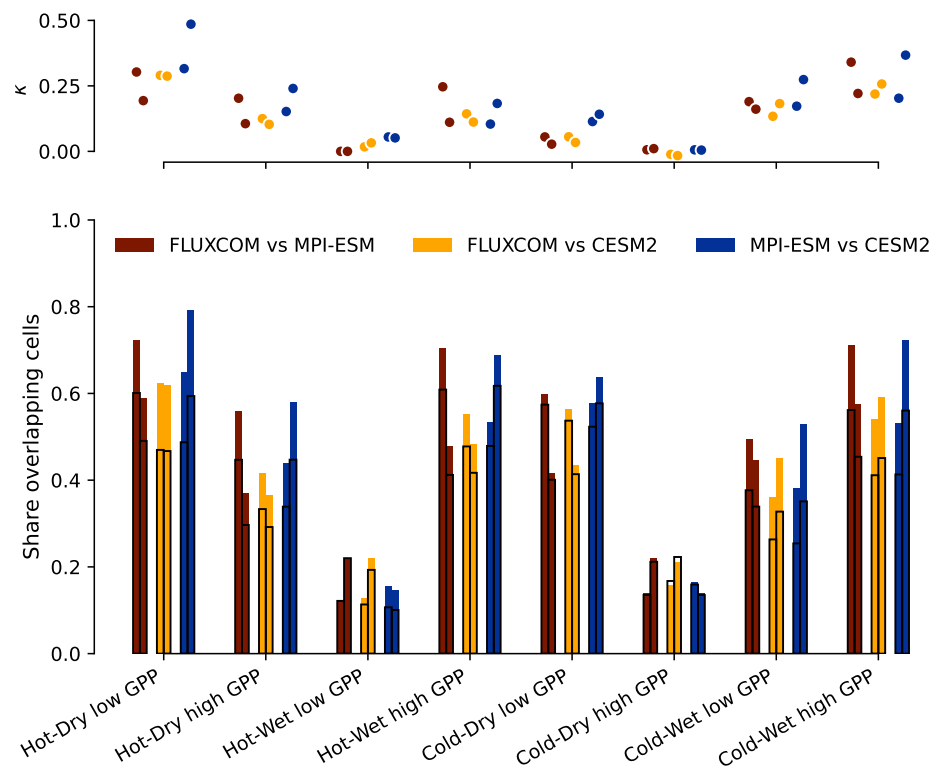


Figure S2 | Overlap between significance patterns in FLUXCOM and the ESMs. Black outlines (bottom panel) represent the average overlap when randomizing the patterns, indicating that patterns overlap by chance. The likelihood of accidentally overlapping patterns is reflected in the κ statistics (upper panel): $\kappa \approx 0$ represents randomness, $\kappa \rightarrow 1$ indicates high confidence in the signal.

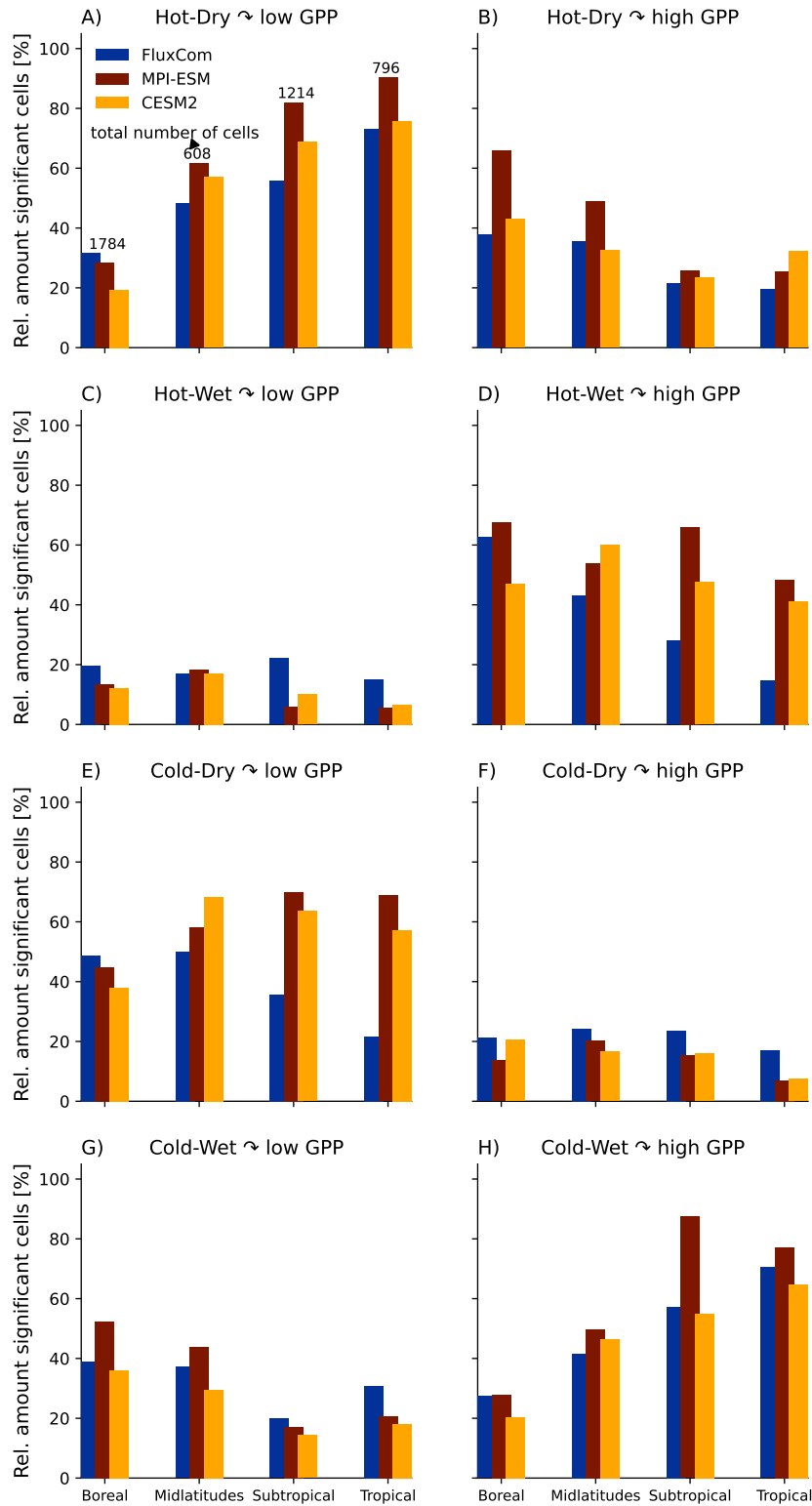


Figure S3 | Share of grid cells with significant statistical coupling between climatic compound and GPP extremes. Here, all grid cells which exceed the null model's 95th quantile at lag one or more are considered significant. Combinations of GPP extremes in the succession of temperature–soil moisture extremes are indicated above individual panels.

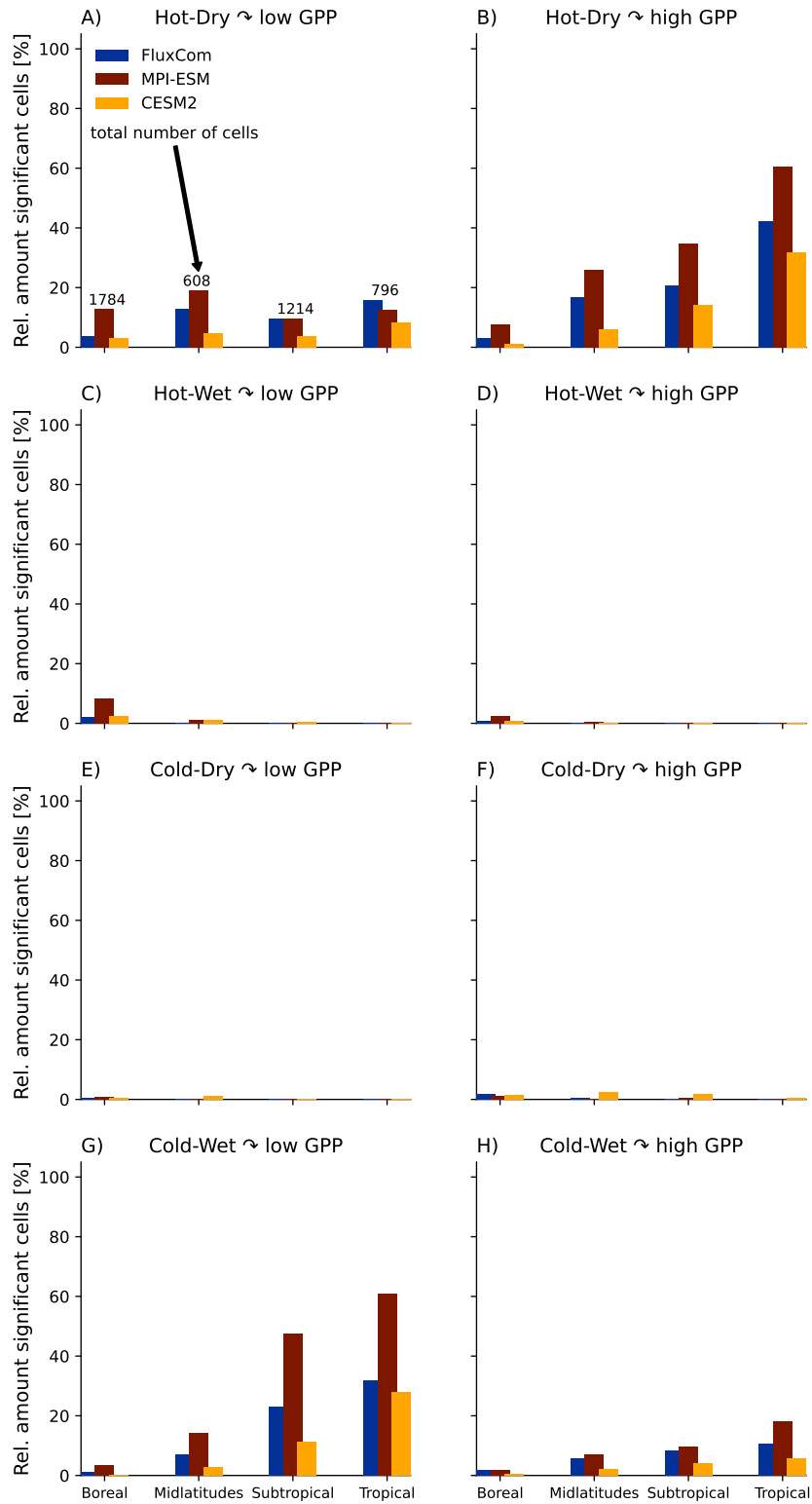


Figure S4 | Analogous to Figure S3 but considering all grid cells which undercut the null model's 5th quantile at lag one or more as significant.

S3 Assignment of IPCC regions to broad climatic zones

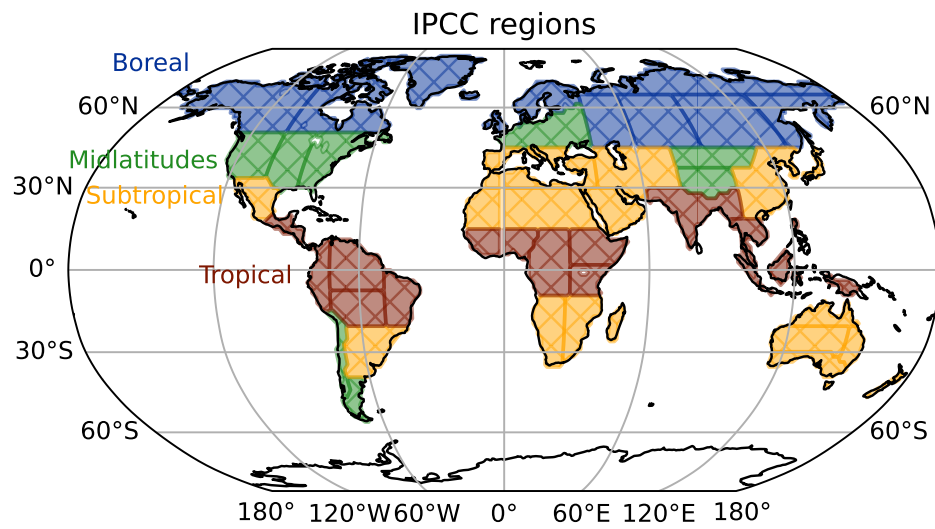


Figure S5 | Assignment of IPCC regions (Iturbide et al., 2020) to broad climatic zones.

S4 Maps of statistical coupling strength and peak timing

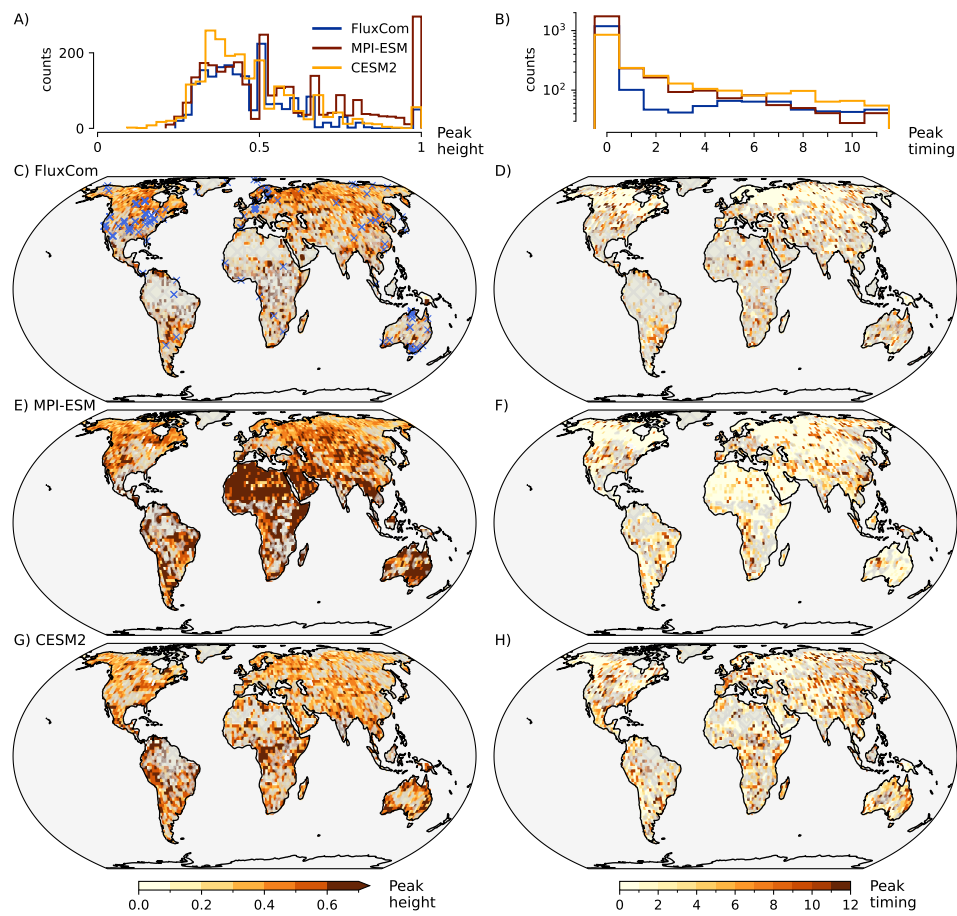


Figure S6 | Highest share of co-occurrences and corresponding timings for hot–wet–high analogous to Fig. 2 of the manuscript.

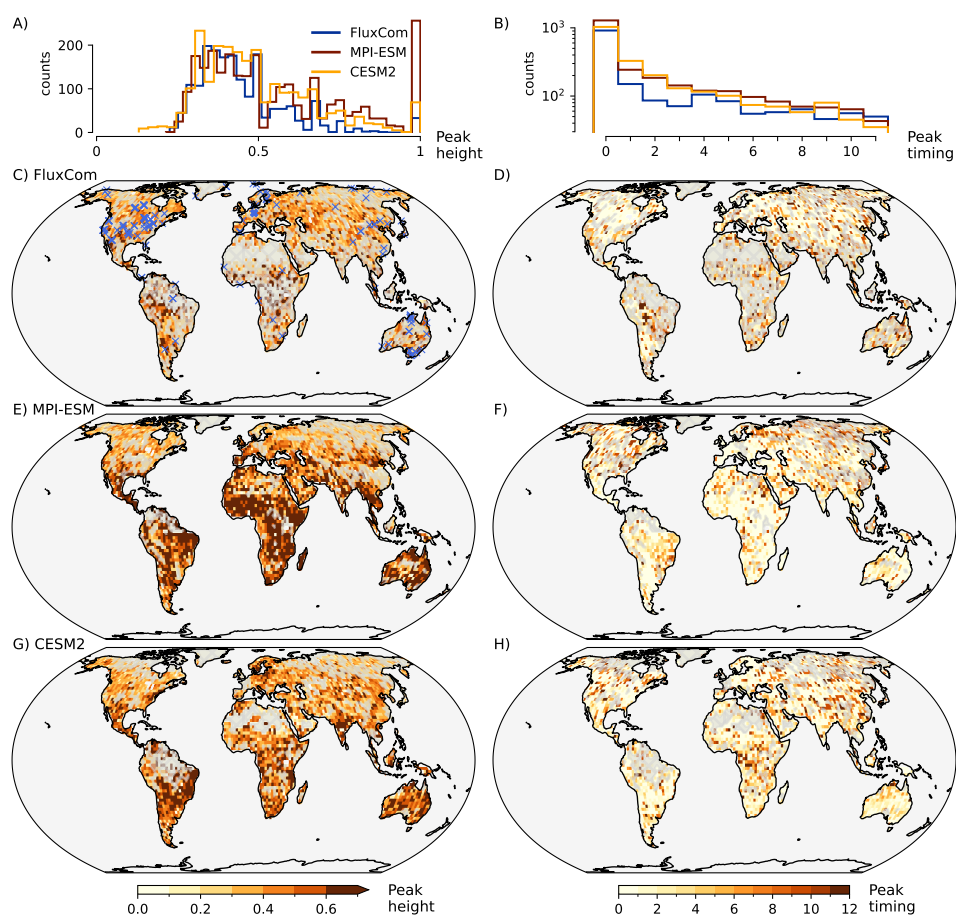


Figure S7 | Analogous to Fig. S6 but for cold-dry-low.

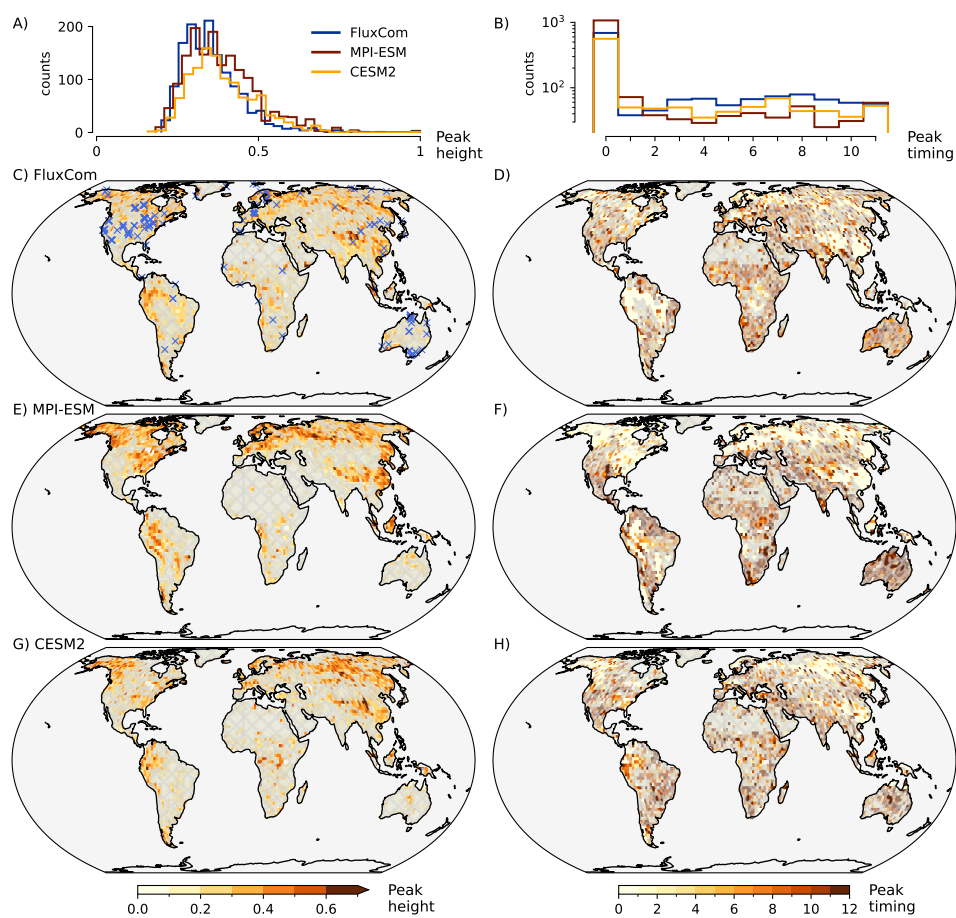


Figure S8 | Analogous to Fig. S6 but for cold-wet-low

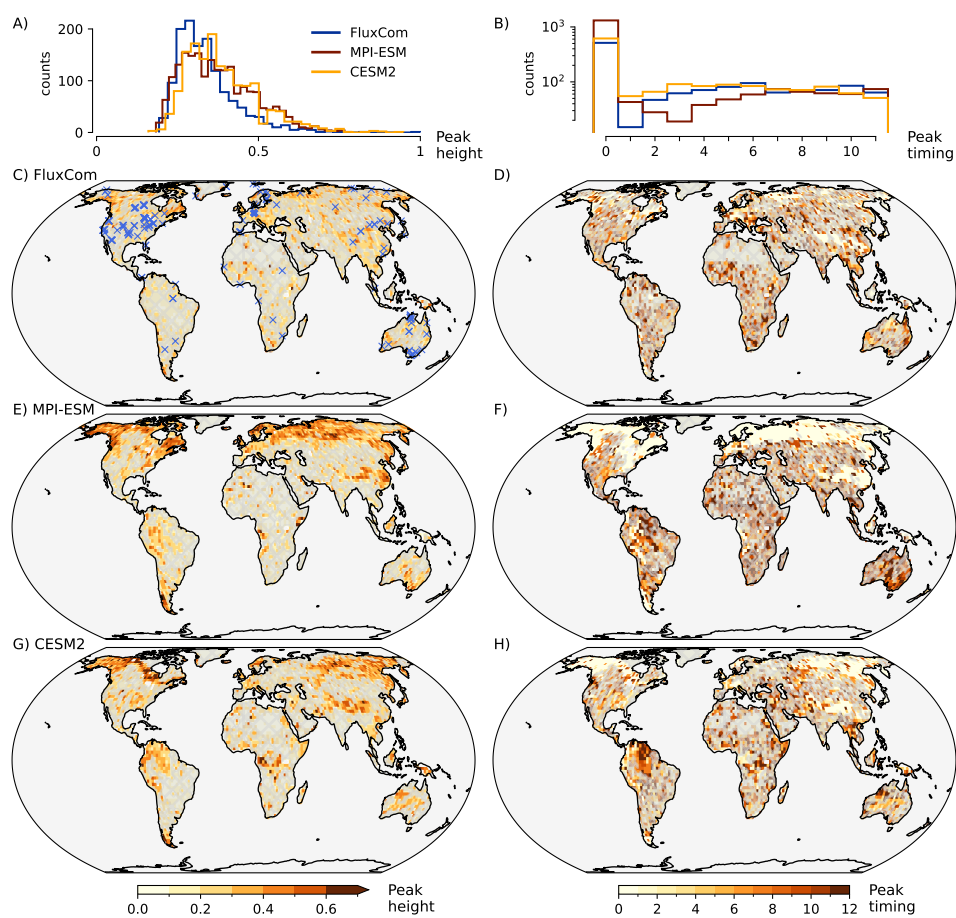


Figure S9 | Analogous to Fig. S6 but for hot-dry-high

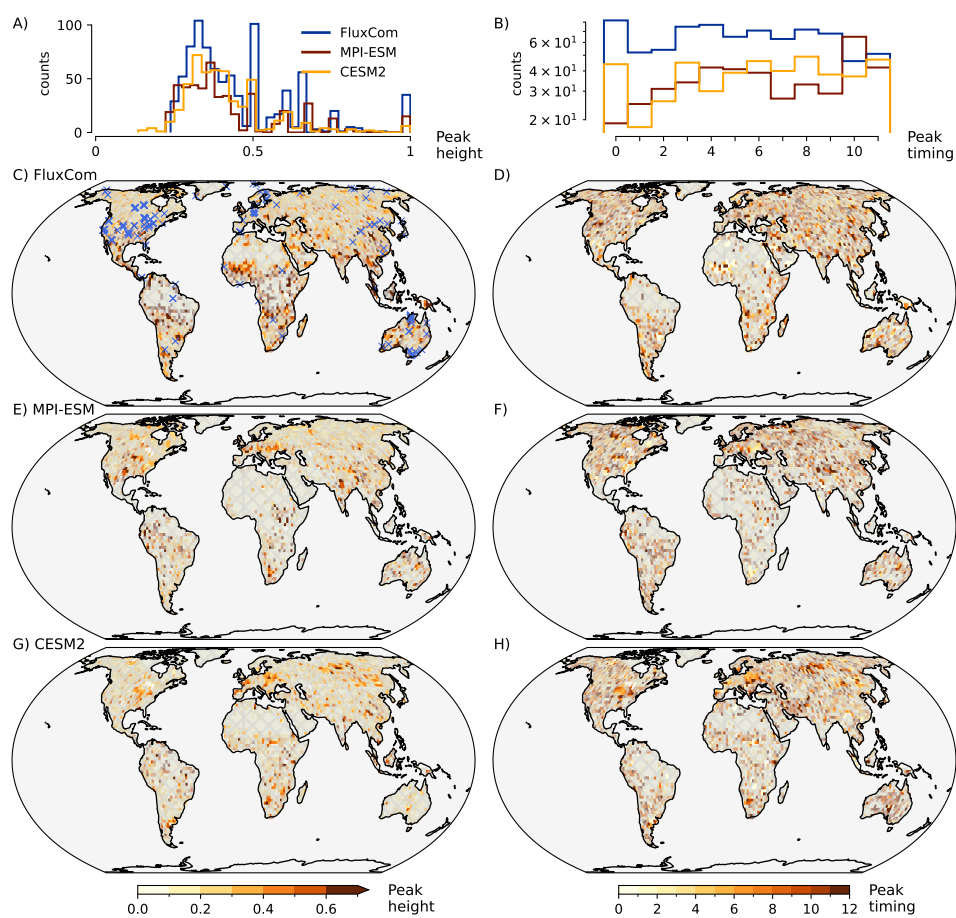


Figure S10 | Analogous to Fig. S6 but for hot-wet-low

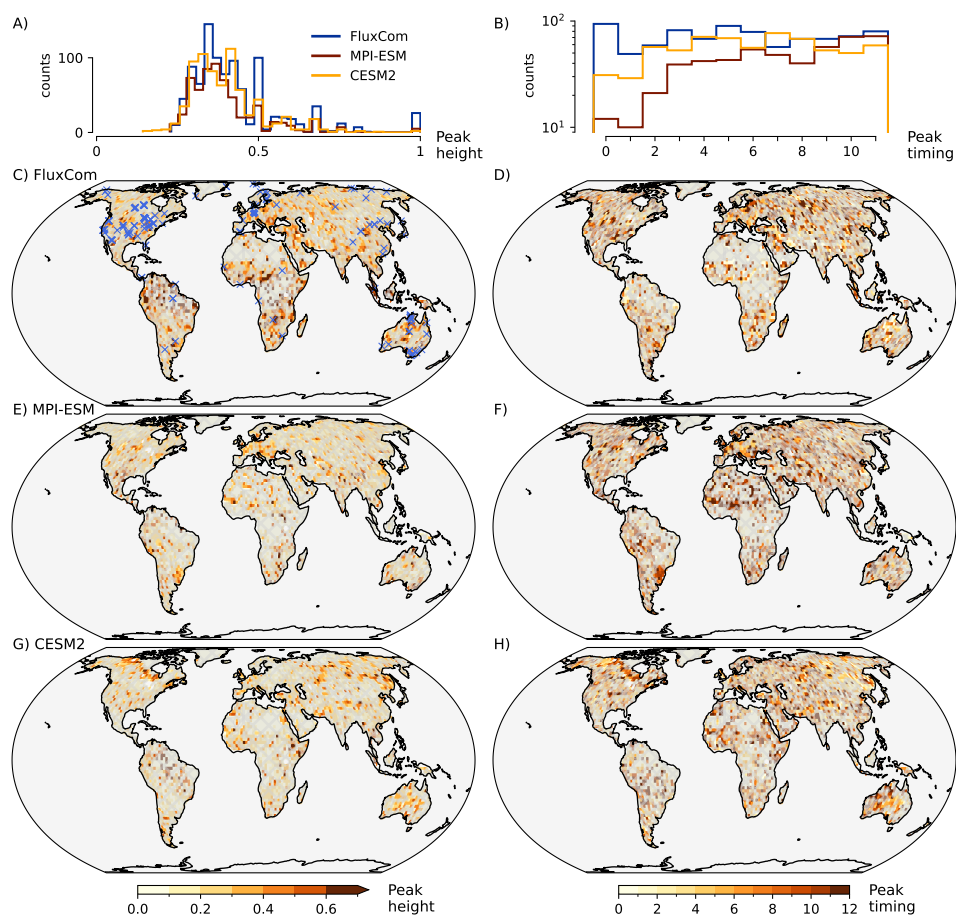


Figure S11 | Analogous to Fig. S6 but for cold-dry-high

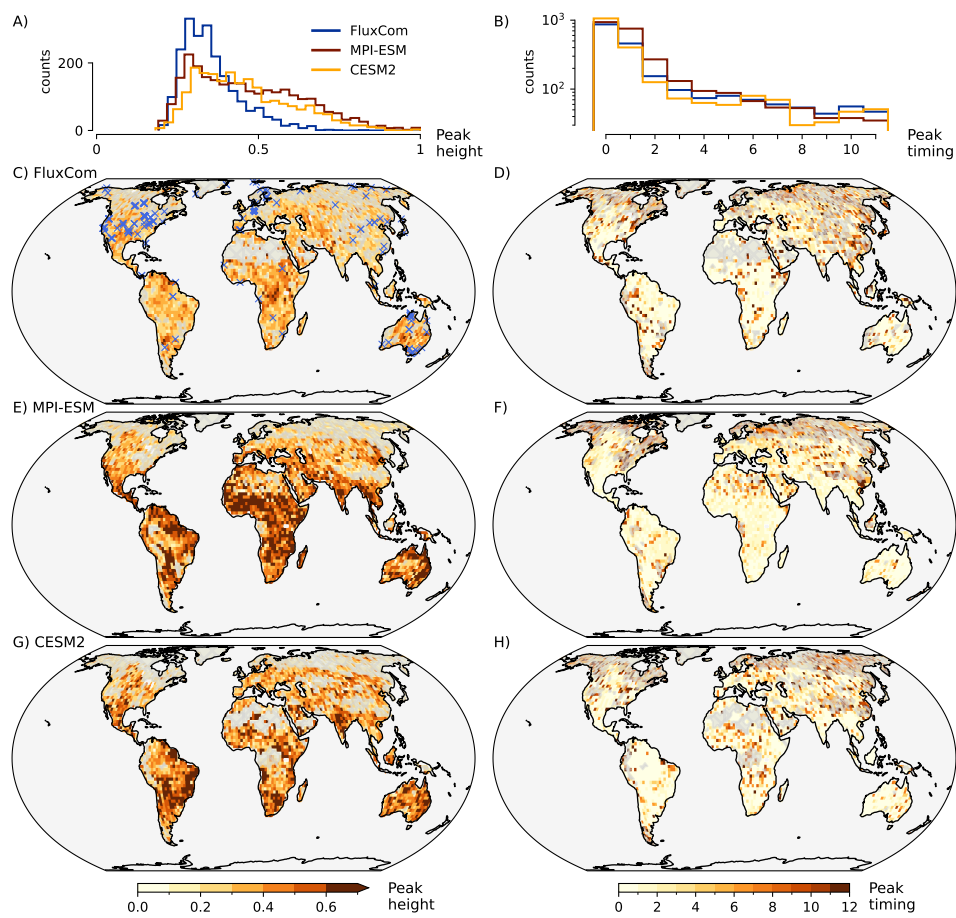


Figure S12 | Analogous to Fig. S6 but for hot-dry-low

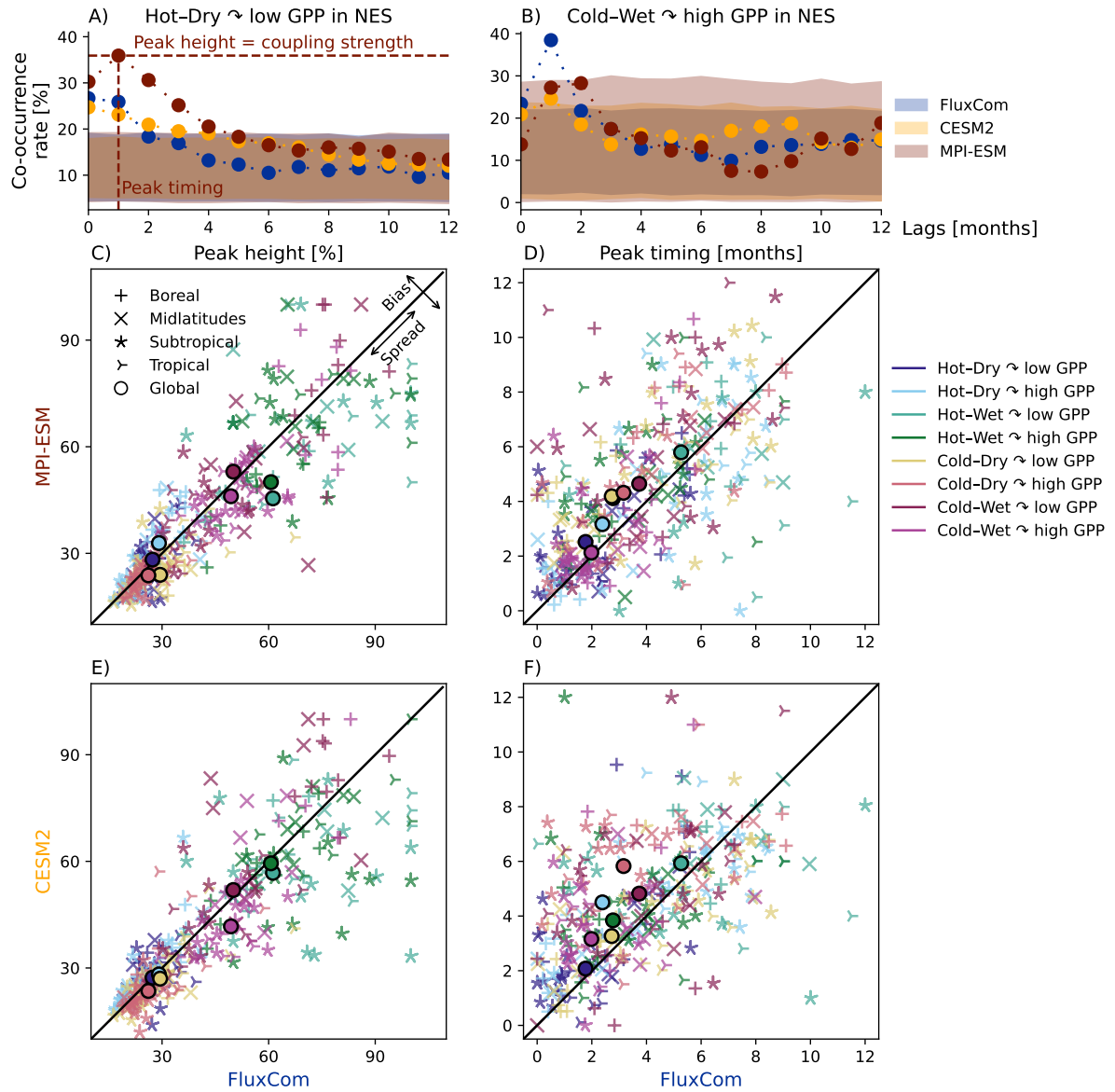
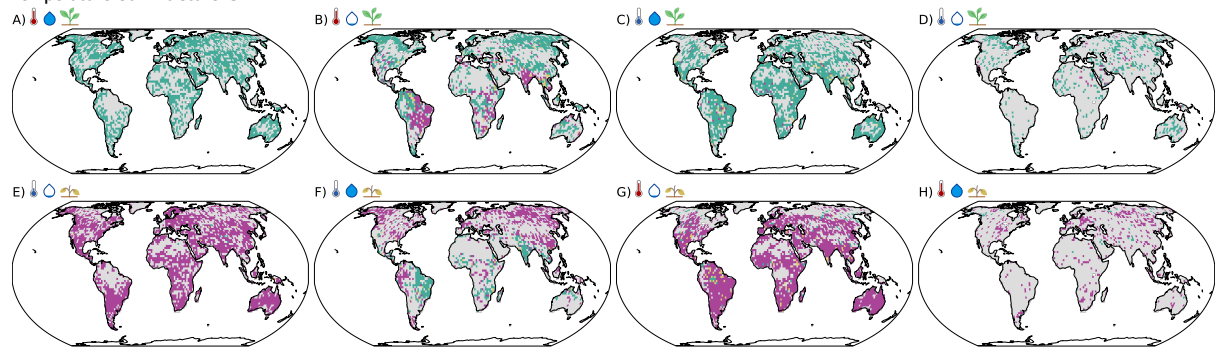


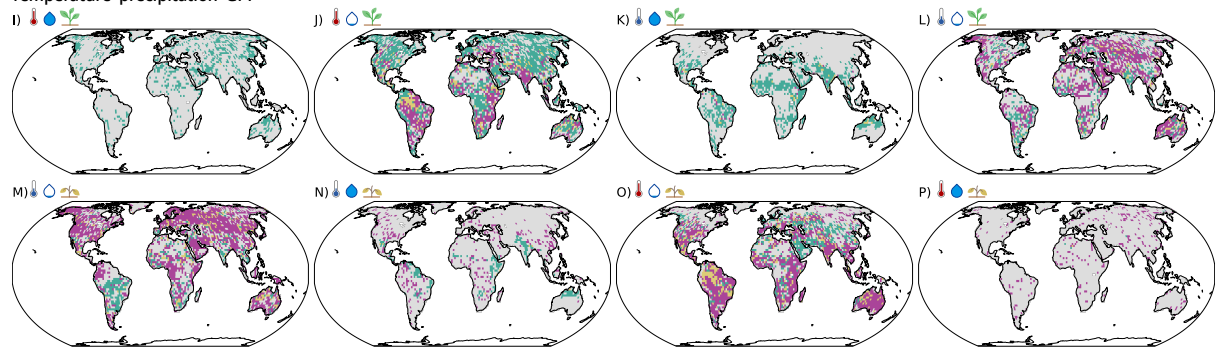
Figure S13 | Agreement in regionally averaged co-occurrence rate and timing between FLUXCOM and the model datasets for precipitation as a moisture indicator. Description analogous to Fig. 4 of the manuscript.

S5 Mechanistic response in the Earth system models

Temperature–soil moisture–GPP



Temperature–precipitation–GPP

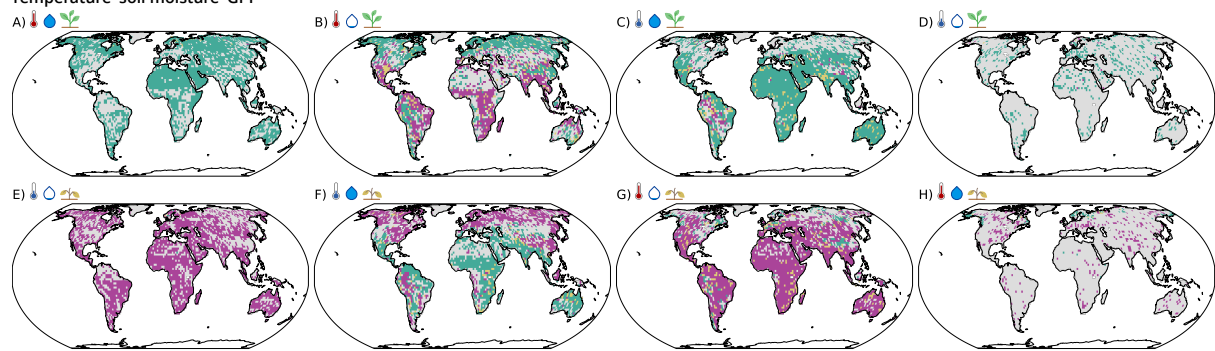


insignificant damaging beneficial both at different times
effect on vegetation productivity compared to baseline

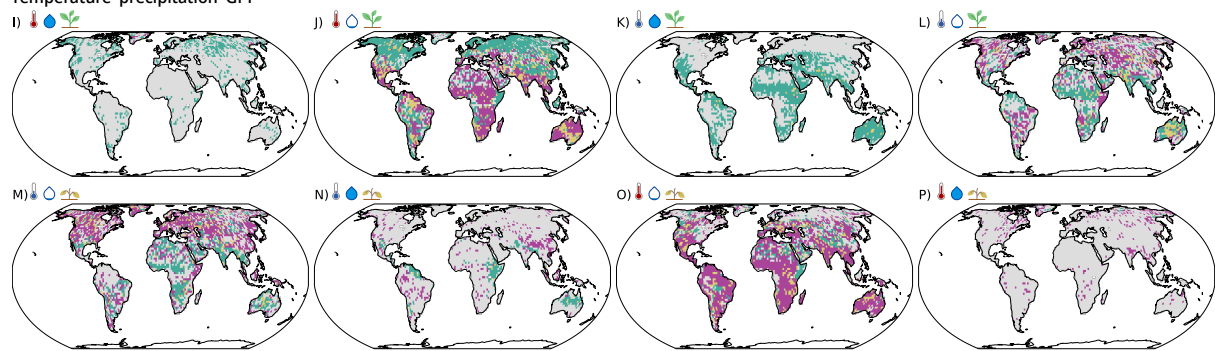
hot/cold wet/dry high/low

Figure S14 | Categorization of enhanced and muted co-occurrence rates between temperature–soil moisture and GPP extremes and between temperature–precipitation and GPP extremes for CESM2. Description analogous to Fig. 5 of the manuscript.

Temperature-soil moisture-GPP



Temperature-precipitation-GPP



insignificant damaging beneficial both at different times
effect on vegetation productivity compared to baseline

hot/cold wet/dry high/low

Figure S15 | Analogous to Fig. S14 but for MPI-ESM.

S6 Mean GPP bias in the Earth system models

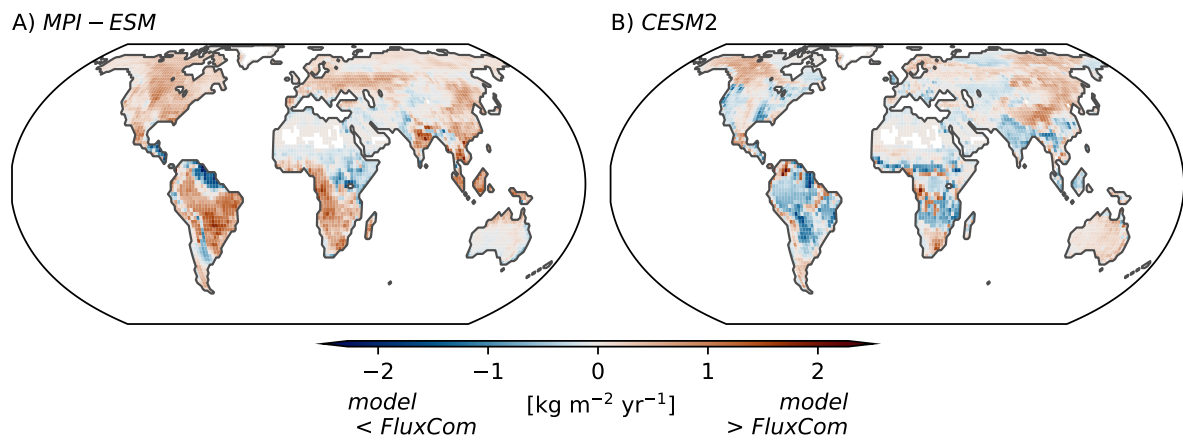


Figure S16 | Mean GPP bias between FLUXCOM and the ESMs. Panels depict the 1999 to 2014 average anomalies to FLUXCOM.

