

Multiple Climate Tipping Points Metrics for Improved Sustainability Assessment of Products and Services

Serena Fabbri,* Michael Z. Hauschild, Timothy M. Lenton, and Mikołaj Owsianiak



Cite This: *Environ. Sci. Technol.* 2021, 55, 2800–2810



Read Online

ACCESS |



Metrics & More

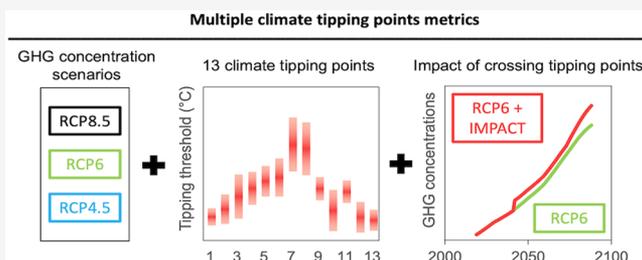


Article Recommendations



Supporting Information

ABSTRACT: Mounting evidence indicates that climate tipping points can have large, potentially irreversible, impacts on the earth system and human societies. Yet, climate change metrics applied in current sustainability assessment methods generally do not consider these tipping points, with the use of arbitrarily determined time horizons and assumptions that the climate impact of a product or service is independent of emission timing. Here, we propose a new method for calculating climate tipping characterization factors for greenhouse gases (carbon dioxide, methane, and nitrous oxide) at midpoint. It covers 13 projected tipping points, incorporates the effect that the crossing of a given tipping point has on accelerating the crossing of other tipping points, and addresses uncertainties in the temperature thresholds that trigger the tipping points. To demonstrate the added value of the new metric, we apply it to emissions stemming from end-of-life of plastic polymers and compare them with commonly used metrics. This highlights the need to consider climate tipping in sustainability assessment of products and services.



INTRODUCTION

There are several elements of the earth system that could pass a tipping point within this century and trigger large abrupt, potentially irreversible changes.¹ Examples of tipping elements include Arctic summer sea ice, the Atlantic thermohaline circulation, and the El Niño-southern oscillation.² The crossing of these elements may be one of the most dangerous consequences of human-induced climate change.³ From the economic perspective only, Cai et al. showed an eight time increase in monetary costs per 1 tonne of carbon dioxide emitted, when compared to the costs without considering the tipping.⁴ These findings stress the need for consideration of climate tipping elements when developing metrics of climate impact for improved environmental sustainability assessment of products and services.

Life cycle assessment (LCA) is a tool that is often used to address the environmental sustainability of products and systems.⁵ In LCA, the climate change impacts of a product or service are traditionally quantified using global warming potentials (GWP)⁶ as characterization factors (CF), representing the impact per unit of emission. Amounts of individual greenhouse gases (GHG) that can be attributed to a specific product or service are first summed up and then multiplied by a GHG-specific GWP; the resulting indicator scores added. The sum represents the climate change impact score (also referred to as carbon footprint)⁷ and expresses the potential contribution of a product or service to change radiative forcing (not the actual warming) over a defined time horizon, typically over 100 years. The procedure for calculating impact scores is the same for all other midpoint indicators of climate change

(where midpoint refers to the location of the indicator in the cause-effect chain linking emission inventories with final damage caused to environment or human health). For another midpoint indicator, global temperature change, the global temperature change potential (GTP)⁸ is used and the resulting impact scores indicate the potential contribution of a product or service to global average temperature increase of the atmosphere at a future point in time, typically at 100 years.

Both GWP and GTP are recommended emission metrics by the IPCC⁶ and have been suggested as complementary CFs for quantification of climate change impacts of products and services by the LCA community.⁹ However, none of them considers climate tipping mechanisms in the earth system.^{9,10} It is challenging to capture the dependence of the impact of emissions on the emission timing in relation to the time of the tipping points. As tipping points represent critical levels of warming that should not be crossed, tipping-orientated GHG emission metrics cannot simply measure radiative forcing (or temperature) change over a fixed time horizon for a pulse emission emitted at an arbitrary time. Instead, they should quantify how much that change can contribute to crossing the tipping points and should assess that for multiple pulse

Received: May 7, 2020

Revised: January 27, 2021

Accepted: January 29, 2021

Published: February 5, 2021



emissions, i.e., emitted at different times. To do this, an approach based on quantification of the carrying capacity of the atmosphere to absorb the emission without crossing the tipping point is necessary.¹¹ In this perspective, the effects of an emission will depend on how much carrying capacity is depleted by the emission and, thus, on the proximity to tipping points. This is at odds with current impact assessment practice where carrying capacities and dependency of impacts on emission timing are not embedded in the CF.^{11,12}

The metric developed by Jørgensen et al.,¹³ the climate tipping potential (CTP), introduced both aspects while accounting for the Arctic summer sea-ice loss as tipping element. Here, the impact of 1 kg GHG emitted at a given year was expressed as the fraction of carrying (or remaining) capacity, i.e., the time-integrated increase in atmospheric CO₂-equivalent concentration that can still occur before Arctic summer sea-ice loss, depleted by the time-integrated change in CO₂-equivalent concentration caused by the emission. However, their metric only considers this one tipping point and thereby neglects several aspects that are required for a robust metric of climate tipping. First, it must consider emissions occurring after the tipping of a given element of the earth system as contributors to crossing other, subsequent tipping points.¹³ Second, potential consequences of crossing a given tipping point on the acceleration tipping of other elements must be accounted for.¹⁴ For instance, the reduction of sea ice albedo in the Arctic amplifies warming making the subsequent tipping point (e.g., Greenland ice sheet melting) occur faster than it would without tipping of the Arctic sea ice. Third, when taking multiple tipping points into account, sequence and timing of occurrence of individual climate tipping points depend on uncertain factors, like temperature thresholds triggering the tipping points,^{2,15} and these uncertainties must be accounted for.

In this paper, we develop new climate tipping characterization factors (CF) for three major anthropogenic GHGs (carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O)), which meet these requirements. We first select relevant tipping elements, present the conceptual framework, and develop a method for computing multiple climate tipping points potentials (MCTPs) at midpoint. We apply the new MCTPs to end-of-life GHG emission inventories for plastic polymers made from different feedstock and spanning a wide range of temporal evolutions of GHG emissions in their end-of-life. We also present practical implications of using the new CFs in LCA, where information about temporal evolution of GHG emissions might not be available or relevant. We argue that the new CFs are a useful supplement to (but not a substitute for) the currently used GWP and GTP CFs recommended by the IPCC.

METHODS

Selection of Climate Tipping Elements. We carried out a literature review to identify a broad list of potential tipping elements without considering potential differences in the formal definition of tipping point given by different authors (Table S1 in Supporting Information). From this broad list, 13 tipping points were selected for inclusion in the study based on a set of criteria that (1) define the tipping mechanism, (2) consider changes in atmospheric GHGs concentration as the potential triggers, and (3) consider modeling of the tipping points feasible when tipping thresholds can be expressed as global mean temperature. The selection criteria are presented

in the Supporting Information. The selected tipping points are Arctic summer sea ice loss (AS), Greenland ice sheet melt (GI), West Antarctic ice sheet collapse (AI), Amazon rainforest dieback (AF), Boreal forest dieback (BF), El Niño-Southern Oscillation change in amplitude (EN), Permafrost loss (P), Arctic winter sea ice loss (AW), Atlantic thermohaline circulation shutoff (TC), North Atlantic subpolar gyre convection collapse (SG), Sahara/Sahel and West African monsoon shift (AM), Alpine glaciers loss (AG), and Coral reefs deterioration (CR) (Table S2).

Conceptual Framework. The method for calculating the climate tipping potential (CTP) for the Arctic summer sea-ice loss as tipping element proposed by Jørgensen et al.¹³ was taken as a starting point. Their method is further developed to consider: (1) other selected tipping elements, (2) uncertainties of tipping points occurrence, and (3) the effect of crossing a tipping point on accelerating tipping of all subsequent tipping points. The new CFs are therefore referred to as multiple climate tipping points potentials (MCTP). Their main features are presented below.

First, the impact of a GHG emission represents time-integrated radiative forcing of 1 kg emission of a greenhouse gas *i* and is expressed as atmospheric CO₂-equivalent concentration (in ppm of CO₂e·yr·kg_{*i*}⁻¹). The integration is from the emission year to the year of tipping (rather than over a fixed time horizon like in the GWP).

Second, this impact is always given in relation to the remaining capacity of the atmosphere to absorb that impact without triggering the tipping point, also expressed in ppm of CO₂e·yr·kg_{*i*}⁻¹ (rather than comparing impacts to that of a reference gas like CO₂ as in GWP). The resulting MCTP CFs therefore represent the fraction of remaining capacity taken up by the unit emission (which is expressed in parts per trillion of remaining capacity, ppt_{rc}·kg_{*i*}⁻¹). MCTPs are dynamic because both the impact and the remaining capacity to absorb the impact without triggering the tipping point depend on emission time.

Third, remaining capacities depend on background anthropogenic GHG emissions, as they ultimately determine when the tipping point is triggered, and furthermore, the impact of a GHG emission attributed to a product or service can be considered as part of this background. Although GHG emissions from an individual product system will never be large enough to cause a tipping, a large number of products that are produced, used, and disposed of in our society and their attributed (often very small) quantities of GHG emissions have a real potential to cause the tipping. Thus, application of MCTP CFs to single product systems that are modeled in LCA gives a meaningful estimate of the product's contribution to passing critical tipping points. This is in line with the attributional approach to LCA, which aims to represent a product system in isolation to quantify the impact that the product is "responsible for".¹⁶ However, considering the effects from crossing a given tipping point on the reduction of the remaining carrying capacity for all subsequent tipping points could be seen as a marginal contribution that adds impact to the background pressure. This is more in line with the consequential approach to LCA, which aims to assess the environmental consequences of using a product or providing a service.

Finally, the aforementioned considerations imply that MCTP CFs are not applicable to assessments of large scale

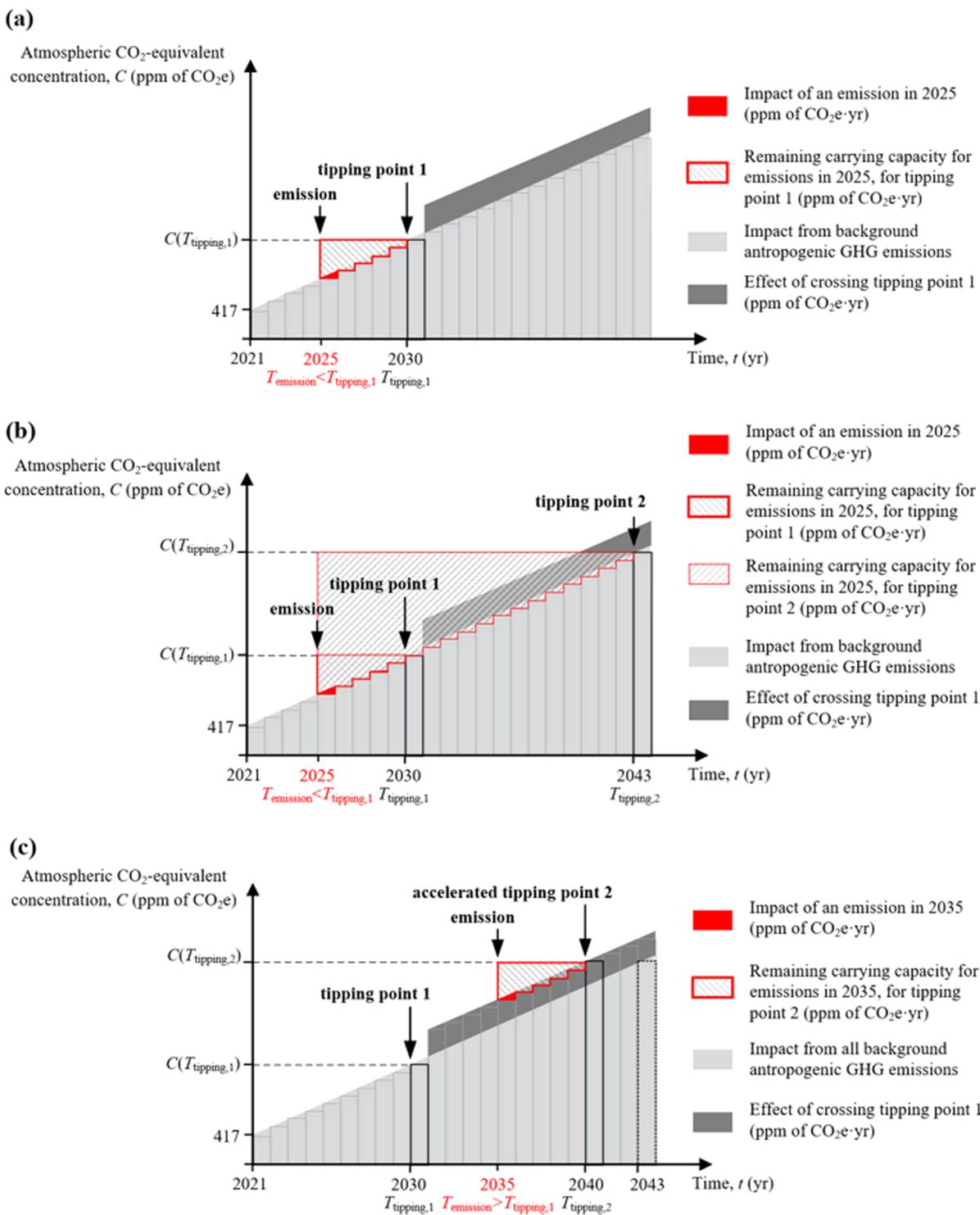


Figure 1. Conceptual illustration of MCTP calculation for a unit (1 kg) emission of GHG i that is part of anthropogenic background GHG emissions, in different years with either one (a) or two (b and c) tipping points. The horizontal time axis is divided in discrete time intervals of 1-year, as indicated with capital letters, and vertical bars represent annual CO₂-equivalents concentration increases. T_{emission} indicates the emission year; $T_{\text{tipping},1}$ and $T_{\text{tipping},2}$ indicate the year of tipping of the first and second tipping point, respectively. Emissions occurring before the first tipping point (at $T_{\text{emission}} < T_{\text{tipping},1}$) will contribute to crossing both tipping points (at $T_{\text{tipping},1}$ and $T_{\text{tipping},2}$). Emissions occurring after the first tipping point but before the second tipping point (at $T_{\text{tipping},1} < T_{\text{emission}} < T_{\text{tipping},2}$) will contribute to crossing the second tipping point only. Crossing the first tipping point speeds up the occurrence of the second tipping point, in practice, reducing the carrying capacity of emissions at $T_{\text{tipping},1} < T_{\text{emission}} < T_{\text{tipping},2}$ for the second tipping point. Note that the effect of crossing the first tipping is irrelevant for part a because this case considers only one tipping point (as presented in Jørgensen et al.¹³) and is not considered in calculation of remaining carrying capacity for an emission occurring before the first tipping point.

systems, e.g., at country level, which have the potential to substantially influence background emission levels.

Figure 1 provides a conceptual illustration of the framework: starting from one tipping element (in practice, CTP of

Jørgensen et al.¹³) (Figure 1a) through adding a second tipping point (Figure 1b) to considering effects from crossing the first tipping point on accelerating tipping of the second tipping point (Figure 1c). The figure is conceptual as (1) increase in atmospheric CO₂-equivalent concentration due to background anthropogenic emissions is assumed linear, (2) the impact of the emission (part of anthropogenic background emissions) is simplified using triangles, (3) the remaining capacity is also simplified using triangle-like shapes, and (4) the effect of crossing the first tipping point is assumed to be equally distributed over the years which follow. Yet, the figure allows us to illustrate the framework. Background production and consumption activities increase atmospheric CO₂-equivalent concentration so that the first tipping point is triggered in 2030. An emission before this tipping point, e.g., in 2025, contributes to the crossing of this tipping point as it consumes part of the carrying capacity that remains until the tipping point is triggered (Figure 1a). This is the principle of the original CTP-framework of Jørgensen et al.¹³ Extension of their framework by considering another tipping element, here triggered in 2043, implies that an emission in 2025 now contributes to crossing of both tipping points as it also consumes part of the carrying capacity that remains until the second tipping point is triggered (Figure 1b). Finally, for an emission occurring after the first tipping point but before the second one, e.g., in 2035, one additional factor must be considered. Namely, crossing of the first tipping point in 2030 speeds up tipping of the second tipping point (from 2043 to 2040) because of the effect from the tipping of the first tipping point itself which adds to the background (Figure 1c). This accelerated tipping of the second tipping point reduces the remaining capacity for those emissions which occur after the first tipping point.

The same mechanisms apply if more tipping points are considered. Mathematical description of these mechanisms is detailed later.

Consideration of Time as a Variable. The MCTP framework requires that the time variable is used with different attributes. Specifically, we distinguish *time interval* (i.e., time step) where time is discrete as opposed to *point in time* where time is continuous. The *interval* is used when time indicates a portion (an interval) of time defined within two specific points in time. It is indicated with capital *T*. For instance, the emission year $T_{\text{emission}} = 2021$ indicates an emission occurred any time between first January, 00:00 and 31st December, 23:59 of the year 2021. Intervals of 1 year were considered the most realistic level of resolution for time-differentiated inventories of emissions and thus for the calculation of MCTPs. *Points in time* were used when integration over time was necessary. Time in those cases is a continuous variable and is indicated with lowercase *t*. We also distinguish between *absolute time* as opposed to *relative time*. Time is generally absolute in our framework because MCTPs depend on the specific years in which tipping points are triggered (e.g., 2021, 2022, etc.). By contrast, whenever the dependent variable does not depend on the proximity to tipping point, then relative time is used (e.g., year 1, year 2, etc.). A summary of the symbols used to refer to the time variable, their meaning, and where they are used in the paper is presented in Table S7 in Supporting Information.

Calculation of Multiple Climate Tipping Points Potentials (MCTP). With a consideration of *m* tipping points, the multiple climate tipping points potential, $MCTP_i$, in [ppt_c·

kg_i⁻¹] (parts per trillion of remaining capacity taken up by a unit emission) of gas *i* emitted at year T_{emission} is defined as the sum of the ratios between the *impact of the emission* (that is part of anthropogenic background emissions) and the corresponding remaining capacity for each of the *m* tipping points occurring after the emission year

$$MCTP_i(T_{\text{emission}}) = \sum_{j=1}^m \frac{I_{\text{emission},i,j}(T_{\text{emission}})}{CAP_j(T_{\text{emission}})} \quad (1)$$

where *j* indicates the *j*th tipping point occurring after the emission year (in order of occurrence) and can take any value from 1 to *m*, which is the total number of exceeded tipping points; $I_{\text{emission},i,j}$ is the *impact of the emission* (part of anthropogenic background emissions) of gas *i* with respect to the *j*th tipping point, CAP_j is the remaining capacity up to the *j*th tipping point, and the emission year T_{emission} can be any year from 2021 (or the year when emissions are expected to start taking place) up to the year of the last tipping point. Defined in this way, the MCTP represents the total fraction of remaining capacity taken up by the unit emission and is expressed in parts per trillion of remaining capacity (ppt_c·kg_i⁻¹). The $I_{\text{emission},i,j}$ [ppm of CO₂e·yr·kg_i⁻¹] (where CO₂e is the CO₂-equivalent concentration) of gas *i* with respect to the *j*th tipping point is here defined as the absolute climate tipping potential (ACTP) of gas *i* in [W·m⁻²·yr·kg_i⁻¹] divided by the radiative efficiency (RE) of 1 ppm of CO₂ [W·m⁻²·ppm of CO₂⁻¹]¹³

$$I_{\text{emission},i,j}(T_{\text{emission}}) = \frac{ACTP_{i,j}(T_{\text{emission}})}{RE_{CO_2}} = \frac{\sum_{k=1}^n RF_i(T_{k-1}) \cdot \Delta T}{RE_{CO_2}} \quad (2)$$

where the ACTP is equal to the radiative forcing of gas *i* (RF_i) integrated over time between the emission and the tipping. This integral is written using Riemann sum notation. In this notation, *n* is the number of time steps (dimensionless). Given that $\lim_{n \rightarrow \infty} (n \cdot \Delta T) = (T_{\text{tipping},j} - T_{\text{emission}})$, the *n* is equal to the difference between the year of tipping $T_{\text{tipping},j}$ (i.e., the year when the *j*th tipping point is exceeded) and the year of emission, T_{emission} , divided by the length of the time step, ΔT (eq 3). The ΔT is always equal to 1 year.

$$n = \frac{T_{\text{tipping},j} - T_{\text{emission}}}{\Delta T} \quad (3)$$

Note that time is relative in the RF function because radiative forcing increase depends on the time that has elapsed from the emission, independently of the emission year. However, the ACTP and the resulting *impact of the emission* are emission-year specific because year of tipping is given. The RF_i is calculated as the product of the radiative efficiency of gas *i* (A_i) (which represents radiative forcing per unit mass increase in atmospheric abundance of gas *i*) and the impulse response function (*IRF*), which for most non-CO₂ GHGs is represented with a single exponential decay and for CO₂ with a sum of exponentials.⁸ However, unlike in the GWP approach, where radiative forcing of gas *i* is divided by the radiative forcing of the reference gas (CO₂), the radiative forcing of gas *i* is divided here by the radiative efficiency of CO₂, the RE_{CO_2} . This makes the unit of the *impact of the emission* consistent with the unit of remaining capacity (both given in ppm of

CO₂e·yr). Details of calculations of the impact are presented in Supporting Information.

The CAP_{*j*} [ppm of CO₂e·yr] represents the increase in atmospheric CO₂-equivalent concentration that can still take place before reaching the concentration level (in ppm of CO₂e) that will trigger the tipping. It is emission-year specific as it depends on CO₂-equivalent concentration from background anthropogenic emissions. The remaining capacity is reduced when the emission year approaches the year of tipping due to the effect of crossing any preceding tipping points, C_{tip} (expressed in terms of CO₂-equivalent concentration increase). This effect reduces the CO₂-equivalent concentration increase that can still occur before reaching the year of tipping of subsequent tipping points thus accelerating their tipping. Equation 4 shows the calculation of the remaining capacity using Riemann sum notation for 1-year time steps

$$\begin{aligned} \text{CAP}_j(T_{\text{emission}}) &= C(T_{\text{tipping},j}) \cdot (T_{\text{tipping},j} - T_{\text{emission}}) \\ &- \sum_{k=1}^n [C(T_{k-1}) + C_{\text{tip}}(T_{k-1})] \cdot \Delta T \end{aligned} \quad (4)$$

where $C(T_{\text{tipping},j})$ is the atmospheric CO₂-equivalent concentration at the year of tipping $T_{\text{tipping},j}$, $C(T)$ is the CO₂-equivalent concentration from background emissions at time T , and $C_{\text{tip}}(T)$ is the change in CO₂-equivalent concentration at time T caused by all the tipping points that occurred before T_{emission} (all terms expressed in ppm of CO₂e). The $C_{\text{tip}}(T)$ is obtained from radiative forcing (RF) change induced by passing each specific tipping event (see Section S1.3.1 of Supporting Information). Time is absolute in eq 4 because both anthropogenic background emissions and effect of the tipping depend on the specific year. To avoid the capacity to become infinitely small and thus returning high peaks in MCTP, a cutoff of 6 [ppm of CO₂e·yr] was applied by taking the annual variability of atmospheric CO₂ concentration as a proxy for the uncertainties in measuring the atmospheric capacity (see Supporting Information).

Our representation of MCTP as a CF is somewhat different from the one that is typically used in LCIA. CFs typically represent either marginal or average “impact due to a unit emission”.^{16–19} The GWPs are derived in a marginal way,¹⁶ and this is also the way the ACTP underlying $I_{\text{emission},ij}$ in numerator of eq 1 is calculated (as in the GWPs, it is derived through radiative forcing per unit mass increase in atmospheric abundance of a given gas; see eq 2 and S1). Yet, the resulting impact $I_{\text{emission},ij}$ is related to the remaining carrying capacity, which depends on the background level, which in turn follows RCP pathway projections that are not influenced by the system being assessed in the LCA. This suggests that the resulting MCTP CFs are more in line with the average approach to calculating characterization factors (which could be supported for this type of impact owing to assumption of additivity of impacts of GHG emissions²⁰). Consideration of carrying capacity in the CF is not usual but has been discussed and tested previously.^{21,22} Bjørn A.²³ showed how carrying capacity can be integrated into characterization factors for terrestrial acidification.

The framework presented above was used to compute the MCTP of the three main anthropogenic GHGs, CO₂, CH₄, and N₂O, considering the selected tipping elements, in 10000 Monte Carlo simulations. Each simulation represents a possible sample scenario of triggered tipping points (i.e.,

different timing and order of occurrence) based on the propagation of current uncertainties in tipping occurrence. An average (geometric mean) MCTP was then calculated. We observe that iterations fail whenever tipping points are triggered in close proximity to each other (either in the same year or in consecutive years) as no remaining capacity can be calculated. This is taken into account by adjusting the number of total iteration runs so that failed iterations are excluded while the total number of runs is ~10000. Implications of this model limitation on the MCTP will be discussed.

Choice of Atmospheric GHG Concentration Development Pathway. Both the determination of the years of tipping and the evolution of the remaining capacity over time depend on the development of atmospheric GHG concentrations, expressed in CO₂-equivalents. Here, the Representative Concentration Pathways (RCPs) and their extensions up to year 2500 are used.^{24,25} The medium stabilization pathway RCP6 (total radiative forcing stabilized at 6 Wm⁻² after 2100) is chosen as baseline, assuming that even though current emission trajectories are closer to RCP8.5 projections,²⁶ ongoing mitigation efforts will prevent a continuous increase and will more likely lead to a peak-and-stabilization pathway as projected in RCP6. The MCTPs were also calculated for RCP8.5 (rising radiative forcing to 8.5 Wm⁻² after 2100) and RCP4.5 (stabilization at 4.5 Wm⁻² after 2100), selected as potentially worst- and best-case (realistic) pathways, respectively. The low emission scenario RCP2.6 is excluded as the massive mitigation efforts required are considered mostly unfeasible.^{26,27} The choice of RCP pathway influences which tipping points are triggered in each simulation as it depends on whether the threshold temperature of a specific tipping element is reached under the RCP pathway.

Determination of Tipping Time. Accurate predictions of the climate conditions triggering a tipping point and the time of occurrence are uncertain.³ On the basis of available estimates of potential thresholds levels (Table S1), we assigned one possible range of temperature thresholds to each selected tipping element (Table S2). Uncertainties in the actual temperature threshold level were accounted for by assigning a triangular probability distribution function to the range of potential threshold levels; $T(a,b,c)$, where a and b are the lower and upper limits of the range, respectively, and the most likely value c is assumed to be the central value of the assigned range. Triangular distribution was chosen because actual distributions were unknown and could not be generated with the limited data available.

The CO₂-equivalent concentration that stabilizes the climate at a given temperature threshold and the year of tipping were obtained by the combination of data on temperature and GHG concentration equivalents development over time, according to the chosen RCP pathway. The data are retrieved with the climate model MAGICC6 (Model for the Assessment of Greenhouse Gas Induced Climate Change, v.6), which is a default model to harmonize projections of RCP and Extended Concentration Pathways (ECP).^{25,28}

Calculation of Effects from Crossing Climate Tipping Points (C_{tip}). Modeling of the possible consequences from passing a tipping point is constrained by the availability of quantitative estimates of the total magnitude of such effects, which are rather scarce in the scientific literature. We considered available estimates of the potential change in RF induced by tipping suggested in previous studies (Table S6),

and to allow for their quantification in relation to the remaining capacity, we converted these to the increase in equivalents of GHG concentrations (ppm of CO₂e) that would lead to the same RF change. In some cases, the effect from tipping could not be modeled due to either lack of data (Atlantic thermohaline circulation shutoff, North Atlantic subpolar gyre convection collapse, Sahara/Sahel and West African monsoon shift, Alpine glaciers) or lack of consequences on the climate from the tipping point (coral reefs) (see Supporting Information). For Arctic summer and winter sea-ice loss, the RF change is due to reduced sea-ice albedo and conversion to annual concentration increase was done using the radiative efficiency of CO₂ per 1 ppm. This effect was assumed to unfold completely from the year after tipping and to remain constant over the years, as the evolution of radiative forcing changes after tipping was unknown. For the other six tipping points, i.e., Greenland ice sheet melt, West Antarctic ice sheet collapse, El Niño-Southern Oscillation change in amplitude, permafrost loss, Amazon rainforest and Boreal forest dieback, the RF change derives from emissions of carbon estimated to occur after tipping (Table S6). Here, C_{tip} was calculated by adapting the dynamic approach of Levasseur et al.,²⁹ originally developed for calculating time-dependent RF impacts of GHG emissions (that is, dynamic global warming potentials), to obtain time-dependent (dynamic) yearly equivalents of GHGs concentration increase due to the carbon emissions. The total carbon emissions, considered to be either CO₂ or methane emissions, depending on the tipping element, were assumed to be equally distributed over the transition period of the tipping event (see Table S6 in Supporting Information), obtaining a constant temporal profile of emissions. An exception is for El Niño-Southern Oscillation change in amplitude for which the release of carbon is considered basically permanent.⁴ The effect of these emissions was then calculated considering the residence time of the two gases in the atmosphere. The result provides the equivalent increase in GHG concentrations at any time *T* after tipping, caused by the emissions released at *T* and the nondecayed fraction of emissions that occurred before *T* since the tipping year. This approach does not account for the gradual changes that in reality occur before a critical point is reached (e.g., albedo changes from melting sea ice at current temperature levels) and may underestimate the actual effects from tipping. However, it was the most feasible modeling option considering model complexity constraints and lack of estimates on the gradual changes expected before reaching some of the considered tipping points. Details of these calculations are presented in Section S1.3.1 of Supporting Information.

Illustrative Application. The CFs proposed here depend on the year of emission, hence for each GHG, a set of year-specific MCTPs is provided and this should be used in combination with a time-differentiated inventory specifying GHG emissions in each year. The resulting impact score is calculated by summing the product of the emitted amount of gas *i* at year *T*_{emission} with the corresponding MCTP factor at *T*_{emission} for each GHG *i* and each emission year *T*_{emission}

$$IS_{MCTP} = \sum_i \sum_{T_{emission}=2021}^{T_{tipping}/last} m_i(T_{emission}) \cdot MCTP_i(T_{emission}) \quad (5)$$

where *IS*_{MCTP} is the MCTP impact score, *T*_{tipping/*i*last} is the last possible year when a tipping point can be triggered across

10000 model runs, *j*_{last} is the last triggered tipping point across 10000 model runs, *m*_{*i*}(*T*_{emission}) is the mass of GHG *i* emitted at year *T*_{emission}, and *MCTP*_{*i*}(*T*_{emission}) is the corresponding MCTP for gas *i* and emission year *T*_{emission}. The double summation indicates that the product (*m*_{*i*}(*T*_{emission}) · *MCTP*_{*i*}(*T*_{emission})) is first summed over time, starting from the first emission of GHG *i* released by the assessed product (assumed to be year 2021 in eq 5) up to the year when MCTPs are relevant (*T*_{tipping/*i*last}), and then summed over each GHG *i*.

We apply the MCTPs calculated for the RCP6 scenario to CO₂ and CH₄ emission profiles (over 100 years) from incineration and landfilling of 1 kg of fossil-based (polycaprolactone (PCL), polybutylene succinate (PBS), polystyrene (PS)) and biobased (poly)lactic acid (PLA)) biodegradable polymers. These materials are selected as they degrade over different timespans when landfilled. Six landfilling scenarios are considered with four representing a possible range of degradation rate constants (corresponding to fast, medium, slow, and very slow first order³⁰ degradation kinetics under anaerobic conditions) and two accounting for delays in GHG emissions for a material with fast kinetics (20 and 50 years delay) as found for different fossil- and biobased plastic types.^{30–33} For each scenario, the assumed carbon content of the degrading material is 0.5 kg C/kg plastic (stoichiometric calculation from a hypothetical polymer with 3 carbon atoms) of which 100% is released as CO₂ in the incineration scenario, whereas 71% is emitted as CO₂ and 29% as methane in the landfilling scenarios.³³ Note that only emissions stemming from the carbon contained in the plastic are considered. By multiplying the yearly emitted amount with the corresponding average MCTPs per unit emission (under RCP6), we used eq 5 to calculate total tipping impacts corresponding to degradation of 1 kg of plastic. For comparison, we also compute impact scores using the complementary CFs GWP20,⁶ GWP100,⁶ GWP100_{ILCD}, i.e., including credits for temporary carbon storage using the method in the ILCD Handbook,³⁴ dynamic GWP100,^{29,35} and GTP100.^{8,10} While GWP100 treats emissions over 100 years as a pulse emission in the first year, dynamic GWP100 expresses the time-dependent contribution of emissions to radiative forcing change over 100 years, accounting for the actual emission timing. GWP100_{ILCD} includes credits for temporary carbon storage to account for the storage due to delayed or incomplete degradation of the plastic materials over 100 years. In consistency with recommended practice,¹² all GWP CFs are inclusive of climate-carbon cycle feedbacks. Methods for calculating impact scores using all these CFs are summarized in Table S9 in Supporting Information.

RESULTS

Multiple Climate Tipping Potentials. Results of two successful Monte Carlo simulations show that the number and type of tipping points actually triggered depends on the probability that the threshold temperature picked in the simulation is within the temperature increase projected under the chosen pathway (Figure 2a,b). They also show that MCTPs are particularly sensitive to the proximity of an emission year to the year of tipping. The MCTP can increase by up to a factor of 6 compared to the MCTP for an emission in year 2021 when emission year approaches the year of tipping, and it drops consistently after the tipping point is

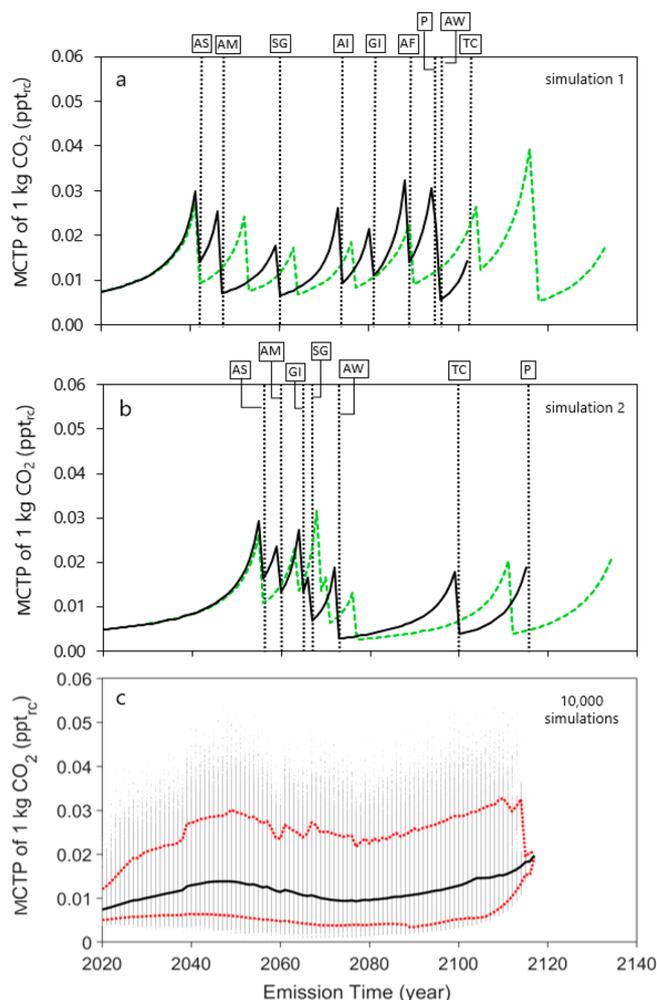


Figure 2. Emission-year specific multiple climate tipping point potentials (MCTP) per emission of 1 kg CO₂ under RCP6. (a, b) MCTPs from two illustrative model simulation runs (solid line). Vertical dotted lines indicate occurrence of tipping points (Table S8). Green dashed curves are the same simulations computed without considering the effect from the tipping (tipping occurrence not shown in this case). AS = Arctic summer sea ice loss, AM = West African monsoon shift, SG = North Atlantic subpolar gyre convection collapse, AI = West Antarctic ice sheet collapse, GI = Greenland ice sheet melt, AF = Amazon rainforest dieback, P = Permafrost loss, AW = Arctic winter sea ice loss, TC = Atlantic thermohaline circulation shutoff. (c) MCTP results for 10000 model simulations (gray dots), their geometric mean (solid line) and uncertainty ranges (5th and 95th percentiles of yearly results, red dotted lines).

crossed, causing discontinuities in the MCTP curve. The steep increases in the MCTP are caused by fast reduction in the remaining atmospheric capacity assigned to these tipping points when emission years approach respective years of tipping (see Figure S3 in Supporting Information). The drop in the MCTP after crossing a given tipping point is caused by capacities assigned to the subsequent tipping always being significantly larger when compared to the remaining capacity assigned to the preceding tipping event. Accounting for direct effects from crossing tipping points in these two simulations reduces the remaining capacity from 10 to 99% (depending on the emission year) when compared to model results without considering the effect from the tipping on remaining capacity

up to the next tipping point(s). This accelerates the occurrence of the subsequent tipping points by 3 to 31 years.

The tendency of MCTP to peak with the proximity to a tipping point is masked by the large uncertainties around the year of tipping, which influence the number and sequence of tipping points and make individual tipping points overlap. Average (geometric mean) MCTP derived from ~10000 Monte Carlo simulations varies from 0.0074 to 0.020 ppt_{rc} per 1 kg of CO₂ emission (Figure 2c). In 90% of the iterations, MCTPs ranged from 0.0034 to 0.033 ppt_{rc} per 1 kg of CO₂ emission across all emission years. Yet, there is a relatively high probability of several tipping points occurring between 2040 and 2060, resulting in a peak of average MCTPs around 2050 with almost a doubling of the MCTP magnitude (average 0.014 ppt_{rc}) in comparison to emissions occurring in 2021 (average 0.0074 ppt_{rc}). Average MCTPs of CH₄ and N₂O follow the same trends as observed for CO₂ in Figure 2c but are on average 83 and 273 times higher, respectively, when compared to CO₂ (Figure S4). The impact of a unit emission of CH₄ is higher than that of CO₂ in the MCTP approach when compared to GWP100, because the time integrations in ACTP are over shorter time periods compared to the 100 years' time horizon of GWP, and with shorter time horizons, the impacts of short-lived gases like CH₄ become larger.

Consideration of direct effects from the tipping increases the average MCTPs by up to 37% when compared to the average MCTP computed without considering the effect from the tipping (with greater increases for emissions occurring later in time). This corresponds to the last tipping point occurring, on average, 17 years earlier (Figure S5).

The MCTPs calculated for different RCP pathways follow different trends (Figure 3). They are larger when assuming a low background concentration pathway (RCP4.5) and become progressively smaller for higher concentration paths RCP6 and 8.5. The MCTPs increase until 2035 in all pathways, but then they fluctuate over the middle in RCP6, increase in RCP4.5, and follow a downward trend in RCP8.5. The number of tipping points that can be triggered also varies between RCP scenarios, depending on whether threshold temperatures are reached (Table S2). In the high emissions pathway RCP8.5, all the 13 elements can have their tipping points crossed. In RCP6, the permafrost loss and Arctic winter sea ice loss are not triggered, while under RCP4.5, additionally Boreal forest dieback, El Niño-Southern Oscillation change in amplitude, and Atlantic thermohaline circulation shutoff are not triggered. These differences in the number of tipping points determine the time horizon for which MCTPs are relevant (until 2085, 2115, and 2210 in the RCP4.5, RCP6, and RCP8.5 scenarios, respectively).

Example of Degradation of Plastic Polymers. We find that using new MCTPs leads to additional insights when compared to those gained from using other metrics (Table 1). Impact scores in the MCTP approach increase with decreasing degradation rates (scenarios 2–4) because there is higher probability that a significant portion of emissions is released in close proximity to tipping points, where MCTPs are the largest (Figure S6). By contrast, impact scores generally decrease with decreasing degradation rate in the GWP-based and GTP100 approaches owing to (1) decreasing emissions released within the 20 (GWP20) and 100 years (GWP100, GTP100) time horizons, (2) increasing benefits from temporary carbon storage (GWP100_{ILCD}), and (3) delayed emissions and smaller values of their matching dynamic GWP100. With MCTP, a 20-

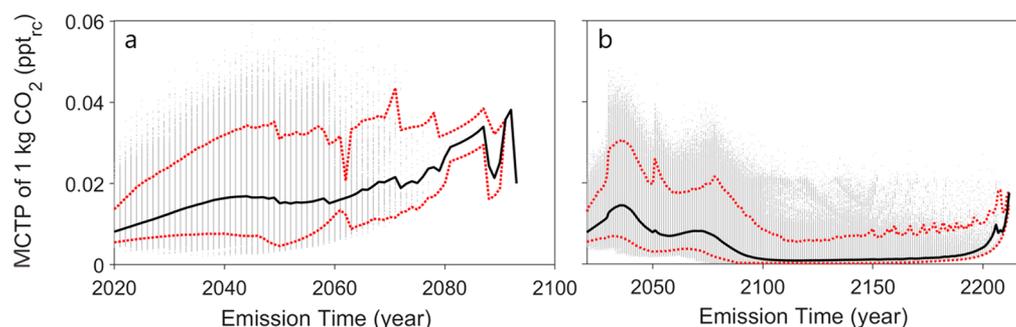


Figure 3. Emission-year specific multiple climate tipping points potentials (MCTP) of 1 kg of CO₂ under RCP4.5 (a) and RCP 8.5 (b) scenarios. MCTPs for 10000 model simulations (gray dots), their geometric mean (solid line), and uncertainty ranges (5th and 95th percentiles, red dotted lines). Notice the different scale of the *x*-axes.

Table 1. Total Impact Scores for Different End-of-Life Scenarios of Plastic Polymers Calculated Using GWP20, GWP100, GWP100_{ILCD}, Dynamic GWP100, GTP100, and New MCTPs^a

End-of-life degradation scenario	GWP20 (kg CO ₂ eq/kg plastic)	GWP100 (kg CO ₂ eq/kg plastic)	GWP100 _{ILCD} (kg CO ₂ eq/kg plastic)	Dynamic GWP100 (kg CO ₂ eq/kg plastic)	GTP100 (kg CO ₂ eq/kg plastic)	MCTP, under RCP6 (ppt _{1c} /kg plastic)
1. Incineration ^a	1.8	1.8	1.8	1.8	1.8	0.014
Plastic degradation rate ^b						
2. Fast ^c	18	8.3	8.2	4.7	3.8	0.089
3. Medium ^d	14	8.3	7.4	4.6	3.8	0.14
4. Slow ^e	6.4	7.3	5.5	3.8	3.4	0.16
5. Very slow ^f	0.036	0.078	0.048	0.052	0.034	0.0020
Delayed degradation ^g						
6. After 20 years (fast rate)	0	8.3	6.9	4.5	3.8	0.21
7. After 50 years (fast rate)	0	8.3	5.1	4.1	3.8	0.16

^aIncineration of fossil-based plastic where all carbon is emitted as CO₂ in the first year. ^bDegradation under anaerobic conditions, resulting in release of methane. ^c90% degradation of polycaprolactone (PCL) in 2 years. ^d90% degradation of polybutylene succinate (PBS) in 31 years. ^e90% degradation of polystyrene (PS) in 105 years. ^f1% degradation of biobased PLA in 100 years. ^gPotential short (20 years) and long (50 years) lag phase in degradation of PCL based on ref 33. ^hRanking between scenarios 1–7 is illustrated within each column with different colors. Red shading indicates the highest impact scores and green the lowest impact scores. The GWP100_{ILCD} includes credits for the temporary carbon storage of delayed or incomplete degradation of the material over 100 years calculated using the ILCD approach.³⁴

and 50-year lag phase of degradation of the polymers are seen as worse and second worst scenarios, respectively, because of proximity of emissions to tipping points, whereas with GWP100 and GTP100, which are not able to capture differences in emission timing, impact scores are the same as without a lag phase (scenario 2). The MCTP results for these two scenarios are also different from GWP20, which does not assign any burden to emissions occurring after the 20 year time horizon. For very slow degradation kinetics, impact scores are almost independent of the type of metric chosen. This is because the vast majority of emissions in this slow degradation scenario occurs beyond the time frames for which MCTP and their complementary GWPs are considered relevant. Incineration is seen as the second best option with all other metrics, because no methane emissions occur and, for MCTP, also because of small CF values for emissions of CO₂ in year 2021.

Ranking of these different end-of-life scenarios was not very sensitive to the RCP pathway for which MCTPs were computed (Table S10); however, slight variations reflect the different contribution to tipping that emissions have in the

three RCPs. In particular, under RCP4.5, the largest contribution is observed after 2060; therefore, a polymer with 50 years lag phase, emitting mostly around 2070, performs worse. In terms of magnitude, impact scores with RCP4.5 are larger for each end-of-life scenario, as the corresponding MCTP factors are larger.

DISCUSSION

Importance of GHGs Development Pathway. We find that the magnitude of the MCTPs is larger under RCP4.5 and lower under RCP8.5. This somewhat counterintuitive finding can be explained by two factors. First, the MCTP is a metric expressing midpoint impacts and, as such, it does not consider the severity of the damage on ecosystems or humans caused by crossing tipping points. These damages are expected to be larger for the RCP8.5 path when compared to those of the two other pathways. Thus, the impact expressed by our midpoint CFs should only be interpreted as the contribution of an emission that is part of the background to crossing tipping points and not as the overall damage caused by the emission or

the damage caused by the tipping itself. Second, climate responds differently to the same increase in GHG concentrations in the three RCPs: for example, to reach a tipping threshold of 2 °C under RCP8.5, the GHG concentrations should rise to about 574 ppm of CO_{2e}, whereas 541 ppm of CO_{2e} are already sufficient according to RCP4.5 projections (Figure S1). This is because the slow heat uptake of the oceans creates a delay in the response of the atmospheric temperature to an increase in CO₂ concentration,³⁶ and this delay depends on the different rate of CO₂ increase projected in each RCP pathway. In RCP8.5, CO₂ concentrations increase rapidly, generating a larger lag in the climate response compared to RCP4.5. Therefore, RCP8.5 reaches 2 °C at higher concentrations, whereas in RCP4.5, the same temperature corresponds to lower concentration levels. This means that the contribution of an emission to crossing tipping points is proportionally larger under RCP4.5 because tipping points are triggered at lower concentrations when compared to RCP8.5 or RCP6. Consequently, for the same emission year, MCTPs are larger for RCP4.5 than for the two other pathways.

Differences in the temporal evolution of MCTPs observed between the RCP pathways are the result of a combination of several additional factors and it is not possible to determine one dominant driver. One factor is the different rate of projected GHGs concentration increase across the RCPs. In RCP8.5, GHGs concentration increases fast and, due to this, differences in concentration between consecutive years became larger over time (remaining capacity depends on the magnitude of the difference). In addition, tipping points are triggered at higher concentration levels, as explained above. This results in numerically larger remaining capacities for emissions in, e.g., 2080 than emissions in 2040 and explains why MCTP decreases over time. For RCP4.5, the opposite is true: MCTP increases over time because of relatively small differences in GHGs concentration between consecutive years (especially when the concentration starts to level off) and because tipping points are triggered at lower concentrations. Other factors to consider are the simultaneous dependency on evolution of *impacts of the emission* (as MCTPs are based on ratios between *impacts of the emission* and remaining capacities), the different number of tipping points that can be triggered in each RCP pathway, and the possibility, in RCP8.5, that tipping points occur at very high concentrations and very late in time (as opposed to no more tipping points beyond 2100 in RCP4.5).

Uncertainties. The major source of uncertainty in the MCTP CFs is that they do not consider interactions between the tipping elements.⁴ Similarly, the MCTPs do not consider situations where tipping points are predicted to occur so close to each other that the remaining capacity is fully consumed by the preceding tipping points. Our results show that the probability that crossing a tipping point causes tipping of another (for at least one pair of tipping elements), even without considering other interactions,³⁷ is equal to 92% for the RCP6 scenario but is somewhat smaller for RCP4.5 and RCP8.5 (79 and 53%, respectively). This is consistent with earlier studies suggesting that the passing of some tipping points increases the likelihood of other tipping points due to positive feedbacks from the tipping.^{38,4} The implication of this model limitation is that the time horizon for which MCTPs are relevant can be shorter. Another implication is that our MCTPs can be underestimated, particularly those occurring later where uncertainties about temperatures triggering the

tipping are larger. The combined effect of more tipping points triggered at once would indeed reduce the remaining capacity to the next tipping even further, resulting in higher MCTPs. This is particularly the case for the RCP6 pathway, where the chances of one or more tipping points triggered at the same time is the highest. However, *impacts of the emission* will simultaneously decrease, as tipping points approach, and whether this results in an increase in MCTP will thus depend on the magnitude of reduction of the *impact of the emission* in relation to the reduction in remaining capacity.

Implications for Life Cycle Assessment. We offer a new method that considers multiple climate tipping points in the quantification of the potential contribution of products to climate change impacts. As no other metric considers the contribution of emissions to deplete the remaining capacity up to multiple tipping points and the variability of this contribution based on emission timing, the new method represents a new life cycle impact category. This new impact category should be seen as being complementary to, but not a substitute for, global warming and global temperature change categories. A ranking of the three well-mixed GHGs (CO₂, CH₄, and N₂O), in terms of their average MCTP, is comparable to the ranking of their GWP20s and ranges from 1:51:238 to 1:107:299 (RCP6), depending on emission year, in comparison to the constant ranking of 1:86:268¹⁰ for the GWP20. This stresses the need to consider short-term climate impacts, as in both CFs, the radiative forcing is integrated over shorter time horizons (through the ACTP and AGWP), resulting in larger impacts assigned to short-lived gases like methane. Despite this similarity, the added value of the MCTP is that it captures those emissions and short-term impacts occurring beyond the 20-year time.

We showed that the use of MCTPs offers new insights when applied to temporarily differentiated GHG emission inventories. The best performance, from the climate tipping perspective, is achieved when emissions from the product occur when their contribution to crossing tipping points is the lowest rather than when these emissions are just delayed. Indeed, there is a high probability of several tipping points occurring from ca. 2040 to 2060, where MCTPs are the largest. An accounting for the uncertainties in the triggering of tipping points eventually results in a more robust, but perhaps less straightforward, assessment of climate tipping impacts from products. These uncertainties are currently so large that individual tipping points are not clearly discernible. Nevertheless, such large uncertainties should not prevent the use of MCTP because we demonstrated that MCTP still allows the capture of differences in performance of products with different temporal emission profiles.

We recall that the availability of time differentiated emission inventories of the assessed products is necessary for a meaningful use of the set of emission-year-specific MCTPs provided here (Supporting Information). The main implications for life cycle inventory (LCI) modelers is the need to focus on modeling and the reporting of emission inventories in temporarily disaggregated forms. The main implication for LCA software developers is the need to develop modules that can calculate impact scores using temporarily disaggregated inventories and time-dependent characterization factors. The same challenges are still relevant for dynamic methods, including the dynamic GWP approach.²⁹ We expect that potential take up of climate tipping as an impact category in LCA will make it attractive to increase the availability of

temporarily differentiated emission inventories and their handling in LCA software. Until then, dynamic approaches, including our MCTP, have to be used offline.

The reader should note, however, that the iterative nature of LCA allows using our MCTP factors even if a full time-differentiated inventory is not available for all processes in a given life cycle. In this case, the ideal would be to identify processes where time-differentiation of emissions is relevant and is expected to really matter for the LCA results (such as end-of-life processes, biomass growth, or deforestation) and obtain a time-differentiated inventory for these processes only. This can be done with a sensitivity analysis. The MCTP impact score for these processes can then be calculated offline using eq 5. The impact score for all the remaining processes not associated with a time-differentiated inventory, or for those processes which do not matter for the LCA results (small contribution to total impact), can be calculated by multiplying the total amount of CO₂, CH₄, and N₂O emissions from these processes by the corresponding MCTP factor relative to the year when their emission is expected to take place. The sum of the two impact scores returns the final MCTP results.

The new metric is expected to be particularly valuable in the life cycle assessments of biodegradable plastics, deteriorating wooden products, or engineered chars used for temporary carbon storage.^{35,39} We recommend the presenting of results for all three considered RCP scenarios to show if, and how, the choice of future uncertain emission pathways could influence conclusions of the study of interest. Our MCTPs are expected to add less value in the comparative LCA context when emissions occur all at once, such as the incineration scenario in our case study, or when there are large differences in the emitted amount of GHGs (e.g., very slow degradation scenario). Further, although emissions do not influence the background emission path, the MCTPs are not directly applicable in the assessment of large-scale systems, like economic sectors or countries.¹³ Other midpoint CFs, like GWP and GTPs, are better suited for this purpose.

The MCTP is proposed as a method for climate change impacts at the midpoint level; therefore, the interest here is to cover only climate change impacts at the midpoint level. If crossing a tipping point leads to loss of species (directly by, e.g., loss of habitat when ice melts, or indirectly via temperature increase), then this should be accounted for at the damage level.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.0c02928>.

Emission-year specific MCTP values (XLSX)

Methods and results (PDF)

■ AUTHOR INFORMATION

Corresponding Author

Serena Fabbri – Quantitative Sustainability Assessment Group, Department of Technology, Management and Economics, Technical University of Denmark, Lyngby, Denmark; orcid.org/0000-0001-8073-5469; Email: serf@dtu.dk

Authors

Michael Z. Hauschild – Quantitative Sustainability Assessment Group, Department of Technology, Management and Economics, Technical University of Denmark, Lyngby, Denmark

Timothy M. Lenton – Global Systems Institute, University of Exeter, Exeter EX4 4QE, U.K.

Mikołaj Owsianiak – Quantitative Sustainability Assessment Group, Department of Technology, Management and Economics, Technical University of Denmark, Lyngby, Denmark; orcid.org/0000-0002-6834-6249

Complete contact information is available at: <https://pubs.acs.org/10.1021/acs.est.0c02928>

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

We acknowledge the financial support given by the European Commission under Horizon 2020; H2020-BBI-JTI-2016: BioBarr, grant agreement 745586. We thank Cedric Wannaz (Eurisko Research; MathWorks) for his assistance with the mathematical notation. We thank Reinout Heijungs for the strong support and valuable suggestions for improving the paper.

■ REFERENCES

- (1) Lenton, T. M.; Rockstrom, J.; Gaffney, O.; Rahmstorf, S.; Richardson, K.; Steffen, W.; Schellnhuber, H. J. Too Risky To Bet Against. *Nature* **2019**, *575* (7784), 592–595.
- (2) Lenton, T. M.; Held, H.; Kriegler, E.; Hall, J. W.; Lucht, W.; Rahmstorf, S.; Schellnhuber, H. J. Tipping Elements in the Earth's Climate System. *Proc. Natl. Acad. Sci. U. S. A.* **2008**, *105* (6), 1786–1793.
- (3) Lontzek, T. S.; Cai, Y.; Judd, K. L.; Lenton, T. M. Stochastic Integrated Assessment of Climate Tipping Points Indicates the Need for Strict Climate Policy. *Nat. Clim. Change* **2015**, *5* (May), 441–444.
- (4) Cai, Y.; Lenton, T. M.; Lontzek, T. S. Risk of Multiple Interacting Tipping Points Should Encourage Rapid CO₂emission Reduction. *Nat. Clim. Change* **2016**, *6* (5), 520–525.
- (5) Owsianiak, M.; Bjørn, A.; Laurent, A.; Molin, C.; Ryberg, M. W. LCA Applications. In *Life Cycle Assessment: Theory and Practice*; Hauschild, M. Z., Rosenbaum, R. K., Olsen, S. I., Eds.; Springer International Publishing, 2018; pp 31–41. DOI: [10.1007/978-3-319-56475-3](https://doi.org/10.1007/978-3-319-56475-3).
- (6) Forster, P.; Ramaswamy, V.; Artaxo, P.; Bernsten, T.; Betts, R.; Fahey, D. W.; Haywood, J.; Lean, J.; Lowe, D. C.; Myhre, G.; Nganga, J.; Prinn, R. G.; Raga, M. S., R. V. D Changes in Atmospheric Constituents and in Radiative Forcing. In *Climate Change 2007: The Physical Science Basic. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press; Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., Miller, H. L., Eds.; Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2007.
- (7) Laurent, A.; Owsianiak, M. Potentials and Limitations of Footprints for Gauging Environmental Sustainability. *Curr. Opin. Environ. Sustain.* **2017**, *25*, 20–27.
- (8) Shine, K. P.; Fuglestedt, J. S.; Hailemariam, K.; Stuber, N. Alternatives to the Global Warming Potential for Comparing Climate Impacts of Emissions of Greenhouse Gases. *Clim. Change* **2005**, *68*, 281–302.
- (9) Jolliet, O.; Anton, A.; Boulay, A.-M.; Cherubini, F.; Fantke, P.; Lévassieur, A.; McKone, T. E.; Michelsen, O.; Mila i Canals, L.; Motoshita, M.; Pfister, S.; Veronesi, F.; Vigon, B.; Frischknecht, R. Global Guidance on Environmental Life Cycle Impact Assessment

Indicators: Impacts of Climate Change, Fine Particulate Matter Formation, Water Consumption and Land Use. *Int. J. Life Cycle Assess.* **2018**, *23*, 2189–2207.

(10) Myhre, G.; Shindell, D.; Bréon, F.-M.; Collins, W.; Fuglestvedt, J.; Huang, J.; Koch, D.; Lamarque, J.-F.; Lee, D.; Mendoza, B.; Nakajima, T.; Robock, A.; Stephens, G.; Takemura, T.; Zhang, H. Anthropogenic and Natural Radiative Forcing. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press; Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P. M., Eds.; Cambridge University Press: Cambridge, 2013.

(11) Bjørn, A.; Hauschild, M. Z. Introducing Carrying Capacity-Based Normalisation in LCA: Framework and Development of References at Midpoint Level. *Int. J. Life Cycle Assess.* **2015**, *20* (7), 1005–1018.

(12) Levasseur, A.; Cavalett, O.; Fuglestvedt, J. S.; Gasser, T.; Johansson, D. J. A.; Jørgensen, S. V.; Rauegi, M.; Reisinger, A.; Schivley, G.; Strømman, A.; Tanaka, K.; Cherubini, F. Enhancing Life Cycle Impact Assessment from Climate Science: Review of Recent Findings and Recommendations for Application to LCA. *Ecol. Indic.* **2016**, *71*, 163–174.

(13) Jørgensen, S. V.; Hauschild, M. Z.; Nielsen, P. H. Assessment of Urgent Impacts of Greenhouse Gas Emissions - The Climate Tipping Potential (CTP). *Int. J. Life Cycle Assess.* **2014**, *19* (4), 919–930.

(14) Lenton, T. M.; Ciscar, J.-C. Integrating Tipping Points into Climate Impact Assessments. *Clim. Change* **2013**, *117* (3), 585–597.

(15) Drijfhout, S.; Bathiany, S.; Beaulieu, C.; Brovkin, V.; Claussen, M.; Huntingford, C.; Scheffer, M.; Sgubin, G.; Swingedouw, D. Catalogue of Abrupt Shifts in Intergovernmental Panel on Climate Change Climate Models. *Proc. Natl. Acad. Sci. U. S. A.* **2015**, *112* (43), E5777–E5786.

(16) de Haes, H. A. U.; Jolliet, O.; Finnveden, G.; Hauschild, M.; Krewitt, W.; Muller-Wenk, R. Best Available Practice Regarding Impact Categories and Category Indicators in Life Cycle Impact Assessment. *Int. J. Life Cycle Assess.* **1999**, *4* (2), 66–74.

(17) Heijungs, R. Is Mainstream LCA Linear? *Int. J. Life Cycle Assess.* **2020**, *25* (10), 1872–1882.

(18) Boulay, A.-M.; Benini, L.; Sala, S. Marginal and Non-Marginal Approaches in Characterization: How Context and Scale Affect the Selection of an Adequate Characterization Factor. The AWARE Model Example. *Int. J. Life Cycle Assess.* **2020**, *25*, 2380–2392.

(19) Huijbregts, M. A. J.; Hellweg, S.; Hertwich, E. Do We Need a Paradigm Shift in Life Cycle Impact Assessment? *Environ. Sci. Technol.* **2011**, *45* (9), 3833–3834.

(20) Heijungs, R. The Average versus Marginal Debate in LCIA: Paradigm Regained *Int. J. Life Cycle Assess.* **2020**. DOI: 10.1007/s11367-020-01835-4.

(21) Bjørn, A.; Diamond, M.; Owsianiak, M.; Verzat, B.; Hauschild, M. Z. Strengthening the Link between Life Cycle Assessment and Indicators for Absolute Sustainability to Support Development within Planetary Boundaries. *Environ. Sci. Technol.* **2015**, *49* (11), 6370–6371.

(22) Bjørn, A.; Chandrakumar, C.; Boulay, A. M.; Doka, G.; Fang, K.; Gondran, N.; Hauschild, M. Z.; Kerkhof, A.; King, H.; Margni, M.; McLaren, S.; Mueller, C.; Owsianiak, M.; Peters, G.; Roos, S.; Sala, S.; Sandin, G.; Sim, S.; Vargas-Gonzalez, M.; Ryberg, M. Review of Life-Cycle Based Methods for Absolute Environmental Sustainability Assessment and Their Applications *Environ. Res. Lett.* **2020**, *15* (8), 083001.

(23) Bjørn, A. (DTU). Better, but Good Enough? Indicators for Absolute Environmental Sustainability in a Life Cycle Perspective. Technical University of Denmark, DTU Management Engineering. PhD Thesis, No. 8.2015, 2015.

(24) van Vuuren, D. P.; Edmonds, J.; Kainuma, M.; Riahi, K.; Thomson, A.; Hibbard, K.; Hurtt, G. C.; Kram, T.; Krey, V.; Lamarque, J.-F.; Masui, T.; Meinshausen, M.; Nakicenovic, N.; Smith,

S. J.; Rose, S. K. The Representative Concentration Pathways: An Overview. *Clim. Change* **2011**, *109* (1–2), 5–31.

(25) Meinshausen, M.; Smith, S. J.; Calvin, K.; Daniel, J. S.; Kainuma, M. L. T.; Lamarque, J.; Matsumoto, K.; Montzka, S. A.; Raper, S. C. B.; Riahi, K.; Thomson, A.; Velders, G. J. M.; van Vuuren, D. P. P. The RCP Greenhouse Gas Concentrations and Their Extensions from 1765 to 2300. *Clim. Change* **2011**, *109* (1), 213–241.

(26) Sanford, T.; Frumhoff, P. C.; Luers, A.; Gullette, J. The Climate Policy Narrative for a Dangerously Warming World. *Nat. Clim. Change* **2014**, *4* (3), 164–166.

(27) van Vliet, J.; den Elzen, M. G.J.; van Vuuren, D. P. Meeting Radiative Forcing Targets under Delayed Participation. *Energy Econ.* **2009**, *31*, S152–S162.

(28) Meinshausen, M.; Wigley, T. M. L.; Raper, S. C. B. Emulating Atmosphere-Ocean and Carbon Cycle Models with a Simpler Model, MAGICC6 – Part 2: Applications. *Atmos. Chem. Phys.* **2011**, *11*, 1457–1471.

(29) Levasseur, A.; Lesage, P.; Margni, M.; Deschênes, L.; Samson, R. Considering Time in LCA: Dynamic LCA and Its Application to Global Warming Impact Assessments. *Environ. Sci. Technol.* **2010**, *44* (8), 3169–3174.

(30) Tansel, B. Persistence Times of Refractory Materials in Landfills: A Review of Rate Limiting Conditions by Mass Transfer and Reaction Kinetics. *J. Environ. Manage.* **2019**, *247*, 88–103.

(31) Ishigaki, T.; Sugano, W.; Nakanishi, A.; Tateda, M.; Ike, M.; Fujita, M. The Degradability of Biodegradable Plastics in Aerobic and Anaerobic Waste Landfill Model Reactors. *Chemosphere* **2004**, *54*, 225–233.

(32) Cho, H. S.; Moon, H. S.; Kim, M.; Nam, K.; Kim, J. Y. Biodegradability and Biodegradation Rate of Poly (Caprolactone)-Starch Blend and Poly (Butylene Succinate) Biodegradable Polymer under Aerobic and Anaerobic Environment. *Waste Manage.* **2011**, *31* (3), 475–480.

(33) Rossi, V.; Cleeve-Edwards, N.; Lundquist, L.; Schenker, U.; Dubois, C.; Humbert, S.; Jolliet, O. Life Cycle Assessment of End-of-Life Options for Two Biodegradable Packaging Materials: Sound Application of the European Waste Hierarchy. *J. Cleaner Prod.* **2015**, *86*, 132–145.

(34) JRC. *International Reference Life Cycle Data System (ILCD) Handbook – General Guide for Life Cycle Assessment – Detailed Guidance*. Publications Office of the European Union; Ispra, Luxembourg, 2010.

(35) Levasseur, A.; Lesage, P.; Margni, M.; Samson, R. Biogenic Carbon and Temporary Storage Addressed with Dynamic Life Cycle Assessment. *J. Ind. Ecol.* **2013**, *17* (1), 117–128.

(36) Hansen, J.; Sato, M.; Kharecha, P.; Von Schuckmann, K. Earth's Energy Imbalance and Implications. *Atmos. Chem. Phys.* **2011**, *11* (24), 13421–13449.

(37) Krieger, E.; Hall, J. W.; Held, H.; Dawson, R.; Schellnhuber, H. J. Imprecise Probability Assessment of Tipping Points in the Climate System. *Proc. Natl. Acad. Sci. U. S. A.* **2009**, *106* (13), S041–S046.

(38) Rocha, J. C.; Peterson, G.; Bodin, Ö.; Levin, S. Cascading Regime Shifts within and across Scales. *Science (Washington, DC, U. S.)* **2018**, *362*, 1379–1383.

(39) Owsianiak, M.; Brooks, J.; Renz, M.; Laurent, A. Evaluating Climate Change Mitigation Potential of Hydrochars: Compounding Insights from Three Different Indicators. *GCB Bioenergy* **2018**, *10* (4), 230–245.