Linearity between temperature peak and bioenergy CO$_2$ emission rates

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OSCAR v2.1

OSCAR v2.1 is a compact global carbon cycle–climate model\textsuperscript{1-3}. The oceanic carbon cycle follows the representation of a mix-layer with impulse response functions as described in ref.\textsuperscript{4}. The sensitivity of the carbonate oceanic chemistry to atmospheric CO\textsubscript{2} and temperature change can be emulated by 3 different non-linear functions, one from ref.\textsuperscript{5}, and two from ref.\textsuperscript{6}. The transportation of surface water to deep ocean can be modeled by 4 different impulse response functions\textsuperscript{4}. The ocean compartment thus has 12 possible parameterizations.

The terrestrial carbon cycle is broadly the same as the one of the original OSCAR model\textsuperscript{3}, albeit it is here aggregated into 9 regions\textsuperscript{7}. Its preindustrial equilibrium is calibrated on up-to-date simulations made with the complex model ORCHIDEE\textsuperscript{8}. The regional sensitivities of net primary productivity (NPP) to CO\textsubscript{2} and climate are calibrated on idealized (i.e. +1\% CO\textsubscript{2} per year) simulations of the IPSL–CM5 model\textsuperscript{9}, and the global sensitivity of heterotrophic respiration (R\textsubscript{h}) follows a “\textit{Q}\textsubscript{10}” law with \textit{Q}\textsubscript{10}=1.4\textsuperscript{10}. Global sensitivities of NPP and R\textsubscript{h} can also be rescaled to those of one of the eleven models of the C\textsuperscript{4}MIP\textsuperscript{11}, or to the average of the C\textsuperscript{4}MIP sensitivities. The sensitivity of NPP to CO\textsubscript{2} is modeled through either a logarithmic or a hyperbolic relationship\textsuperscript{12}. This yields 26 possibilities of parameterization for the terrestrial carbon–cycle. In the latest OSCAR version, other greenhouse gases and reactive species were also added, following the characteristics of the MAGICC6 model\textsuperscript{13}.

OSCAR computes the radiative forcing (RF) from a perturbation in the atmospheric CO\textsubscript{2} concentration (\Delta C), relative to a reference concentration (C\textsubscript{0}), using the equation RF = \alpha\textsubscript{c} \cdot \text{ln}\left[\frac{(C\textsubscript{0}+\Delta C)}{C\textsubscript{0}}\right] (ref.\textsuperscript{14}), where \alpha\textsubscript{c} = 5.35 W m\textsuperscript{-2} and C\textsubscript{0} is the atmospheric CO\textsubscript{2} concentration at preindustrial times (278 ppm). To estimate global mean surface temperature change, the model can use 28 different impulse response functions (e.g., see\textsuperscript{15}), whose parameters were calibrated on the 27 Earth system models that made the “4x CO\textsubscript{2}”
simulation of the CMIP5\textsuperscript{16}. The remaining parameterization is based on the average of the CMIP5 models. For instance, the dynamics of the response calibrated on the average is formulated as follows: \( f(t) = 1-0.3884 \exp(-t/63.10)-0.6116 \exp(-t/2.774); \) and it has a climate sensitivity of about 0.72 K W\(^{-1}\) m\(^2\).

In this specific study, the OSCAR v2.1 model thus has a potential of 8736 combinations of parameters for the carbon–climate system: 12 from the ocean component, 26 from the terrestrial component, and 28 to estimate the global mean temperature change. The 1000 simulations used in this paper to estimate the uncertainty range and the ensemble means are drawn among these, with equal-probability. Supplementary Figure S1 compares the responses to a CO\(_2\) emission pulse from OSCAR v2.1 with those from other models.
Figure S1. Impulse response functions (IRF) from a CO₂ emission pulse at year 0. Figure S1a shows the fraction of CO₂ in the air following a pulse emission. Figure S1b the change in average global surface temperature. The red solid line shows the ensemble mean and the colored area represents the results within one standard deviation. The responses are computed under a constant climate following the standard protocol defined in ref.17. The CO₂ atmospheric concentration response is compared with the multimodel mean "Joos et al., 2013" from ref17 (used in the 5th IPCC Assessment Report18) and the IRF in the 4th IPCC Assessment Report"Forster et al., 2007". The temperature response is compared with the multimodel mean "Joos et al., 2013" from ref17 and that from ref15 "Boucher and Reddy, 2008".
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Figure S2. Net Ecosystem Exchange (NEE) chronosequences of the post–harvest ecosystem carbon response fed into OSCAR v.2.1. Table: normalized mean instantaneous NEE fluxes. Graph: normalized cumulative NEE (CumNEE) fluxes, including the CO₂ emission pulse at year zero from combustion. Each chronosequence is normalized to the size of the original pulse so to achieve the carbon neutrality along the prescribed turnover times. As indicated by the CumNEE flux, the harvest event will occur when the net cumulative emissions reach zero. These chronosequences are representative of three different CO₂ flux rates and time spans dictating the replenishment of the biomass resource. Negative values of NEE means net CO₂ removal from the air, while positive values correspond to emissions. The NEE profile for the short turnover time is based on an eucalyptus plantation from ref.20, case BL1 (with all the bark, understorey, slash and litter retained on site and assuming an average resource turnover time of 6 years). The NEE chronosequence for the medium turnover time is adapted from the so–called “Wisconsin” chronosequence in ref.21 after averaging observed values at each time step of the chronosequence. This case is representative of a cold temperate forest plantation dominated by aspen (*Populus tremuloides*). In this area, all stands less than 100 years old are regenerated following commercial harvest with forestry statistics reporting an average turnover time of 55 years22. The NEE profile for the long turnover time is representative of a hemiboreal forest plantation dominated by pine (*Pinus sylvestris*) from ref.23 (case “12”, turnover time 103 years). Values in the table are from a linear interpolation of the data.
Figure S3. Comparison of the IRFs from OSCAR v2.1 following a CO₂ emission pulse from fossil fuels or bioenergy. Solid lines show the ensemble means and the colored areas represent the respective results within one standard deviation. These responses are computed following the protocol for simulations under a constant climate. Figure S3a is the CO₂ atmospheric concentration response, and using a simple first order decay model the atmospheric lifetimes of the perturbations can be approximated to 2.2, 17, and 27 years for the short, medium and long turnover time, respectively. Figure S3b shows the temperature response. While an emission of fossil carbon causes a permanent warming, the temperature maximum from bioenergy is reached within a few decades and is limited in time, as the temperature change gradually decreases thanks to the additional CO₂ uptake by the biomass re-growth. In the bioenergy cases, the emission pulse is associated with the following ecosystem carbon response which is modeled as a series of small negative pulses whose cumulative value over the turnover time equals the initial pulse. Case specific net carbon losses or gains at the end of the biomass turnover time would proportionally shift the responses upwards or downwards, respectively, as shown elsewhere.
Figure S4: Temperature response (ensemble means only) to a CO₂ emission pulse in 2100 considering the changes in atmospheric CO₂ concentration along the 21st century according to the four RCP scenarios. Colored areas represent the range between the 2 extreme RCP scenarios, i.e. RCP2.6 and RCP8.5. The other two intermediate scenarios, i.e. RCP4.5 and RCP6.0, generally fall within this range. In these simulations, the protocol is extended considering the specific RCPs from 2010 up to 2100, with the stabilization of CO₂ background concentration and other anthropogenic forcings to the 2100 level. After that, a pulse emission of 100 GtonC is added to the atmosphere in the year 2105. The figure shows that at increasing CO₂ atmospheric concentrations a CO₂ emission pulse will become gradually less effective on the average global temperature. Under the most pessimistic scenario (i.e., RCP8.5), the addition of CO₂ to the atmosphere has less effect on average global surface temperature than under the lowest forcing scenario (RCP2.6), especially in the short term. Over time the temperature decreases more quickly under RCP2.6 because of the lower level of saturation of the terrestrial and ocean sinks that uptake the CO₂ excess.
Figure S5. Model simulations (ensemble means only) of the CCR as a function of time under varying CO₂ background concentration levels in 2100. CCR is measured from 2100 after letting CO₂ concentration change during the 21st century according to the four RCP scenarios. Colored areas represent the range between the 2 extreme RCPs, i.e. RCP2.6 and RCP8.5. In all simulations CCR values decrease with the increasing background CO₂ concentration, and hence with the level of cumulative CO₂ emissions associated with each RCP. The sensitivity of CCR to time in fossil experiments becomes noticeable in the RCP8.5 case, where cumulative emissions are higher than 2 TtC, which is the upper limit identified for the CCR time constancy²⁵,²⁶. In the bioenergy simulations, variations among the RCPs can be mainly observed in the first decades and then the results tend to converge over time.
Figure S6. Global temperature peak rise versus cumulative emissions (graphs on the left hand side) and maximum emission rates (graphs on the right hand side) for CO₂ from fossil fuels and bioenergy (a, b), CH₄ and N₂O (c, d), and the other GHGs selected in this study (e, f). Results (ensemble means only) are for emission trajectories characterized by 500 combinations of maximum emission rates between 0 and 20 GtC per year and resulting in cumulative emissions between 0 and 4 TtC. Values of the R² of each linear fit (intercept set equal to zero) are also shown. The linear correlation between ΔT_{peak} and E_{max} (b) can be used to build a simple relationship between maximum CO₂ emission rates from bioenergy and temperature peak (units in °C per GtonC/year): ΔT_{peak} = 0.0049·E_{max} for the short turnover time, ΔT_{peak} = 0.063·E_{max} for the medium turnover time, and ΔT_{peak} = 0.0946·E_{max} for the long turnover time.
Figure S7: Correlation ($R^2$) between temperature peak and cumulative emissions ($\Delta T_{\text{peak}}, \Sigma E$) and between temperature peak and maximum emission rates ($\Delta T_{\text{peak}}, E_{\text{max}}$) for the selected well-mixed GHGs. Correlations are derived from the simulations in Figure S6. The dotted red line marks the equal correlation. Following the same approach used in ref. 28, GHGs can be distinguished into shorter- and long-lived. CO$_2$ emissions from bioenergy show characteristics similar to shorter-lived species.
Figure S5. Temperature peak ($\Delta T_{peak}$) from idealized emission trajectories of non-CO$_2$ GHGs as a function of cumulative emissions ($\Sigma E$) or emission rates ($E_{max}$). Graphs on the left hand side (a, c) show the dependency of the temperature peak on different levels of cumulative emissions under a constant maximum peak rate (10 Mtons/year for CH$_4$ and N$_2$O and 0.01 Mton/year for the other GHGs). Graphs on the right hand side (b, d) show the dependency of the temperature peak on maximum emission rates under constant cumulative emissions (1000 Mtons for CH$_4$ and N$_2$O and 1 Mton for the other GHGs). These data are used to compute the normalized temperature ranges of the non-CO$_2$ gases shown in Figure 3c of the main text.
References


