

1 **Supplementary Information for**  
2 **CARBON SYSTEM STATE DETERMINES WARMING POTENTIAL OF**  
3 **EMISSIONS**

4 **Winkler et al.**

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7 **This PDF file includes:**

8     Supplementary text

9     Figs. S1 to S7

10    Tables S1 to S2

11    References for SI reference citations

## 12 Supporting Information Text

### 13 S1. Simplifications in the Prevailing Modeling Paradigm of the Coupled Climate Carbon Cycle 14 System

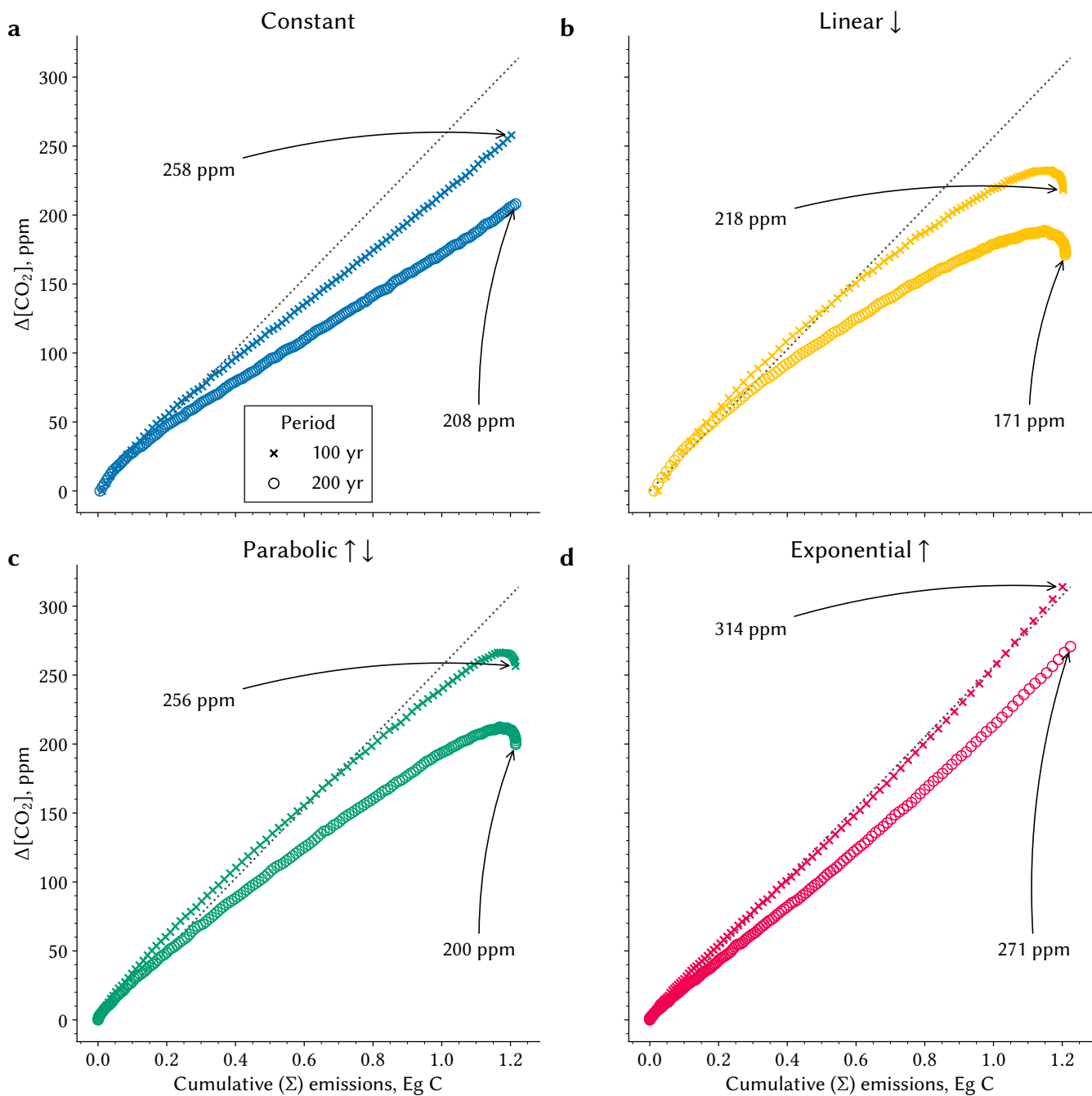
15 CO<sub>2</sub> emissions translate into a change in global temperature, *i. e.*, TCRE, primarily via three key processes:  
16 terrestrial and oceanic CO<sub>2</sub> uptake, the radiative forcing due to atmospheric CO<sub>2</sub>, and ocean heat uptake  
17 (1, 2). These processes are governed by complex nonlinear mechanisms, but they appear to balance each  
18 other, so that TCRE emerges to be a constant in the coupled climate-carbon cycle system as shown by many  
19 modeling exercises (1–3). However, the TCRE proportionality and its underlying properties may only hold  
20 for the prevailing modeling paradigm and because of the simplifications made in most modeling exercises,  
21 as an analysis of simulations of CMIP5 generation Earth system models has already shown (ESMs; 4).

22 Firstly, the prevailing modeling paradigm, *e. g.*, in the Coupled Climate Carbon Cycle Model Intercom-  
23 parison Project community (C4MIP; 5, 6), is to force the system with a prescribed atmospheric CO<sub>2</sub> timeline  
24 (concentration-driven runs) which suppresses the carbon cycle feedback to atmospheric CO<sub>2</sub> as opposed  
25 to emission-driven runs. This paradigm tenaciously persists as it is assumed that the feedback is linear  
26 and thus can be reconstructed from concentration-driven runs (7–9). However, Boer *et al.* (10) already  
27 demonstrated that the complexity and nonlinearity of the system in fully-coupled emission-driven runs  
28 cannot be simplified to a linear behavior.

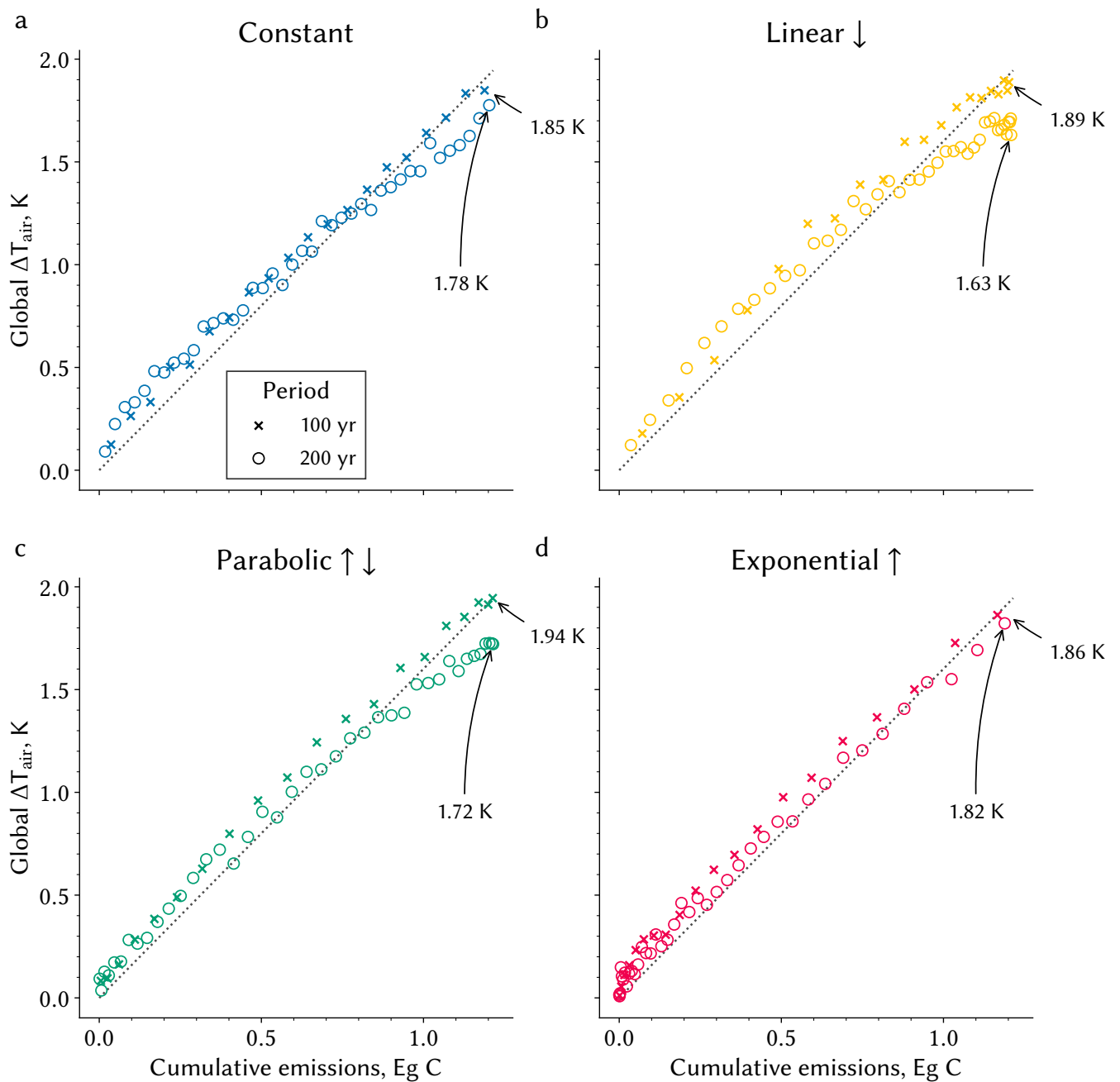
29 Secondly, the ESM modeling community focuses on studying TCRE in forcing trajectories that follow a  
30 (quasi-)exponentially increasing CO<sub>2</sub> concentration (*e. g.*, 1pctCO2 and RCP8.5 forcing; 6–9). Many key  
31 features of TCRE, *e. g.*, the assumption of the linear carbon-cycle feedback, might only hold for this specific  
32 scenario. Raupach (11) has analyzed in detail the special case of exponential forcing of the climate carbon  
33 cycle and has shown that many aspects of TCRE are scenario specific.

34 Thirdly, another key shortcoming of TCRE research until today is the focus on atmosphere-ocean  
35 coupling and the use of simplified modelling approaches therein, such as analytical models (12) or so-  
36 called ESMs of intermediate complexity (EMICs; *e. g.*, in 13–17). The last studies using complex ESMs to  
37 investigate pathway dependence in fully-coupled emission-driven runs date back nearly a decade (18–20),  
38 and used only a rudimentary representation of the terrestrial biosphere, particularly without consideration  
39 of vegetation dynamics. Winkler *et al.* (4), however, suggested that those models from the last generation  
40 of complex ESMs (CMIP5 models) with a more comprehensive representation of the terrestrial biosphere  
41 reflect strong pathway and state dependence in carbon uptake processes. The C4MIP community also  
42 explicitly acknowledges that the lack of accounting for dynamic vegetation in these ESMs could lead to  
43 overly conservative estimates of the climate-carbon cycle feedbacks (6).

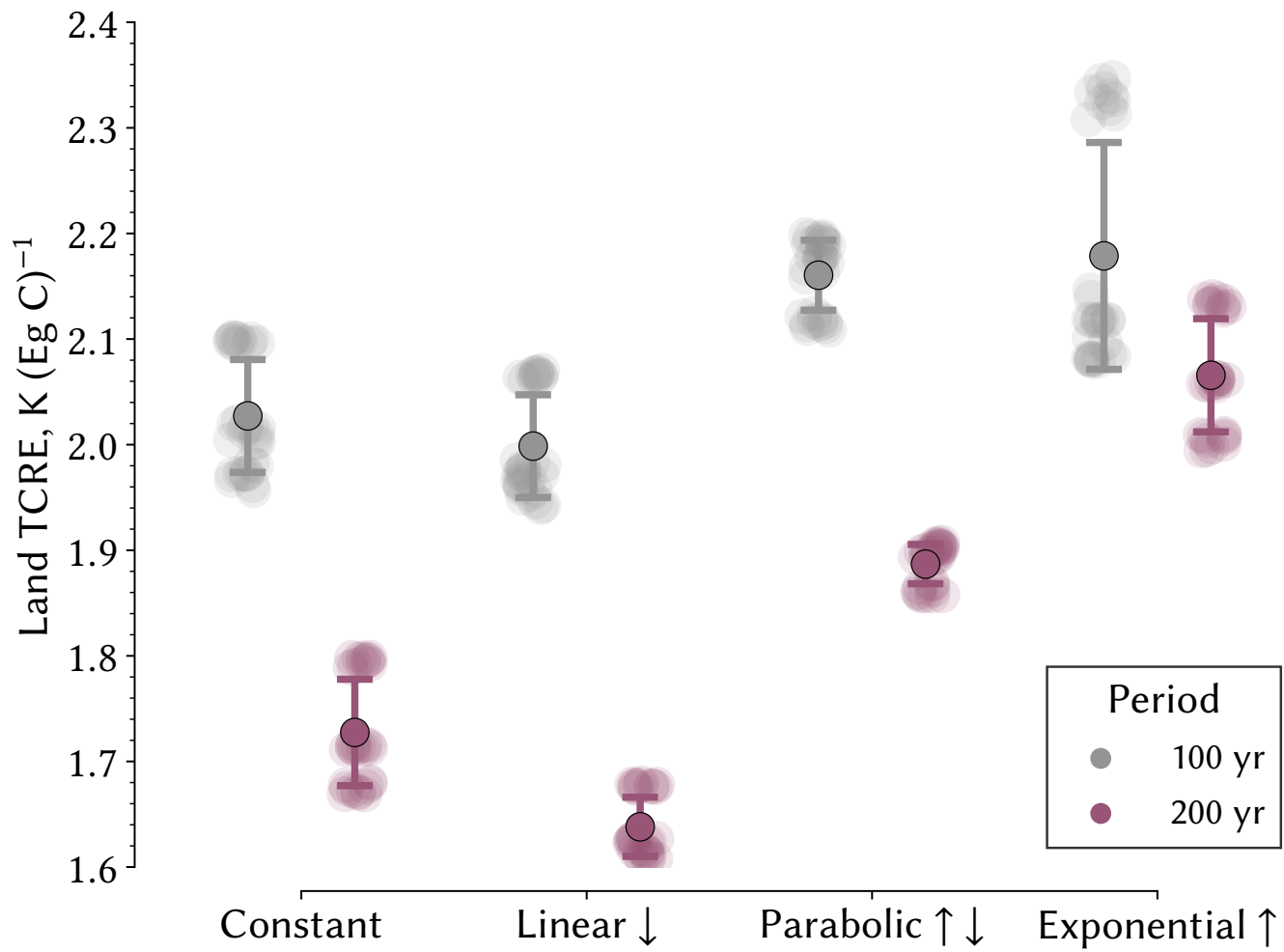
44 All three of the shortcomings outlined above, taken together, may be the reason why the climate-carbon  
45 cycle feedback connected to vegetation dynamics, and the resulting state dependency of the climate-carbon  
46 cycle system has been overlooked to date.



**Fig. S1. Change in atmospheric CO<sub>2</sub> concentration across the different pathways and different periods for the same amount of emitted carbon.** a–d Relationship between cumulative carbon emissions (x-axis) and the change in atmospheric CO<sub>2</sub> concentration ( $\Delta[\text{CO}_2]$ ) is shown, where the colors refer to the four different pathways analogous to Figure 1 and the markers refer to the different time periods. The arrows annotate the final  $\Delta[\text{CO}_2]$  in each model experiment. The dotted black line facilitates comparison between the pathways.



**Fig. S2. Change in global mean air temperature across the different pathways and different periods for the same amount of emitted carbon.** a–d Relationship between cumulative carbon emissions (x-axis) and the change in global mean air temperature ( $\Delta T_{air}$ ) is shown, where the colors refer to the four different pathways analogous to Figure 1 and the markers refer to the different time periods. To reduce inter-annual variability, five-year averages across the three realizations are displayed. The arrows annotate the final  $\Delta T_{air}$  in each model experiment. The dotted black line facilitates comparison between the pathways.

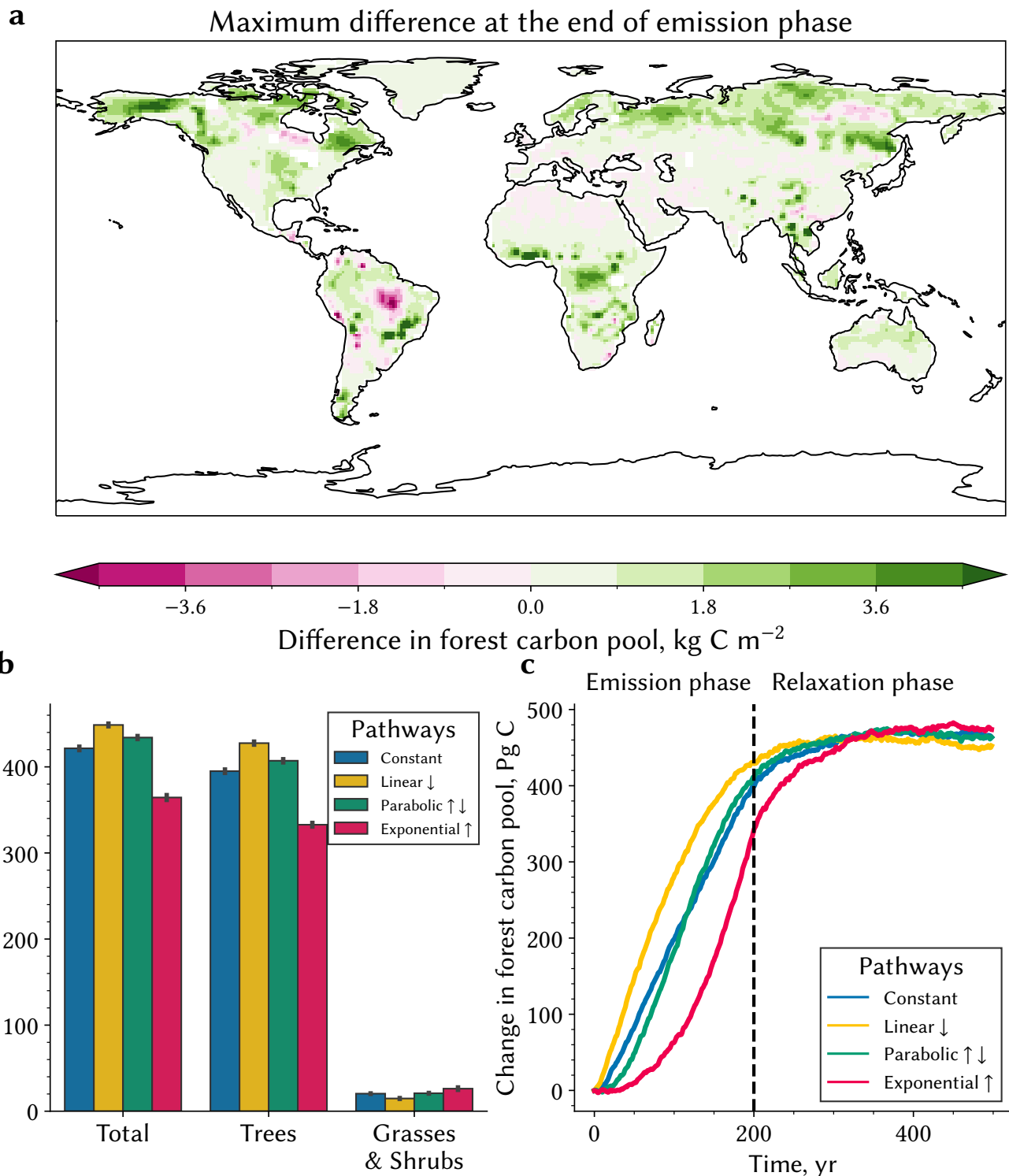


**Fig. S3. Pathway dependence of the global carbon cycle response translates into different warming potential of the land for a given emission.** Transient Climate Response to Cumulative Emissions (TCRE) for different pathways (x-axis) and simulation periods (colors), focusing on the warming of the land surface. Land TCRE is estimated using the conventionally used linear regression method (8). Shaded dots exhibit the spread in the estimates of the final five years when 1.2 Eg C have been emitted as well as among different realizations. Pointplot with whiskers show the mean and standard deviation of the spread.

58 **Table S1. Best-fit values for parameters of the double exponential decay function (Equation 5 in main document)**  
 59 **including the standard error (68% confidence) are shown for the CMIP6 ZecMIP multi-model ensemble and the**  
 60 **four different emission pathways simulated using MPI-ESM1-2-LR.**

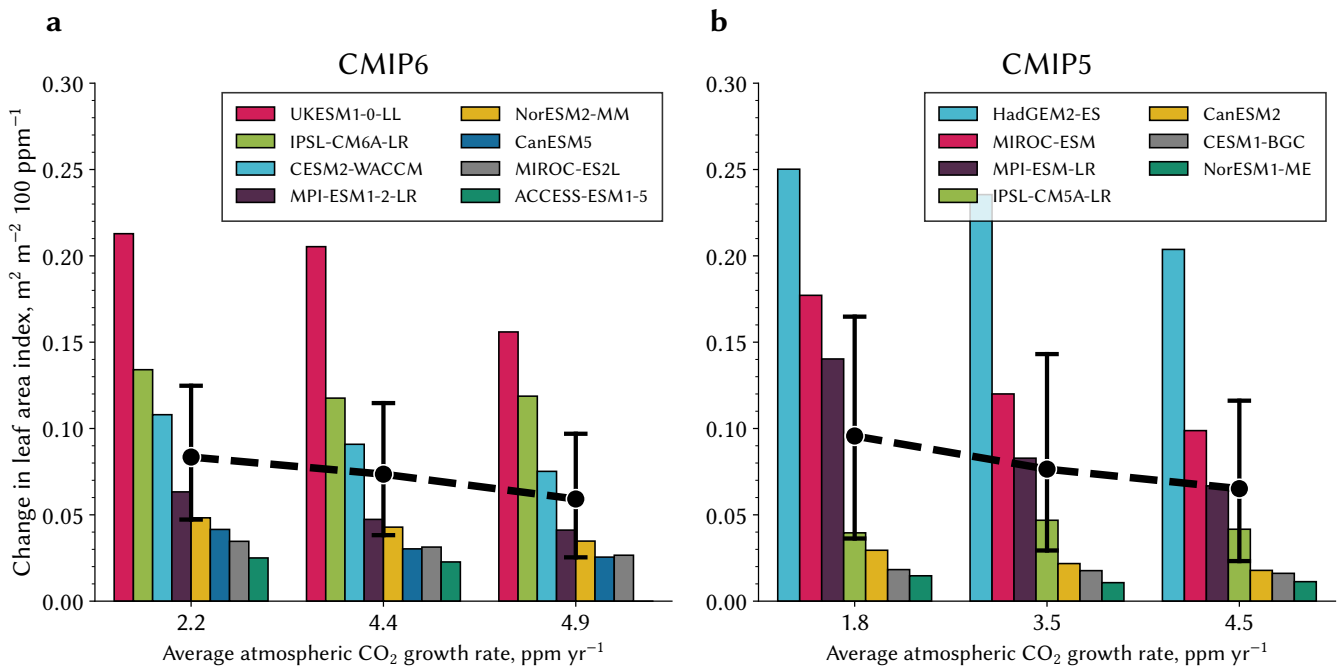
Model	$\eta$	$\tau_F$	$\tau_S$	$C_T^0$	$C_{OL}^0$	$R^2$
Unit	-	yr	yr	Pg C	Pg C	-
<b>ZecMIP (1000 Pg C)</b>						
ACCESS-ESM1-5	0.13 ± 0.008	20.29 ± 2.01	512.15 ± 29.48	586.78 ± 1.69	418.37	0.996
CESM2	0.34 ± 0.002	28.01 ± 0.22	807.37 ± 12.78	579.10 ± 0.37	425.60	1.000
CanESM5	0.33 ± 0.002	21.74 ± 0.30	1033.38 ± 14.78	498.36 ± 1.06	498.02	0.998
GFDL-ESM4	0.31 ± 0.003	26.12 ± 0.58	598.97 ± 11.19	505.69 ± 1.18	496.66	0.998
MIROC-ES2L	0.22 ± 0.003	23.88 ± 0.71	660.19 ± 8.10	516.92 ± 1.49	472.20	0.997
MPI-ESM1-2-LR	0.25 ± 0.003	21.87 ± 0.52	383.24 ± 4.08	536.14 ± 1.17	464.27	0.999
NorESM2-LM	0.35 ± 0.005	27.62 ± 0.42	639.66 ± 28.25	564.94 ± 0.41	439.26	1.000
UKESM1-0-LL	0.17 ± 0.002	30.98 ± 0.76	808.04 ± 7.59	568.75 ± 0.92	426.34	0.998
<b>MPI-ESM1-2-LR Pathways (1200 Pg C)</b>						
Constant	0.28 ± 0.01	70.92 ± 2.58	1152.43 ± 54.47	434.98 ± 0.72	773.10	0.998
Linear ↓	0.24 ± 0.01	80.40 ± 3.96	1694.86 ± 127.91	364.70 ± 0.59	843.32	0.997
Parabolic ↑ ↓	0.31 ± 0.01	92.89 ± 4.05	1700.77 ± 163.26	417.87 ± 0.58	793.13	0.998
Exponential ↑	0.35 ± 0.01	61.72 ± 1.67	943.89 ± 36.29	559.11 ± 1.04	652.48	0.998

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48 **Fig. S4. Vegetation dynamics explain the pathway dependence in the terrestrial carbon cycle.** **a** Global map of the difference in the total forest carbon pool between the L and E pathways (yellow and red in b and c, respectively) at the end of the emission phase, calculated with MPI-ESM1-2-LR in the 200-year runs. **b** Change in carbon pool for forest, grass- and shrublands, and total vegetation for the different emission pathways. The whiskers represent the uncertainty between the different realizations. **c** Change of forest carbon pool across the four pathways as a function of time for both the emission and relaxation phases.

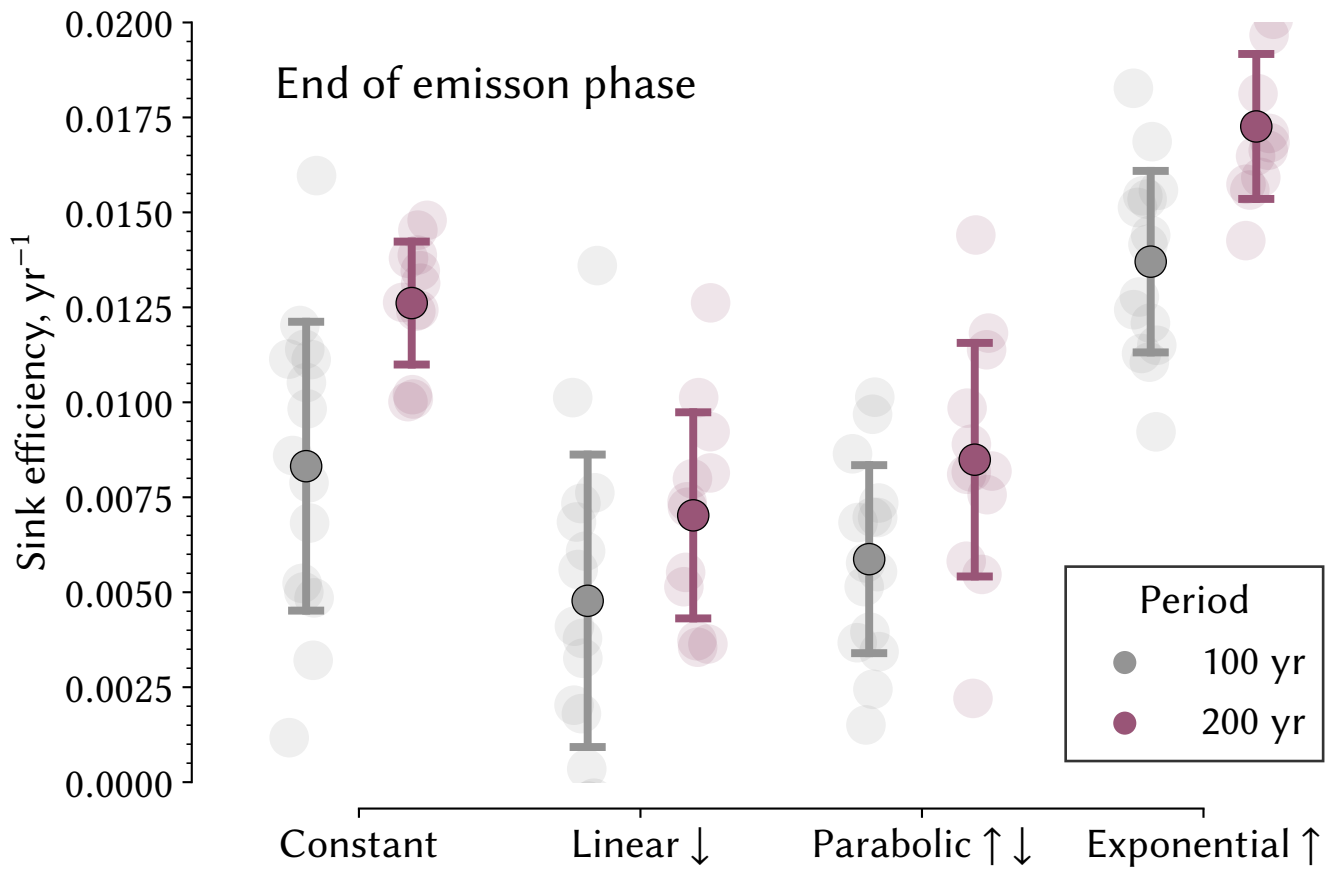


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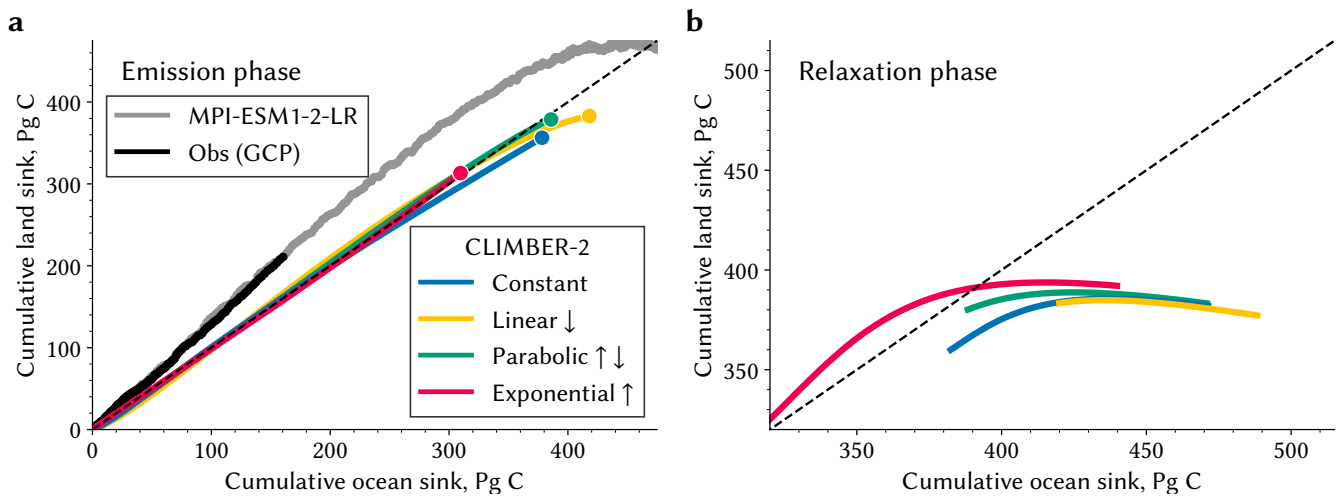
54 **Fig. S5. Leaf area sensitivity to different  $\text{CO}_2$  growth rates in CMIP ensembles** **a** Change in leaf area index at latitudes above  $60^\circ \text{N}$  per a 100 ppm change in  
 55 atmospheric  $\text{CO}_2$  across three different future scenarios in CMIP6 reflecting different  $\text{CO}_2$  growth rates (x-axis). The black dot refers to the multi-model mean value  
 56 for each growth rate, where the whiskers represent the standard deviation. **b** as in **c** but for CMIP5.

63 **Table S2. Best-fit values for parameters of the double exponential decay function (Equation 5 in main document)**  
64 **are shown, where  $\eta$  is sampled from the parameter space determined in Table S1. The uncertainty estimate refers**  
65 **to one standard deviation of the individual parameter estimates between samples. Results are shown for the**  
66 **CMIP6 ZecMIP multi-model ensemble and the four different emission pathways simulated using MPI-ESM1-2-LR.**

Model	$\eta$	$\tau_F$	$\tau_S$	$C_T^0$	$C_{OL}^0$	$R^2$
Unit	-	yr	yr	Pg C	Pg C	-
<b>ZecMIP (1000 Pg C)</b>						
ACCESS-ESM1-5	[0.13 - 0.35]	20.52 ± 3.66	519.06 ± 63.81	586.29 ± 0.82	418.37	0.995 ± 0.000
CESM2	[0.13 - 0.35]	28.40 ± 5.39	1037.60 ± 622.43	577.74 ± 2.53	425.60	0.999 ± 0.001
CanESM5	[0.13 - 0.35]	23.33 ± 3.52	1269.50 ± 628.47	493.79 ± 11.17	498.02	0.992 ± 0.005
GFDL-ESM4	[0.13 - 0.35]	27.47 ± 5.50	647.11 ± 168.05	502.13 ± 3.07	496.66	0.997 ± 0.001
MIROC-ES2L	[0.13 - 0.35]	26.22 ± 5.03	689.80 ± 95.04	512.74 ± 5.50	472.20	0.995 ± 0.001
MPI-ESM1-2-LR	[0.13 - 0.35]	23.17 ± 4.37	394.77 ± 50.94	532.64 ± 3.23	464.27	0.998 ± 0.001
NorESM2-LM	[0.13 - 0.35]	27.57 ± 4.25	830.64 ± 521.07	564.98 ± 2.09	439.26	1.000 ± 0.000
UKESM1-0-LL	[0.13 - 0.35]	33.26 ± 6.19	831.35 ± 92.55	565.85 ± 3.03	426.34	0.998 ± 0.001
<b>MPI-ESM1-2-LR Pathways (1200 Pg C)</b>						
Constant	[0.24 - 0.35]	75.53 ± 10.00	1318.27 ± 291.27	434.38 ± 1.27	773.10	0.998 ± 0.000
Linear ↓	[0.24 - 0.35]	101.18 ± 11.81	3483.91 ± 1738.02	363.31 ± 0.74	843.32	0.997 ± 0.000
Parabolic ↑↓	[0.24 - 0.35]	90.62 ± 10.56	1708.37 ± 438.07	418.08 ± 0.84	793.13	0.998 ± 0.000
Exponential ↑	[0.24 - 0.35]	50.18 ± 7.10	742.98 ± 111.07	561.10 ± 0.97	652.48	0.997 ± 0.001



**Fig. S6. Sink efficiency differs across pathways after emission cessation of the same amount of carbon.** Sink efficiency for different pathways (x-axis) and simulation periods (colors) at the end of the emission phase. Shaded dots exhibit the spread in the estimates of the final five years when 1.2 Eg C have been emitted as well as among different realizations. Pointplot with whiskers show the mean and standard deviation of the spread.



**Fig. S7. Partitioning of emissions into land and oceans sinks across the pathways in the EMIC CLIMBER-2** **a** Cumulative land and ocean sinks are juxtaposed across all pathways. The markers denote the final state at the end of the emission phase of 1.2 Eg C. The dashed line indicates equal magnitude of cumulative land and ocean sinks. The gray and black lines refer to the relationships inferred from MPI-ESM1.2-LR simulations and GCP estimates, respectively. **b** As in a, but for relaxation phase. The Climate-Biosphere model (version 2) CLIMBER-2 is an Earth System Model of Intermediate Complexity (EMIC) and consists of a statistical-dynamical atmosphere component ( $51^\circ \times 10^\circ$  spatial resolution), a 2D ocean component with three zonally averaged basins, and a land component including dynamic vegetation (21). The same model version of CLIMBER-2 is used, which was also used for the ZecMIP runs (22).

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