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Linearity between temperature peak and bioenergy CO_2 emission rates

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Many future energy and emission scenarios envisage an increase of bioenergy in the global primary energy mix[1–4]. In most climate impact assessment models and policies, bioenergy systems are assumed to be carbon neutral, thus ignoring the time lag between CO_2 emissions from biomass combustion and CO_2 uptake by vegetation[5]. Here, we show that the temperature peak caused by CO_2 emissions from bioenergy is proportional to the maximum rate at which emissions occur and is almost insensitive to cumulative emissions. Whereas the carbon–climate response (CCR; ref. 6) to fossil fuel emissions is approximately constant, the CCR to bioenergy emissions depends on time, biomass turnover times, and emission scenarios. The linearity between temperature peak and bioenergy CO_2 emission rates resembles the characteristic of the temperature response to short-lived climate forcers. As for the latter[7–9], the timing of CO_2 emissions from bioenergy matters. Under the international agreement to limit global warming to 2 °C by 2100[3], early emissions from bioenergy thus have smaller contributions on the targeted temperature than emissions postponed later into the future, especially when bioenergy is sourced from biomass with medium (50–60 years) or long turnover times (100 years).

Bioenergy is part of many future low CO_2 emission scenarios and it is the most important renewable energy option in studies designed to align with future RCP projections, reaching approximately 250 EJ yr^{-1} in RCP2.6 (ref. 1), 145 EJ yr^{-1} in RCP4.5 (ref. 2) and 180 EJ yr^{-1} in RCP8.5 (ref. 4) by the end of the twenty-first century. Integrated assessment models and policy directives have mainly focused on the quantification and mitigation of risks associated with deforestation and land-use changes[10], and only recently has the default 'carbon neutrality' assumption applied to CO_2 emissions from bioenergy come under scrutiny by governmental authorities[11].

In bioenergy systems, the CO_2 exchanges with the atmosphere are usually characterized by fast emissions from biomass combustion and slow CO_2 uptake by vegetation re-growth. As succinctly mentioned in the 5th IPCC Assessment Report[12], this yields a non-zero climate forcing even if the net CO_2 fluxes sum up to zero over time. The climate impact from this temporal asymmetry can be quantified at different points of the carbon–climate cause–effect chain[12], from a simple sum of CO_2 fluxes informing about an initial carbon debt[5] to radiative forcing and subsequent temperature change[13]. Whereas the temperature response to a CO_2 pulse from fossil fuels is sustained for many centuries at an approximately constant or slightly decreasing value[6,14–16], recent studies showed that the temperature change from bioenergy CO_2 emissions is characterized by an initial warming followed by a smaller long-term cooling and asymptotically tend to zero[12,13,17]. However, an analysis that disentangles the role of CO_2 emissions from bioenergy within the policy-relevant framework[3,7,8,18] linking temperature peak (ΔT_{peak}) and emissions is still missing. Many studies found that the temperature peak of long-lived greenhouse gases (GHG) is roughly proportional to cumulative emissions[6,14,19], whereas the ΔT_{peak} from short-lived species is constrained by their maximum emission rate[7–9,12,20]. The reason is that the atmospheric perturbation from long-lived GHGs such as CO_2 is lasting so long that the induced temperature rise will stabilize only if emissions are reduced to zero[19], whereas the temperature change from short-lived species decreases after a maximum once emission rates have peaked[9]. Within a two-basket approach in which GHGs are differentiated into long- and short-lived[8], a specific global warming target could therefore be achieved by setting a dual objective to limit cumulative emissions of long-lived GHGs and maximum emission rates of short-lived species[8].

Here, we show that there is a linear relationship linking the global temperature peak from bioenergy to maximum CO_2 emission rates, as it is observed for short-lived climate forcers. Using the global carbon-cycle climate model OSCAR v2.1 (ref. 21), whose technical description is available in the Supplementary Information, we investigate the climate system response to CO_2 emissions from bioenergy sourced from biomass resources with short (6 years), medium (55 years) and long (103 years) turnover times. The latter case study can be taken as the upper bound for the regeneration period of commercial forest plantations. Summarized in Table 1, the bioenergy experiments are based on post-harvest chronosequences of CO_2 net ecosystem exchanges (NEE) that dictate the rates at which the biomass energy resources can be replenished. We treat biomass as a renewable source, with the system being carbon neutral along the biomass turnover time. Simulations are performed under a constant background climate following the protocol[15] recently used by the IPCC (ref. 12) for the computation of emission metrics and temperature responses (see Methods for specific details). The direct carbon and climate responses to CO_2 pulses for the cases analysed in this study are reproduced in the Supplementary Information, where the possible effects of a changing climate are also explored (Supplementary Figs 3–5).

In Fig. 1 we show the carbon–climate response (CCR (ref. 6), also referred to as TCRE (ref. 22)), computed as the ratio of temperature change to cumulative emissions in °C per teraton Carbon (TtonC), for the default experiment with +1% yearly increase in carbon emissions. The results are generated after 1,000 repetitions of

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Table 1 | Characteristics of the biomass and post-harvest net ecosystem exchanges (NEE) used in the bioenergy experiments.

Simulation case	Location	Plantation type	Dominant species	Turnover time (years)	Mean annual precipitation (mm d^{-1})	Mean annual air temperature (°C)	Source
Biomass, short turnover time	23° 00′ S; 48° 52′ W	Subtropical	*Eucalyptus grandis*	6	4.0	22.0	Ref. 28
Biomass, medium turnover time	46° 30′ N; 91° 06′ W	Cold temperate	Hardwood, mainly *Populus tremuloides*	55	2.1	5.2	Ref. 29
Biomass, long turnover time	60° 05′ N; 17° 28′ E	Hemiboreal	*Pinus sylvestris*	103	1.85	6.09	Ref. 30

These cases are representative of short, medium and long biomass turnover times (that is, the time required to replenish the biomass resource). The NEE fluxes are used to model the ecosystem carbon response fed into OSCAR v.2.1. Further details about these case studies are available in Supplementary Fig. 2.

the model experiments with variations of key global carbon-cycle and climate parameters. The CCR is a metric that consistently generalizes previously proposed temperature-based metrics, such as the temperature response to a pulse or sustained emission[15,23], into a single metric which allows one to infer CO_2-induced temperature change directly from cumulative emissions[6,22]. In the fossil simulations, the CCR is time-invariant after an adjustment period, owing to the compensation between the saturation of carbon sinks and the saturation of CO_2 radiative forcing with increasing atmospheric CO_2 (ref. 6). Our value of 1.7 ± 0.4 °C per TtonC (mean ± one standard deviation)is in line with more sophisticated carbon–climate and earth system models: C^{4}MIP models show an ensemble mean of 1.6 °C per TtonC emitted (range 1.0–2.1; ref. 6), whereas a range of 0.8–2.4 °C per TtonC is found across 15 CMIP5 models[22]. In contrast with fossil fuels, the CCR in the bioenergy simulations shows a clear time dependency, declining after a maximum, with the rate of the decline increasing with decreasing turnover times. In bioenergy systems with medium and long turnover times, CCR temporarily exceeds the value from fossil fuel emissions, reaching a maximum at approximately 1.95 ± 0.35 °C per TtonC. This stems from the fact that, in addition to emissions from biomass combustion, ecosystems are in these cases net CO_2 sources to the atmosphere for about two decades after harvest, because CO_2 respiration fluxes are larger than the CO_2 uptake by net primary productivity (Methods).

The CCR in bioenergy experiments is thus dependent on time and resource turnover times. The influence of different annual growth rates is explored in Fig. 2. CCR of fossil fuel emissions is almost constant across the different emission pathways (Fig. 2a). By contrast, the CCR in the bioenergy experiments is dependent on the specific emission scenario. Figure 2b shows that CCR values remain relatively small for quickly regenerating biomass resources. When bioenergy is sourced from biomass with medium (Fig. 2c) or long (Fig. 2d) turnover times, the CCR at the beginning is almost insensitive to time and emission growth rates, but after this initial phase it gradually decreases over time down to lower values at a rate dependent on the emission growth rate and resource turnover time. Unlike for fossil fuel emissions, a specific CCR value for CO_2 emissions from bioenergy cannot therefore be used as a simple metric to infer the induced temperature change from cumulative emissions, owing to its clear dependency on time, resource turnover times and emission pathways.

We gather further insights into the climate system response to CO_2 emissions from bioenergy by investigating the temperature peak from a variety of idealized emission trajectories with different combinations of emission growth rates, peak year and post-peak decline rates. In Fig. 3 we single out the sensitivity of ΔT_{peak} to cumulative emissions (ΣE) or to the maximum emission rate (E_{max}) by constraining the emission trajectories either at

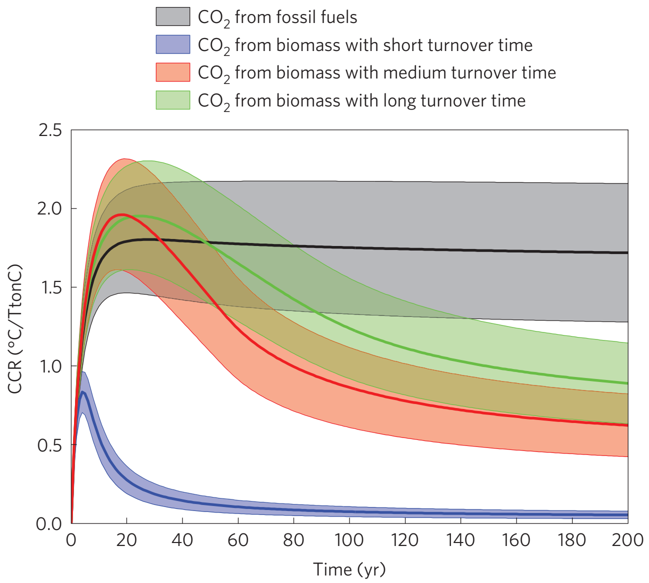

Figure 1 | Carbon–climate response (CCR) as a function of time under a 1% per year increase in emission rates. Results for fossil fuels are in grey and those for bioenergy are in blue, red and green for the short, medium and long biomass turnover times, respectively. The solid lines are the ensemble means and the coloured areas represent the outcomes within one standard deviation from uncertainties in the carbon and climate system.

E_{max} = 10 GtonC yr^{-1} (Fig. 3a), or at ΣE = 1 TtonC (Fig. 3b). For reference, CO_2 emissions from fossil fuels and cement production were about 9.5 GtonC yr^{-1} in 2011[24]. As previously shown[6,14,22], the ΔT_{peak} from fossil fuel emissions is proportional to the total amount of emissions and insensitive to emission rates. The total allowable cumulative carbon emissions for the 2 °C target can here be approximated to 1.25 TtonC, in line with previous estimates in the range of 1.0–1.5 TtonC (refs 16,19,25), with approximately 0.5 TtonC emitted so far from pre-industrial times[24]. In Fig. 3b, where emission trajectories result in ΣE = 1 TtonC, the ΔT_{peak} from fossil CO_2 approximately follows the respective CCR value. The temperature peak from bioenergy shows opposite characteristics: there is an almost linear relationship between ΔT_{peak} and the maximum emission rates (Fig. 3b) and the ΔT_{peak} is almost insensitive to cumulative emissions (Fig. 3a). Although fossil carbon emissions cause an equal temperature rise for each additional unit of emission, ΔT_{peak} from bioenergy does not depend on the total amount of CO_2 emitted, but rather on the maximum rate at which emissions occur. Figure 3b shows that extreme maximum CO_2 emission rates from bioenergy are required to approach a ΔT_{peak} per

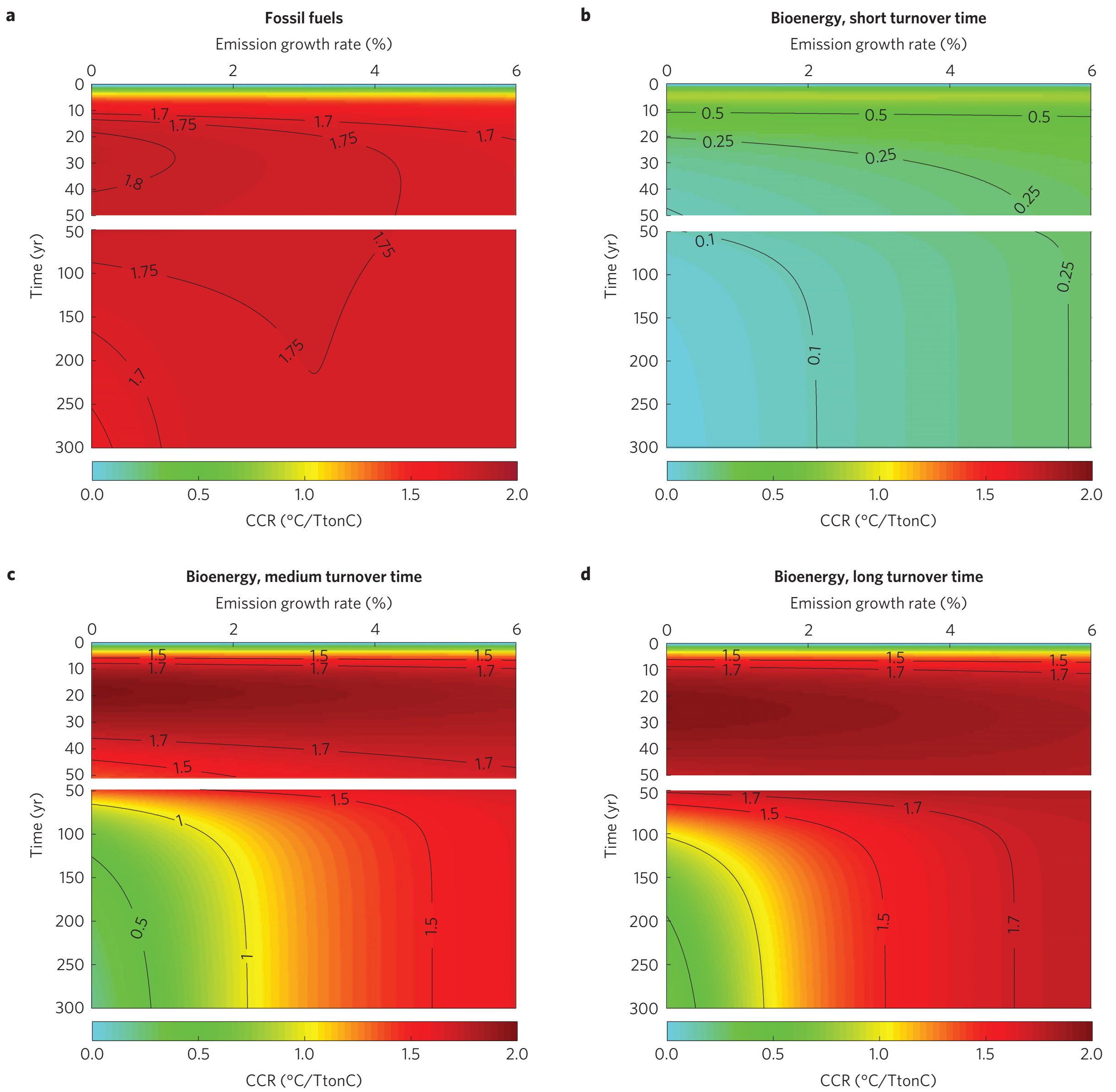

Figure 2 | Carbon–climate response (CCR, ensemble mean only) in °C per TtonC as a function of time and emission growth rate. Simulations are based on CO_2 from fossil fuels (**a**) and CO_2 from biomass energy production with short (**b**), medium (**c**) and long (**d**) turnover times. CCR isolines are marked by a solid black line. In **c** and **d** the isolines also show the mean CCR value in the fossil fuel experiment (1.7 °C per TtonC).

1 TtonC close to that from fossil fuels. This occurs for E_{max} around 30 GtonC yr^{-1} in the case of a long turnover time, and further higher rates would be needed for biomass with smaller turnover times. The sensitivity of ΔT_{peak} to ΣE and E_{max} is compared in Fig. 3c, which is based on the normalized temperature peak ranges of the ensemble means in Fig. 3a,b. We also consider, as a benchmark, non-CO_2 well-mixed GHGs with different lifetimes (CH_4, N_2O, some CFCs and HFCs). Similarly to short-lived species such as CH_4 and HFC-41, CO_2 emissions from bioenergy show a higher sensitivity of ΔT_{peak} to E_{max}. For these species the climate system has insufficient time to fully respond before the perturbation has disappeared, because the atmospheric lifetimes are shorter than the timescale required by the climate system to respond to a forcing[7,23]. On the other hand, if the gas is long-lived the climate system has time to fully respond to the perturbation. This is the case for long-lived GHGs such as CO_2 emissions from fossil fuels, which exhibit a higher ΔT_{peak} dependency on the amount of cumulative emissions. The similarity between CO_2 emissions from bioenergy and short-lived species is confirmed by further simulations in which ΔT_{peak} shows a higher linear correlation with E_{max} (Supplementary Figs 6 and 7). This linear relationship can be used to build simple metrics for bioenergy with which one can infer the induced temperature peak from the maximum rate at which emissions take place. For example, within an emission rate range of $0 < E_{max} < 20$ GtonC yr^{-1} (Supplementary Fig. 6b), the peak temperature rise from bioenergy is equal to 0.095 ± 0.029, 0.063 ± 0.02 and 0.005 ± 0.002 °C per GtonC yr^{-1} for the long, medium and short turnover times, respectively.

Under the framework of the two-basket approach, CO_2 emissions from bioenergy sourced from renewable biomass can therefore be assigned to the basket of short-lived emissions. For these species the timing of emissions does matter, because their impact gradually dissipates over time, whereas for long-lived GHGs it will persist for centuries. This means that early emissions from bioenergy have a smaller contribution than late emissions to a global warming target occurring in several decades from now—such as the 2 °C target in 2100.

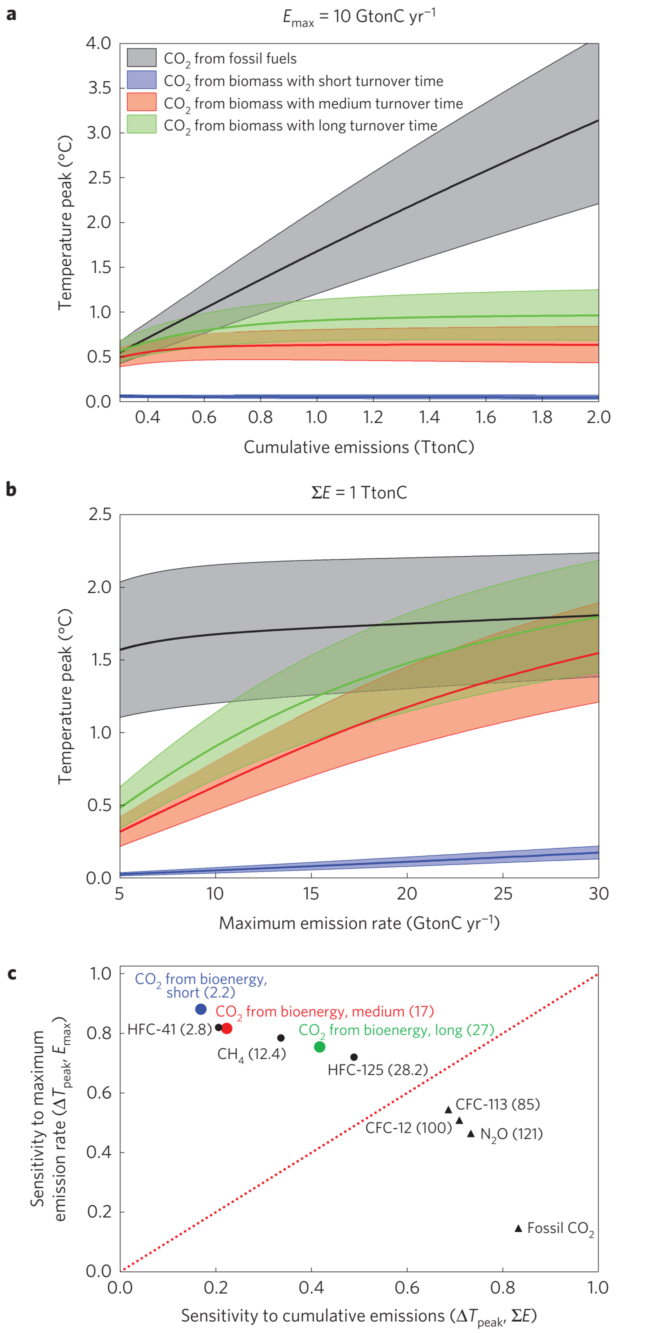

Figure 3 | Sensitivity of ΔT_{peak} from idealized emission trajectories as a function of ΣE or E_{max}. **a**, Sensitivity of ΔT_{peak} on ΣE from emission trajectories with the same E_{max} (10 GtonC yr^{-1}) and resulting in different levels of ΣE (0.3–2.0 TtonC). **b**, Sensitivity of ΔT_{peak} on E_{max} from emission trajectories resulting in the same amount of ΣE (1 TtonC) but with different E_{max} (5–30 GtonC yr^{-1}). **c**, Comparison of the sensitivity of ΔT_{peak} to ΣE (ΔT_{peak}, ΣE) or to E_{max} (ΔT_{peak}, E_{max}) using the normalized temperature range of ΔT_{peak} dynamics for the cases in **a** and **b**; the dotted red line marks the equal sensitivity. The temperature peak dynamics over ΣE or E_{max} of the non-CO_2 GHGs are in Supplementary Fig. 8. The ensemble mean of ΔT_{peak} with one standard deviation is shown in **a** and **b**, whereas **c** shows the ensemble mean only. In **c** numbers in parenthesis indicate the approximate lifetimes of the gas[12]; species that can be assigned to the short-lived basket are marked with a circle and those to the long-lived basket with a triangle. CO_2 emissions from bioenergy are less sensitive to ΣE than can be inferred from the lifetimes when compared with the other GHGs. This is because the lifetime is approximated with a first-order decay model that does not take into account negative values of the response.

The results presented in this study distinctively reflect the quintessential difference of the climate responses to CO_2 emissions from bioenergy and fossil fuels. Both emissions induce perturbations to the carbon and climate system, but biomass is a renewable resource that can be replenished within a timescale of year(s) to decades, whereas fossil reservoirs are generated through geological timescales and cannot be replenished[24]. Within the goal of mitigating climate change, bioenergy is unequivocally recognized as a key option[1,3]. Our analysis shows that CO_2 emissions from bioenergy can be assessed in ways that are consistent with those of other GHGs, and that relevant insights are achieved by explicitly considering the resource-specific turnover times and the temperature peak dynamics. By going beyond the 'carbon neutrality' convention, these insights can be included into the existing variety of emission metrics[12] and frameworks to facilitate the assessment of bioenergy CO_2 emissions under specific climate targets, and ultimately enhance the identification of effective climate change mitigation options. The latter should also take into account, when appropriate, other climate-regulating mechanisms (for example, biogeophysical effects, aerosols and N_2O emissions from fertilization)[26] and case-specific constraints (for example, land availability, water demand, soil degradation and associated yield losses)[27] not considered in this study.

Methods

These results are obtained after integration of a global carbon-cycle climate model and empirical observations of biosphere–atmosphere exchanges of CO_2 following harvest disturbance. The responses in atmospheric CO_2 and global mean surface temperature are computed using OSCAR v2.1 (ref. 21), a compact coupled carbon-cycle and climate model that simulates the redistribution of anthropogenic carbon among the main carbon reservoirs (atmosphere, terrestrial biosphere and oceans). A technical description of OSCAR v2.1 is available in the Supplementary Information, together with a description of the origin of the uncertainty ranges shown in the results. The performance of OSCAR v2.1 with respect to other models is benchmarked in Supplementary Fig. 1. The carbon and climate responses of this paper are calculated under constant background climate conditions according to the standard protocol for emission metrics[15]—that is, the model is initially forced with historical concentrations up to the reference year (namely, 2010), thereafter the concentration and other anthropogenic forcings are stabilized at the 2010 level (for example, atmospheric CO_2 concentration is kept constant at the value of 389 ppm), and then a CO_2 emission pulse of 100 GtC is added to the atmosphere five years after the reference year (namely, in 2015). The size of this pulse is compatible with the responses to infinitely small pulses, as shown elsewhere for both the carbon-cycle[15] and the climate (temperature) system[6]. The results presented in this study can thus be downscaled to characterize impacts from emissions of smaller size. The atmospheric lifetime of the CO_2 perturbation in the bioenergy cases is computed by fitting the ensemble mean curves in Supplementary Fig. 3a with a first-order decay model. CCR is computed from emission pathways growing at a rate between 0 and 6% as the ratio of the instantaneous global average surface temperature change (in °C) to cumulative carbon emissions (in TtonC). The possible influence of varying background CO_2 atmospheric concentration and climate on the temperature response and CCR are investigated by reproducing the same experiments in 2100 after letting CO_2 concentration change during the twenty-first century according to the four RCP scenarios (Supplementary Figs 4 and 5).

We created two independent groups of 500 idealized emission trajectories (with a ten-year peak phase occurring between 2030 and 2160, followed by a post-peak phase with a decline to zero within a maximum of 100 years) to study the sensitivity of ΔT_{peak} to ΣE or E_{max}. In the experiment aiming at testing the sensitivity of ΔT_{peak} to ΣE (Fig. 3a), emission trajectories are constrained to $E_{max} = 10$ GtonC yr^{-1} and result in ΣE ranging between 0.3 and 2 TtonC. The dependency on E_{max} (Fig. 3b) is studied over emission trajectories of $5 < E_{max} < 30$ GtC yr^{-1} and resulting in the same amount of cumulative emissions ($\Sigma E = 1$ TtonC). The normalized temperature ranges in Fig. 3c are computed as $\left(\Delta T_{peak}^{max} - \Delta T_{peak}^{min}\right) / \Delta T_{peak}^{max}$ using the corresponding temperature peak dynamics. Another set of unconstrained emission trajectories in which E_{max} and ΣE span between 0 and 20 GtonC yr^{-1} and between 0 and 4 TtonC, respectively, are generated to distinguish short- and long-lived species as in ref. 8 (Supplementary Figs 6 and 7). Units for the emission trajectories of the non-CO_2 GHGs: ΣE are in 1,000 Mtons and E_{max} are in Mtons per year for CH_4 and N_2O; ΣE are in Mtons and E_{max} are in ktons per year for the other GHGs.

In the bioenergy simulations, emissions from combustion are associated with the ecosystem carbon responses represented by the NEE chronosequences

(Supplementary Fig. 2 shows the data used in this study). NEE values include CO_2 sequestration by net primary productivity (NPP) and ecosystem respiration (that is, oxidation of carbon from soil and dead biomass). In the chronosequences representative of a medium and long turnover time, the ecosystem is a net carbon source for approximately the first couple of decades following disturbance, owing to the dominant respiration flux (mainly from the decomposition of harvest residues) over NPP, which then becomes dominant and ecosystems turn to be net carbon sinks. These ecosystem responses are prescribed to OSCAR v2.1 in the form of a series of small pulses whose cumulative value over the turnover time is equal to the emission pulse. Many woody bioenergy cases can be expected to fall between the short and long turnover time; biomass species with turnover times shorter than six years, such as perennial grasses and short rotation coppice, cause a perturbation smaller than that shown here for the short turnover case, and can be approximately considered climate neutral. The simulations in this paper are based on the assumption that bioenergy is a renewable resource—that is, it fully regenerates along the turnover time—although on a case-specific basis some net carbon losses (for example, in the first succession) or gains (for example, in fertilized plantations) can be expected.

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Author contributions

F.C. and T.G. conducted the preliminary design of the study and the experiments; all authors discussed the specific goal and scope of the analysis and the presentation of the results; T.G. computed the carbon-cycle and climate responses; F.C. elaborated the data and ran the simulations under various emission scenarios; F.C. wrote the paper with contributions from all the authors.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to F.C.

Competing financial interests

The authors declare no competing financial interests.