

Prospective Characterization Factors for Assessing Climate Change Impacts in Life Cycle Assessments

Marcos D. Barbosa Watanabe* and Francesco Cherubini



Cite This: *Environ. Sci. Technol.* 2026, 60, 3202–3215



Read Online

ACCESS |



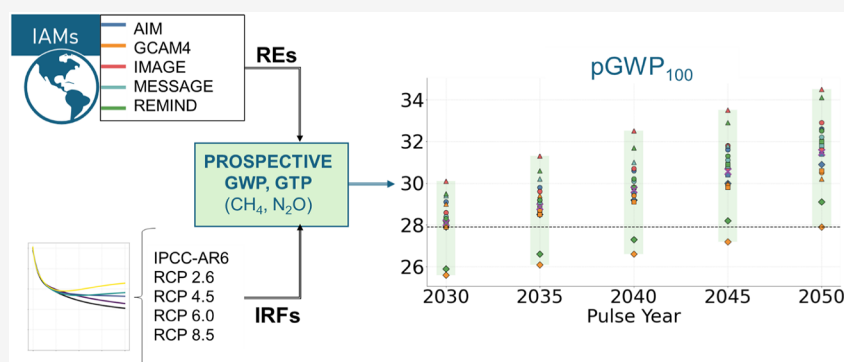
Metrics & More



Article Recommendations



Supporting Information



ABSTRACT: Prospective life cycle assessment (pLCA) is a future-oriented approach that estimates the environmental impacts of products and systems under future technological changes, market dynamics, and policy shifts. However, pLCA lacks consistent prospective characterization factors (pCFs) to assess the climate impacts of future emissions and align the inventory and impact assessment phases. This work produces pCFs by integrating gas-specific climate parameters with future emission scenarios from the Integrated Assessment Models (IAM). Prospective Global Warming Potential (pGWP₂₀, pGWP₁₀₀) and Global Temperature change Potential (pGTP₅₀, pGTP₁₀₀) are computed for emission years until 2050. Relative to present-day CFs, methane pGWP₁₀₀ varies from −8% to +23%, and nitrous oxide varies from −17% to +7%. CH₄ pGTP₁₀₀ shifts from −24% to +22%, while N₂O pGTP₁₀₀ shifts from −27% to +8%. For non-CO₂-dominated activities such as rice production, climate impacts increase by 8% in terms of pGWP₁₀₀. With pGTP₁₀₀, impacts of ammonium nitrate decrease by 9%. When pCFs are combined with prospective background inventories, impacts are substantially lower in sectors such as steel (−44%), road transport (−58%), and cement (−31%) under pGTP₁₀₀. Overall, the availability of pCFs for multiple climate metrics and IAM scenarios enables a consistent coupling of impact assessment with future-oriented inventory data, improving the robustness and coherence of pLCA.

KEYWORDS: prospective life cycle assessment, characterization factors, integrated assessment models, climate impacts, life cycle impact

1. INTRODUCTION

Prospective life cycle assessment (pLCA) is an emerging methodology designed to evaluate the future environmental impacts of technologies and their associated products.¹ In recent years, the application of pLCA has grown significantly,² triggering improved definitions and methodological frameworks to increase consistency and transparency in comparative assessments.^{3–6} Despite these advancements, progress across the quantitative stages of pLCA has been uneven. While several methods have been developed to advance the Life Cycle Inventory (LCI) phase, the life cycle impact assessment (LCIA) phase notably remains underdeveloped.³ Addressing this gap is critical, as unresolved limitations in LCIA can undermine an accurate and consistent evaluation of environmental burdens, potentially leading to incomplete or misleading conclusions.^{7,8}

In LCI, developments entailed both foreground and background system processes. Many studies explored ap-

proaches to scale-up foreground inventories to assess emerging technologies within a more realistic industrial-scale context,⁹ using methods based on process-based calculations,¹⁰ learning curves and scaling factors,^{9,11,12} expert elicitation through interviews,^{11,13} and the integration of technical parameters with assumptions on efficiency improvements.¹ In parallel, aligning background inventories with projections from Integrated Assessment Models (IAMs) has emerged as a crucial step in recent years to improve pLCA studies and make them more consistent among each other and with the main

Received: September 4, 2025

Revised: January 14, 2026

Accepted: January 15, 2026

Published: January 21, 2026



future global policy scenarios.^{14–20} Scenario-based modeling in IAMs captures possible future developments in technology and emissions, and it offers a structured and scientifically robust foundation for defining key parameters in pLCAs. The further development of the open-source tool *Premise*²¹ consolidated this approach into a transparent and reproducible framework for generating background databases among practitioners.

Despite these advances in modeling future LCIs, the corresponding progress in the LCIA phase has not occurred at the same pace or depth. CFs are based on present-day environmental conditions and are assumed to remain constant when used in pLCA, even if these conditions change in the future. For example, CFs used to estimate climate change impacts in LCA rely on climate metrics computed using radiative efficiencies and impulse response functions that reflect the current atmospheric concentration of GHGs and the saturation levels of terrestrial and ocean carbon sinks.²² Using these CFs to characterize GHG emissions occurring far in the future is therefore inconsistent as the background conditions of the atmosphere receiving an emission in the future may substantially differ from those on which the CFs are originally based.

Existing studies on time-dependent CFs for climate change impacts are limited, as most of the discussions focus on dynamic rather than prospective LCIA aspects.²³ A few examples that are relevant in the context of the prospective analysis exist. Reisinger et al. (2011)²⁴ linked Representative Concentration Pathways (RCPs) to projections of Global Warming Potentials (GWPs).^{25,26} Although not explicitly connected to the LCA field and to the need for pCFs, this work shows how future background concentrations of GHGs influence radiative efficiencies (RE) and climate–carbon cycle feedbacks, thereby affecting the GWPs of methane (CH₄) and nitrous oxide (N₂O). The findings suggest potential increases in GWP of up to 20% for CH₄ and approximately 30% for N₂O by 2100. However, a direct applicability of these metrics as CFs in LCA is hindered by several barriers, such as the lack of integration with IAM-based scenarios, the use of complex and nonopen-source climate models, the challenge to adjust metric values to the specific year at which emissions occur, a lack of regular updates, and the absence of alternative metrics such as the Global Temperature change Potential (GTP).^{27,28} More recent work provided new projections of climate metrics for CH₄ and N₂O by incorporating changes in RE in line with only RCP scenarios.²⁹ However, these results follow a different trajectory than that reported by Reisinger et al. (2011),²⁴ do not incorporate IAM-based prospective scenarios, and do not consider other climate indicators such as GTP.

In this study, we address the gap of missing CFs for climate change impacts in pLCA by proposing an approach that is consistent with the method used by the IPCC to compute climate metrics, such as GWP and GTP. RE and impulse response functions (IRFs) for the three most important GHGs (CO₂, CH₄, and N₂O) are adapted to future changes in background concentrations as those underpinning IAM scenario outputs that are used to modify background process inventories. The study considers IRFs for CO₂ that are specific to each main RCP scenario and relies on the most updated parameters from the IPCC Sixth Assessment Report²⁶ to estimate changes in RE, and hence CFs, for methane (CH₄) and nitrous oxide (N₂O). Prospective metrics for both GWP (pGWP₁₀₀ and pGWP₂₀) and GTP (pGTP₁₀₀ and pGTP₅₀) are computed for emissions of GHGs occurring between 2030 and

2050. To facilitate their adoption from pLCA studies and tools, the pGWPs and pGTPs are provided in tabular form for emission years up to 2050 and open-access code is available to reproduce the method to compute pCFs within different modeling frameworks and to generate values through 2100. This approach extends beyond previous efforts by incorporating the full range of Shared Socioeconomic Pathways (SSPs) and enabling the calculation of year-specific metrics for any future pulse emissions. The new pCFs are applied to a range of case studies to explore how much and under which circumstances they can affect LCA results, either in isolation (i.e., relative to the use of existing CFs) or within a full pLCA framework that includes both pCFs and changes in background process inventories. This investigation also shows how the choice of IAM type can influence results, even under the same climate policy scenario.

2. MATERIALS AND METHODS

2.1. Prospective CFs

2.1.1. Prospective GWP (pGWP). The method to estimate pCFs follows the equations and definitions of climate metrics that are used by the IPCC in its series of periodical assessments.^{25,26,30} The GWP is formulated as

$$\text{GWP}_i(H) = \frac{\text{AGWP}_i(H)}{\text{AGWP}_{\text{CO}_2}(H)} = \frac{\int_0^H \text{RF}_i(t) dt}{\int_0^H \text{RF}_{\text{CO}_2}(t) dt} \quad (1)$$

where $\text{AGWP}_i(H)$ is the absolute global warming potential associated with a pulse emission of gas i for the time horizon H (year), which is computed as the integrated radiative forcing (RF_i) exerted by the gas i until H . The denominator denotes the same but for CO₂, which is the gas used as reference (hence the characterized results are expressed in CO₂-equivalents). RF_i is, in turn, described by eq 2:

$$\text{RF}_i = \text{RE}_i \cdot \text{IRF}_i \quad (2)$$

where RE_i is the radiative efficiency of gas i and IRF_i is the impulse response function, which indicates the fraction of species i remaining in the atmosphere over time after a pulse emission. The RE of a greenhouse gas is defined as the instantaneous radiative forcing per unit mass or concentration increase of that gas, and it is expressed in terms of watts per square meter per ppm increase or kg emission ($\text{W m}^{-2} \text{ ppm}^{-1}$ or $\text{W m}^{-2} \text{ kg}^{-1}$). For CO₂, the RE_i values can be calculated through a logarithmic relationship with CO₂ concentration³¹ in eq 3:

$$\text{RF}_i = 5.35 \cdot \ln(C/C_0) \quad (3)$$

Where C is the new CO₂ concentration and C_0 is the reference concentration. Alternatively, they can be estimated from the derivative of radiative forcings:²⁵

$$\text{RE}_i = \frac{d\text{RF}_i}{dC_i} \quad (4)$$

where RF_i is the radiative forcing (in W m^{-2}) and C_i is the concentration of species in the atmosphere (ppb). Considering the time-dependent nature of RE_i and C_i , it is possible to project time-specific RE_i (in $\text{W m}^{-2} \text{ ppb}^{-1}$) for CO₂, CH₄, and N₂O. To secure consistency with the prospective inventories, the projections for RE are produced according to eqs 5, 6, and 7. RE_i are extracted from changes in both radiative forcings and GHG concentrations from the outputs of IAM-SSP marker scenarios, based on time steps for the period 2030–2050³² as follows:

$$\text{RE}_{\text{CO}_2}(t) = \frac{d\text{RF}_{\text{CO}_2}}{dC_{\text{CO}_2}} \approx \frac{\text{RF}_{\text{CO}_2}(t) - \text{RF}_{\text{CO}_2}(t')}{C_{\text{CO}_2}(t) - C_{\text{CO}_2}(t')} \quad (5)$$

$$\text{RE}_{\text{CH}_4}(t) = \frac{\text{dRF}_{\text{CH}_4}}{\text{dC}_{\text{CH}_4}} \approx \frac{\text{RF}_{\text{CH}_4}(t) - \text{RF}_{\text{CH}_4}(t')}{\text{C}_{\text{CH}_4}(t) - \text{C}_{\text{CH}_4}(t')} \quad (6)$$

$$\text{RE}_{\text{N}_2\text{O}}(t) = \frac{\text{dRF}_{\text{N}_2\text{O}}}{\text{dC}_{\text{N}_2\text{O}}} \approx \frac{\text{RF}_{\text{N}_2\text{O}}(t) - \text{RF}_{\text{N}_2\text{O}}(t')}{\text{C}_{\text{N}_2\text{O}}(t) - \text{C}_{\text{N}_2\text{O}}(t')} \quad (7)$$

Where t denotes a given year and t' represents the preceding time step from the IAM. Equations 5, 6, and 7 follow the average RE approach to align with the IPCC method to estimate GWP and GTP, which are derived from the marginal formulation (eq 4) using finite differences of RF and concentration over 5-year intervals. This interval reflects the temporal resolution of publicly available IAM outputs and therefore provides a numerical approximation of the marginal efficiency. To derive annualized results, the RE values calculated at each five-year step are linearly interpolated, providing a continuous one-year time series suitable for finer-resolution analyses. Our paper focuses on the 2030–2050 period to ensure a readable size of figures and tables, and because 2050 is a key target year for the time frame of many of the existing sustainable policies and mitigation goals. However, the codes and data provided in the [Supporting Information \(SI\)](#) file allow users to compute prospective characterization up to 2100.

In line with the IPCC method, the IRF for CO_2 is based on Joos et al. (2013).²² The default climate metrics provided by the IPCC use IRF parameters of a multimodel mean based on the atmospheric background CO_2 concentration in 2010 of 389 ppm (and thereby held constant in the calculation of the metric values). IRFs are also available for pulse emissions in 2100 under different future scenarios of background concentrations: 421 (RCP 2.6), 538 (RCP 4.5), 670 (RCP 6.0), and 936 ppm (RCP 8.5). However, while the standard IRF of CO_2 typically used in GWP calculations is derived from a multimodel ensemble of 16 Earth System Models (ESMs),²² the ones for future conditions are produced from the Bern3D-LPJ model^{33,34} only. To overcome this inconsistency, we apply a delta function to reproduce the relative differences between the Bern3D-LPJ IRF_{CO_2} and the multimodel IRF_{CO_2} observed at 2010's concentration to IRF curves under varying background atmospheric CO_2 concentrations. This enables us to estimate future IRF_{CO_2} for different RCP scenarios that can be used to estimate climate metrics to be used as pCFs maintaining consistency with the IPCC framework. For the non- CO_2 GHGs, the IRF is modeled as a simple exponential decay based on the atmospheric lifetime of each gas (11.8 years for CH_4 and 109 years for N_2O) according to the IPCC-AR6.²⁶ These lifetimes have remained relatively stable over time: for CH_4 (and N_2O), they were 12 (and 114) years in the 2001 IPCC-TAR,³⁵ 12 (and 114) in the 2007 IPCC-AR4,³⁰ and 12.4 (and 121) in the 2013 IPCC-AR5,²⁵ despite increases in atmospheric concentrations of these gases (from 1,750 to 1,896 ppb for CH_4 and from 316 to 335 ppb for N_2O). Therefore, the IRFs for these gases are less sensitive to changes in background concentrations than those of CO_2 and can be considered to remain constant.

The time-varying IAM-RCP-specific REs derived from eqs 5, 6, and 7 are input into eq 2. This equation is then combined with the RCP-specific IRF curves to derive the AGWPs and the pGWPs, as described in eq 1. In the AGWPs, the carbon cycle responses and other indirect contributions from both CH_4 and N_2O are also included by using parameter values from IPCC-AR6.²⁶ These include carbon cycle feedbacks, CH_4 -induced effects on tropospheric ozone (O_3) and stratospheric water vapor, as well as the indirect effects of N_2O on stratospheric O_3 and the lifetime of CH_4 . Although AGWPs are calculated by using time-varying RE over the integration horizon, our approach remains consistent with the GWP definition adopted by the IPCC, where the impact of a given pulse emission is assessed in an atmosphere with constant background concentrations and a steady-state climate system. This means that for a given pulse year (e.g., 2040), the RE value from that year is used and then held constant throughout the entire integration horizon.

2.1.2. Prospective GTP (pGTP). The absolute global temperature change potentials (AGTPs) associated with the pulse emission of gas i are based on eq 8:^{27,28}

$$\text{AGTP}_i(H) = \int_0^H \text{AGWP}_i(\tau) R(H - \tau) d\tau \quad (8)$$

where H denotes the time horizon at which the temperature change is evaluated, and τ represents earlier times from 0 to H . The term $R(H - \tau)$ captures the climate system's response at time H to a forcing that occurred at time τ . The temperature responses to changes in RFs are modeled using the framework established in the IPCC-AR6.²⁶ Our approach considers a two-layer energy balance model, representing the surface layer (comprising the upper ocean and atmosphere) and the deep ocean layer. This model incorporates key parameters such as the efficacy of deep ocean heat uptake, the surface–deep ocean heat exchange rate, and the radiative damping coefficient. To facilitate the reproducibility of the results, our calculations build on the modeling framework developed by Persson and Johansson (2022),³⁶ which reflects the equations and parametrizations used for estimating GHG metrics in the latest IPCC-AR6.²⁶

After computing the AGTPs based on IAM-specific emission trajectories, we derive the prospective global temperature change potentials (pGTPs) for CH_4 and N_2O using eq 9:

$$\text{GTP}_i(H) = \frac{\text{AGTP}_i(H)}{\text{AGTP}_{\text{CO}_2}(H)} \quad (9)$$

While GWP compares the integrated RF of a pulse emission of a given species relative to that of CO_2 over a specified time horizon,³⁷ GTP compares the resulting temperature change at a specific point in time from a pulse emission to that caused by an equivalent pulse of CO_2 . The GTP accounts for both the time-dependent radiative forcing of different species and the temporal response of the climate system's temperature. Therefore, the GTP reflects changes at the end of the chosen time horizon, whereas the GWP represents the integrated impacts over that period.²⁸ As noted by Tanaka et al. (2019),³⁸ emission metrics are also sensitive to the selected time scale, particularly for species whose atmospheric lifetimes differ substantially from that of CO_2 . For instance, CO_2 can persist in the atmosphere for centuries or even millennia,²² whereas CH_4 largely disappears within several decades after emission.³⁹ As noted by Allen et al. (2016),⁴⁰ the GWP_{100} of CH_4 is approximately equivalent to GTP_{40} , indicating that the cumulative radiative forcing over 100 years has a climate impact similar to the instantaneous temperature increase observed 40 years after an emission pulse. This means that GWP_{100} can be interpreted as a metric to assess temperature impacts after about 40 years (midterm impacts), while GTP_{100} assesses impacts after 100 years (long-term impacts). GWP_{20} or GTP_{50} are instead more suitable to evaluate impacts in the short term. Because of these complementary perspectives, using multiple metrics and time horizons has been recommended to better capture how impacts change under different temporal dimensions.^{40–42} No single climate metric can fully represent the temporal profile of the climate response to emissions of GHGs with varying lifetimes, making a multimetric approach essential to disentangle short- and long-term impact dynamics.

2.2. Sensitivity to Prospective CFs

We assess the sensitivity of climate change impacts to pCFs in two steps. First, the analysis starts with two representative products extracted from the ecoinvent 3.9 database:⁴³ production of non-basmati rice in India (IN) and nitric acid in 50% solution state from the European market (RER w/o RU). These processes are selected due to their relatively high emission factors of non- CO_2 GHGs, particularly N_2O and CH_4 . The analysis is executed with Brighthway2 after loading the new sets of IAM-specific CFs for climate change impact assessment presented above (pGWP_{100} , pGTP_{100} , pGWP_{20} , and pGTP_{50}). For simplification, a *pLCA* limited to the year 2040 is considered in this paper. Although the set of new CFs enables more detailed dynamic-prospective analyses (i.e., considering the specific

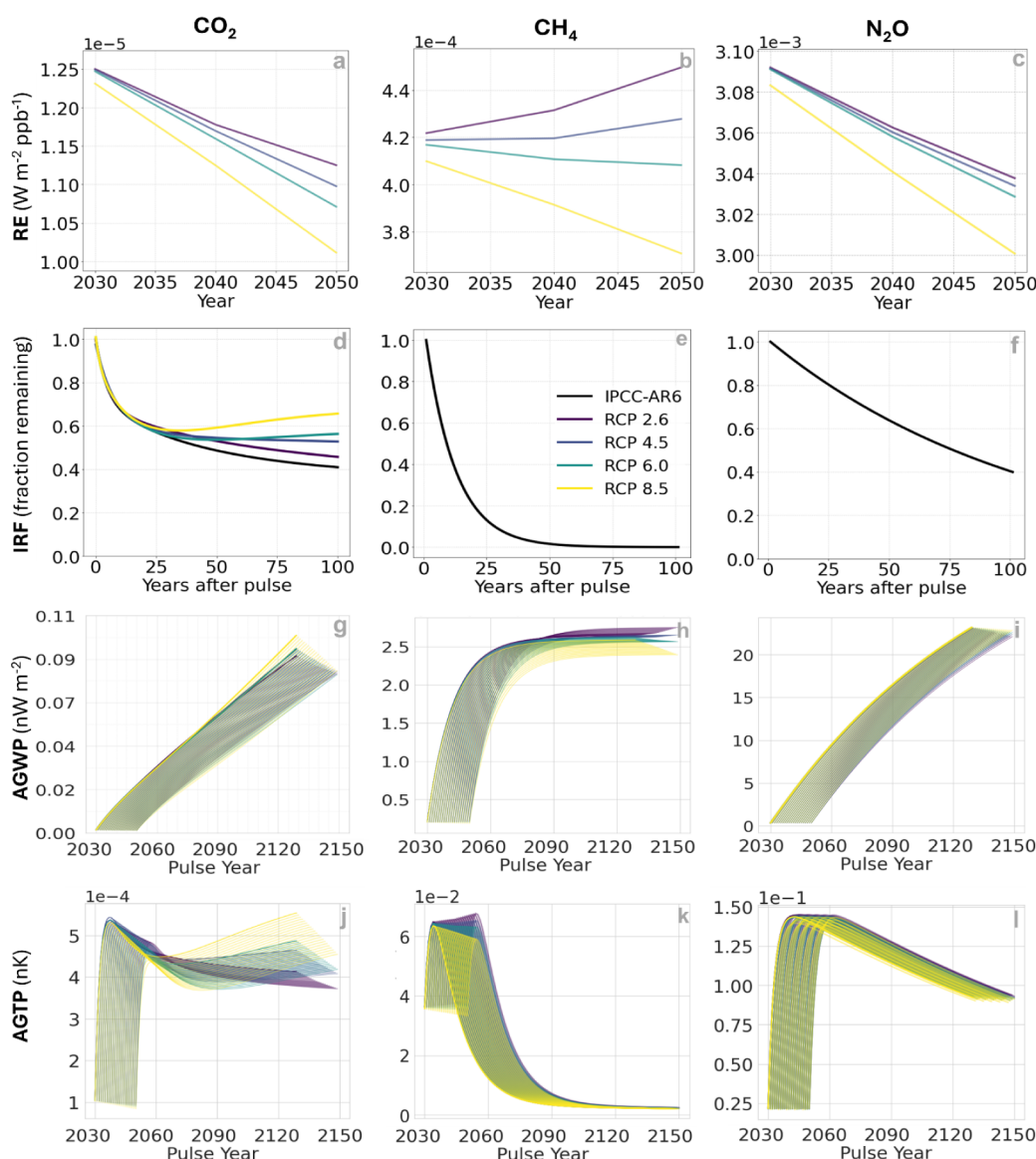


Figure 1. Prospective radiative efficiencies (RE), impulse response functions (IRFs), absolute global warming potentials (AGWP), and absolute global temperature change potentials (AGTP) under different RCP scenarios for the REMIND-MAGPIE-SSP5 scenario.³² Panels (a–c) show REs for a one ton pulse of CO₂, CH₄, and N₂O under RCPs 2.6, 4.5, 6.0, and 8.5 from 2030 to 2050. Panels (d–f) show the IRFs for CO₂, CH₄, and N₂O under varying concentration pathways. Panels (g–i) present AGWPs and panels (j–l) show AGTPs for pulse emissions of CO₂, CH₄, and N₂O at different future years (2030–2050) and for the investigated RCP scenarios.

years at which emissions will occur in the future), selecting a single pulse year better isolates the sensitivity of climate impacts from different product systems to the new CFs. Because of the differences in functional units and product systems, we further normalize the comparison of variability in characterized results to the percentage difference relative to the case in which the present-day CFs from IPCC-AR6²⁶ are used. The second part aims to extend the approach to cover a broader group of activities from ecoinvent 3.9⁴³ including power generation, transport, food, materials, and chemicals production.

2.3. Application of Prospective LCA to Both Inventories and CFs

The combination of evolving background systems and changes in climate change CFs is jointly investigated to explore the effects of integrating the prospective LCI and LCIA phases. Background transformations were implemented for the year 2040 using the Premise tool (version 2.2.7²¹), which modifies the ecoinvent database to reflect future conditions projected by IAMs. As only the REMIND-

MAGPIE model provided projected databases for more than one RCP scenario in the Premise tool (RCP 2.6 and RCP 8.5), our analysis was limited to this IAM and these two scenarios. In addition to transforming background databases, Premise also introduces changes in foreground systems of sectors, such as power generation, cement, steel, transport, fuels, and heat production. As a result, the IAM-based projected technological improvements directly modified the foreground inventories for the following activities: electricity production from natural gas using combined cycle power plants; Portland cement production; unalloyed steel production via a converter; and the market for freight transport by unspecified lorry.

Climate impacts were recalculated using pCFs, and the results were expressed as percentage deviations from a reference case based on present-day characterization factors from IPCC-AR6²⁶ and the unmodified ecoinvent 3.9 database.⁴³ Activities were then ranked according to their sensitivity to these changes.

3. RESULTS

3.1. Prospective AGWP and AGTP

The evolution of prospective REs, IRFs, AGWPs, and AGTPs is shown in Figure 1 for the different RCPs connected to the REMIND-MagPIE-SSP5 scenario. Results for IMAGE-SSP1, MESSAGE-GLOBIOM-SSP2, AIM-CGE-SSP3, and GCAM4-SSP4 are presented in Figures S1–S30 in the SI.

The RE of CO₂ steadily declines under the least stringent climate scenario (RCP 8.5), reaching approximately $1.01 \times 10^{-5} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$ by 2050 (Figure 1a). This represents a 25% reduction compared with the IPCC-AR6 reference value of $1.33 \times 10^{-5} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$. Generally, as the atmospheric concentration of a gas increases, its RE decreases. This trend reflects the logarithmic relationship between CO₂ concentration and its absorption of infrared radiation (eq 3), which diminishes the marginal impact of additional CO₂ on radiative forcing.²⁴ Under RCP 2.6, CO₂ RE remains relatively higher than in other scenarios but still falls to $1.13 \times 10^{-5} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$ by 2050, which is 15% lower than the current reference value. A similar declining trend is observed for N₂O (Figure 1c). Under RCP 8.5, the RE of N₂O decreases more sharply, reaching $3.00 \times 10^{-3} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$ by 2050 (6% below the IPCC AR6 reference of $3.20 \times 10^{-3} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$). For other RCPs (2.6, 4.5, and 6.0), the RE values remain relatively similar until 2050, ranging between 3.03 and $3.04 \times 10^{-3} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$. CH₄, which has a shorter atmospheric lifetime, exhibits a different pattern (Figure 1b). RE values under RCPs 2.6 and 4.5 tend to increase up to 2050, reflecting a faster rise in RF relative to the increase in CH₄ concentrations. In contrast, RE remains nearly constant under RCP 6.0, while under RCP 8.5 it declines to around $3.75 \times 10^{-4} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$, a 4% decrease from the IPCC AR6 reference value of $3.89 \times 10^{-4} \text{ W}\cdot\text{m}^{-2}\cdot\text{ppb}^{-1}$. These dynamics reflect the varying CH₄ atmospheric concentration under these scenarios (lower for RCPs 2.6 and 4.5, and higher for RCPs 6.0 and 8.5).

The IRF of CO₂ is sensitive to the background conditions of the gas (Figure 1d). In general, a pulse emission of CO₂ emitted to the atmosphere is never fully reabsorbed by the climate system within millennial time scales, with the fraction that remains in the air depending on the saturation of the carbon sinks.⁴⁴ This long-term legacy of CO₂ atmospheric perturbation underpins the irreversibility of CO₂-induced global warming and the need to bring net anthropogenic emissions down to zero to stabilize temperature changes.^{45–47} The fraction of CO₂ remaining in the air 100 years after a pulse emission increases from 41% (present-day IRF) to 46%, 53%, 56%, and 66% for RCPs 2.6, 4.5, 6.0, and 8.5, respectively. In all cases, the IRFs follow a similar decay for about 20 years, but thereafter their patterns start to diverge. The decay continues for RCP 2.6, as this is the scenario with the lowest addition of carbon to the atmosphere and in which the carbon removal rates of the natural carbon sinks (oceans and terrestrial vegetation) are more efficient. By increasing CO₂ concentrations, the carbon sinks become increasingly saturated and less efficient at removing CO₂ from the atmosphere.^{48,49} In RCP 4.5, the fraction of CO₂ remaining in the air tends to stabilize after about 40 years. In the cases of RCPs 6.0 and 8.5, the CO₂ fraction declines for the first 30 years, but then there is a sharper increase in the fraction remaining in the air until year 100. This is due to the relatively high CO₂ emission levels in these scenarios that lead to an excess of atmospheric CO₂ that is beyond the absorption capacity of the natural sinks,

which become saturated. More technical descriptions about the behavior of the global carbon cycle at varying atmospheric CO₂ concentrations are available elsewhere.^{49–51} As discussed in the methods, the IRF for CH₄ (Figure 1e) and N₂O (Figure 1f) is simpler and follows a single exponential decay model that is rather insensitive to their background atmospheric concentrations.

By combining IRFs with REs, the AGWPs associated with the emission of 1 ton of CO₂ for multiple pulse years under various RCP scenarios can be estimated (Figure 1g). Across all RCPs, AGWP values tend to decrease for later pulse years, primarily due to a consistent decline in RE values over the 100 year evaluation period. In RCPs 8.5 and 6.0, this downward trend in REs offsets the slight increase in IRFs observed around 40 years after the emission pulse, yet AGWP values remain relatively higher compared to those of other scenarios. When benchmarked against the IPCC AR6 reference estimate (where the 100-year AGWP for CO₂ is projected to reach $0.090 \text{ nW}\cdot\text{m}^{-2}$ per ton of CO₂), only the 2030 pulse emissions under RCPs 6.0 and 8.5 exceed this threshold. By contrast, for 2050 pulse emissions, AGWP values converge to approximately $0.084 \text{ nW}\cdot\text{m}^{-2}$ across all RCPs, which is about 7% lower than the IPCC AR6 reference. This reduction reflects the reduced marginal impact of a CO₂ emission in a future atmosphere with elevated background CO₂ concentrations.

For CH₄ AGWPs (Figure 1h), RCP scenarios that result in higher radiative forcing by 2100 are associated with lower REs, leading to a reduction in AGWP values for later pulse years. This downward trend is reversed in RCPs 4.5 and 2.6, where AGWPs increase slightly over time. The variability in CH₄ AGWPs by 2050 is notably greater than that observed for CO₂, highlighting the larger sensitivity of CH₄'s RE values to different RCP scenarios. In contrast, N₂O (Figure 1i) exhibits the lowest AGWP variability, as the relative differences in RE values across RCPs are much smaller than those for CO₂ and CH₄. Interestingly, N₂O AGWPs are slightly higher under RCP 8.5 compared to RCP 2.6, a pattern opposite to that of CH₄. Although N₂O REs decrease from RCP 2.6 to 8.5, this effect can be offset by the reduction in CH₄ REs under RCP 8.5, which leads to less spectral overlap and reduced competition for infrared absorption. This interaction may enhance the effective radiative impact of N₂O in high-CH₄-concentration scenarios.

When analyzing the AGTPs, the response curves for the CO₂ peak within approximately a decade following the emission pulse and then gradually decline under RCPs 2.6, 4.5, and 6.0 (Figure 1j). In contrast, for the earliest pulse years (2030–2035) under RCP 8.5, AGTP values continue to increase beyond the initial peak, primarily driven by a more rapid rise in AGWPs associated with those pulse years—as previously shown in Figure 1g. While the greater variability in CO₂ AGTPs largely reflects the diversity in RE trajectories across scenarios, the AGTP curves for later pulse years begin to closely mirror the trends of the IRF curves shown in Figure 1d. As with AGWPs, later pulse years consistently correspond to lower AGTP values across all RCPs. This again illustrates the declining marginal warming impact of a CO₂ emission in a future atmosphere with elevated background concentrations. AGTPs of RCP 2.6 can approach a value close to that based on current IPCC parameters (which stabilize at around 4 nK per ton of CO₂ after 100 years) for the earliest pulse emissions. However, for later pulse years under RCP 2.6, AGTP values decline to approximately 3.8 nK after 100 years, which is about

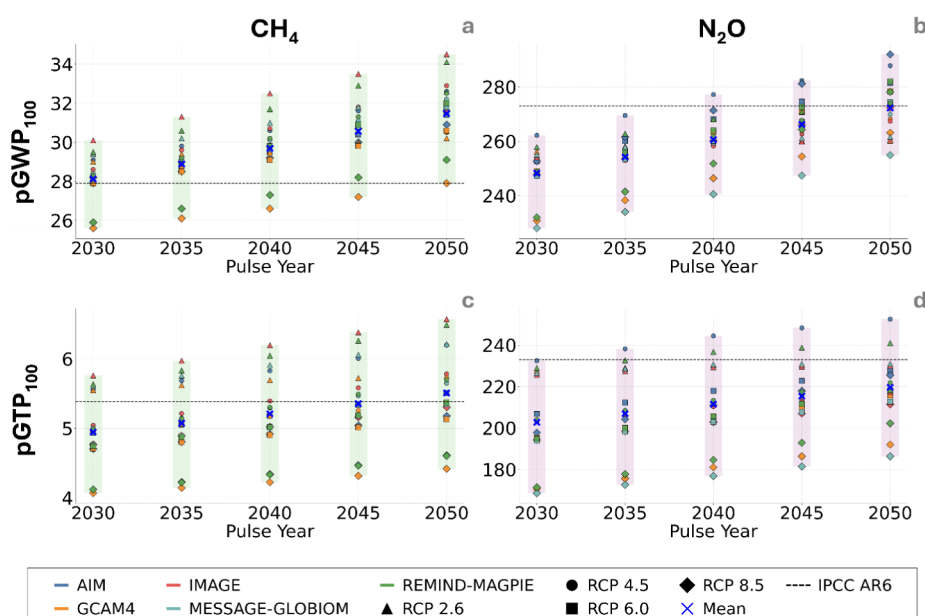


Figure 2. Prospective global warming potential over 100 years (pGWP_{100}) and global temperature change potential 100 years (pGTP_{100}) after a pulse emission at year 2030–2050 for methane (CH_4) and nitrous oxide (N_2O). Results are based on outputs from multiple Integrated Assessment Models (IAMs) for different RCPs; the green and purple shaded bars illustrate the possible span of the CH_4 and N_2O metric values, respectively, for each pulse year. Mean values are calculated based on the results obtained from the 18 different IAM-RCP combinations.

5% lower than the present-day reference values. Conversely, under RCP 8.5, AGTPs can reach 4.5 nK, or 12% above the reference level, highlighting the amplified warming potential of CO_2 in a high-emissions trajectory due to a higher fraction of CO_2 remaining airborne at more saturated ocean and terrestrial carbon sinks.

The CH_4 AGTPs exhibit a different pattern than that of CO_2 and N_2O (Figure 1k). Although the temperature response peaks around 5–6 years after the emission pulse, all trajectories converge to the same value of approximately 2×10^{-4} nK per ton of CH_4 by the end of the 100-year period. This sharp decline reflects methane's short atmospheric lifetime and the rapid adjustment of radiative forcing as CH_4 concentrations decay over time. Unlike CO_2 and N_2O , CH_4 is classified as a short-lived climate pollutant, with warming effects that are largely reversible within decades after a single emission pulse.^{52,53} In the first three decades following a pulse, CH_4 AGTPs behave differently depending on the scenario: AGTP values increase for later pulse years under RCP 2.6, while they decrease under RCP 8.5. Nonetheless, by year 100, AGTPs across all RCPs converge to a value slightly below the one derived from present-day IPCC parameters ($\sim 4 \times 10^{-4}$ nK after 100 years), further highlighting the short-term nature of methane's warming influence.

For N_2O (Figure 1l), the AGTP values show minimal variability across RCPs and pulse years. Although RCP 2.6 yields slightly higher AGTPs, the values for all scenarios practically overlap within a narrow range of 0.091–0.095 nK after the 100-year period. These are slightly higher than the estimate derived using current IPCC parameters (~ 0.090 nK) and indicate relatively stable long-term warming impacts of N_2O under future emission scenarios.

3.2. Prospective Characterization Factors

Figure 2 shows the projected pGWP_{100} and pGTP_{100} values, derived from evolving background concentrations of GHGs

under various IAMs, for selected pulse years from 2030 to 2050 at five-year intervals.

For CH_4 (Figure 2a), the average pGWP_{100} increases from 28.1 ± 1.2 in 2030 to 31.4 ± 1.7 in 2050 (mean $\pm$ one standard deviation across all future IAM-RCP scenario combinations). Among individual estimates, the lowest pGWP_{100} value is 25.6, or 8% below the present-day CF, which occurs for a 2030 pulse under the GCAM4-SSP4 RCP 8.5 scenario. This lower value is primarily driven by the higher CO_2 AGWPs in this scenario, which increase the denominator in the GWP equation and thereby reduce methane's relative warming impact. In contrast, the highest pGWP_{100} value is 34.5, or 23% above the present-day value, and it occurs for a 2050 pulse in the IMAGE-SSP1 RCP 2.6 scenario. In this case, the CH_4 AGWPs peak and the CO_2 AGWPs peak are at their lowest, amplifying the ratio. Overall, CF values tend to rise with later pulse years with most projections exceeding the present-day CFs described in IPCC-AR6.²⁶ In general, values are higher at lower RCPs. The findings are consistent with Reisinger et al. (2011),²⁴ where the lowest projected GWP_{100} values for CH_4 are reported for RCP 8.5, largely due to the rapid near-term increase in CH_4 concentrations that reduces RE and the methane's marginal climate impact over a 100-year time frame.

For N_2O pGWP_{100} , the mean values increase from 248.2 ± 9.2 in 2030 to 272.0 ± 10.1 in 2050. As shown in Figure 2b, all mean values remain slightly below the present-day GWP_{100} value of 273, with only a few exceptions. The lowest projected pGWP_{100} value, 228, is associated with a 2030 pulse under the MESSAGE-GLOBIOM-SSP2 RCP 8.5 scenario. This low value results from the relatively higher CO_2 AGWP, which increases the denominator in the GWP equation, thereby lowering the overall pGWP_{100} for N_2O . Unlike CH_4 and CO_2 , no consistent trend with the RCP level is observed for N_2O pGWP_{100} . Notably, the maximum value of 292, which is about 7% above the present-day GWP_{100} , is found under RCP 8.5,

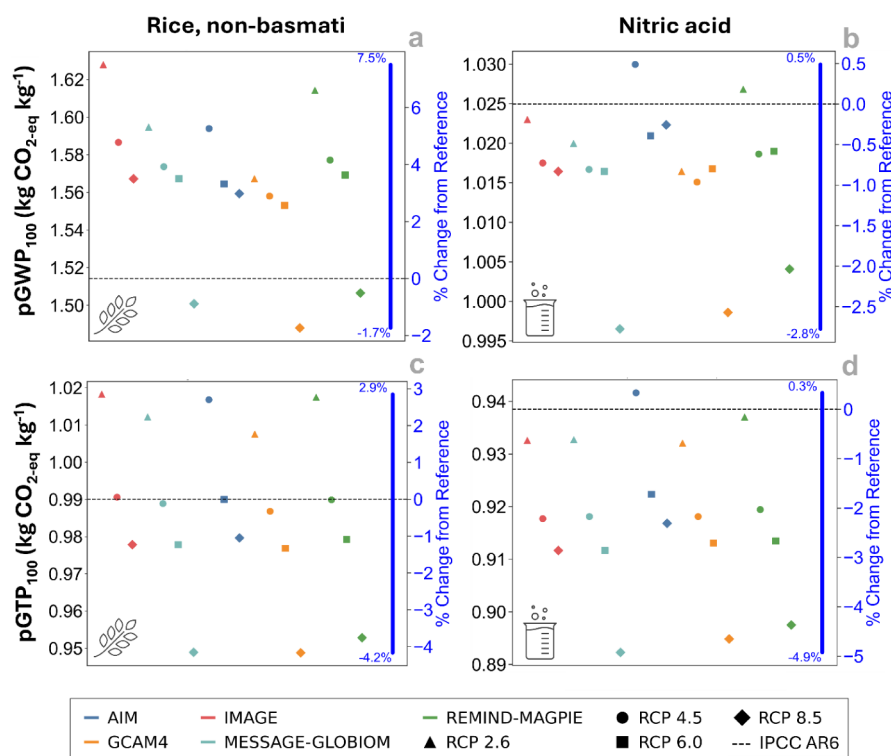


Figure 3. Sensitivity analysis of climate impacts in 2040 for nonbasmati rice production and nitric acid production in 50% aqueous solution. Panels (a,b) illustrate the sensitivity to pGWP₁₀₀ and panels (c,d) pGTP₁₀₀. Blue bars represent percentage changes relative to the present-day characterization factors from IPCC-AR6 (indicated by dashed lines).

namely, the AIM/CGE-SSP3 scenario for a pulse year in 2050. Reisinger et al. (2011)²⁴ also identified RCP 8.5 in 2050 as yielding the highest pGWP₁₀₀ values for N₂O, while values across RCPs were relatively similar in 2030. Our findings, however, highlight a stronger influence of the underlying IAM framework on projected GWP values, rather than RCP trajectory alone. In general, the highest pGWP₁₀₀ values for N₂O are driven by the AIM/CGE-SSP3 scenario, while the lowest originate from MESSAGE-GLOBIOM-SSP2.

The pGTP₁₀₀ for CH₄ increases from 4.92 ± 0.52 in 2030 to 5.47 ± 0.62 in 2050 (Figure 2c), exhibiting a trend similar to that of pGWP₁₀₀, with values rising over time. The minimum and maximum projected values are 4.1 and 6.6, respectively, and represent changes of −24% and +22% relative to the present-day GTP₁₀₀ value of 5.38. Across various RCP and IAM scenarios, this pattern mirrors that of pGWP₁₀₀, with lower values associated with RCP 8.5 and higher values linked to RCP 2.6. For the pGTP₁₀₀ of N₂O (Figure 2d), values increase from 201.7 ± 19.9 in 2030 to 218.9 ± 15.9 in 2050, with the lowest values occurring under RCP 8.5. The pGTP₁₀₀ values for N₂O are generally lower than the present-day N₂O GTP₁₀₀ of 233, a behavior largely driven by the increased AGTP of CO₂, which exceeds current levels, particularly in scenarios with earlier emission pulses. In contrast to CH₄, the REs of N₂O do not increase over time—and consequently AGTP—consistently decline across all RCP scenarios. The lowest value, 168.6, represents a 27% decrease relative to current GTP₁₀₀. Exceptions to this trend occur in both the AIM-CGE-SSP3 and REMIND-MAGPIE-SSP5, where the maximum value of 252 is observed under RCP 4.5 for a 2050 pulse year, which is an increase of approximately 8% relative to the present-day value.

3.3. Impact of Prospective Characterization Factors on LCA Results

Figure 3 presents the sensitivity to pGWP₁₀₀ and pGTP₁₀₀ of the life-cycle climate change impacts of two production activities, namely, nonbasmati rice and nitric acid. For this example, a prospective LCA fixed at the year 2040 without updates to the background database is considered. Climate change impacts for rice characterized with pGWP₁₀₀ range from −1.7% to +7.5% relative to the results calculated with present-day CFs (blue bars in Figure 3a). The largest deviation occurs under the IMAGE-SSP1 RCP 2.6 scenario, which yields the most extreme CFs. Since CH₄ and N₂O contribute 38% and 9% of rice life-cycle impacts, respectively, pGWP₁₀₀ values can reach up to 1.62 kg of CO₂-eq per kg of rice, compared to about 1.5 kg of CO₂-eq with current CFs. For nitric acid (Figure 3b), impacts are lower and less variable, with deviations from −2.8% to +0.5% relative to the baseline of 0.94 kg of CO₂-eq. This is largely due to the higher share of N₂O (18%) compared to that of CH₄ (7%) in its impact profile. Since N₂O CFs under pGWP₁₀₀ can be lower than present-day values, they partially offset CH₄ increases, resulting in net changes typically between −1% and +0.5%.

Under pGTP₁₀₀ (Figure 3c,d), the largest reductions for both rice and nitric acid occur under the GCAM-SSP4 and MESSAGE-GLOBIOM SSP2 models with RCP 8.5, which yield the lowest combined CFs for CH₄ and N₂O. Nitric acid shows slightly more pronounced negative deviations, with the lowest reaching −4.9% due to its strong dependence on N₂O emissions. For rice production, a slightly broader range of changes from the reference (blue bars in Figure 3) is observed compared to nitric acid due to the greater contribution from CH₄.

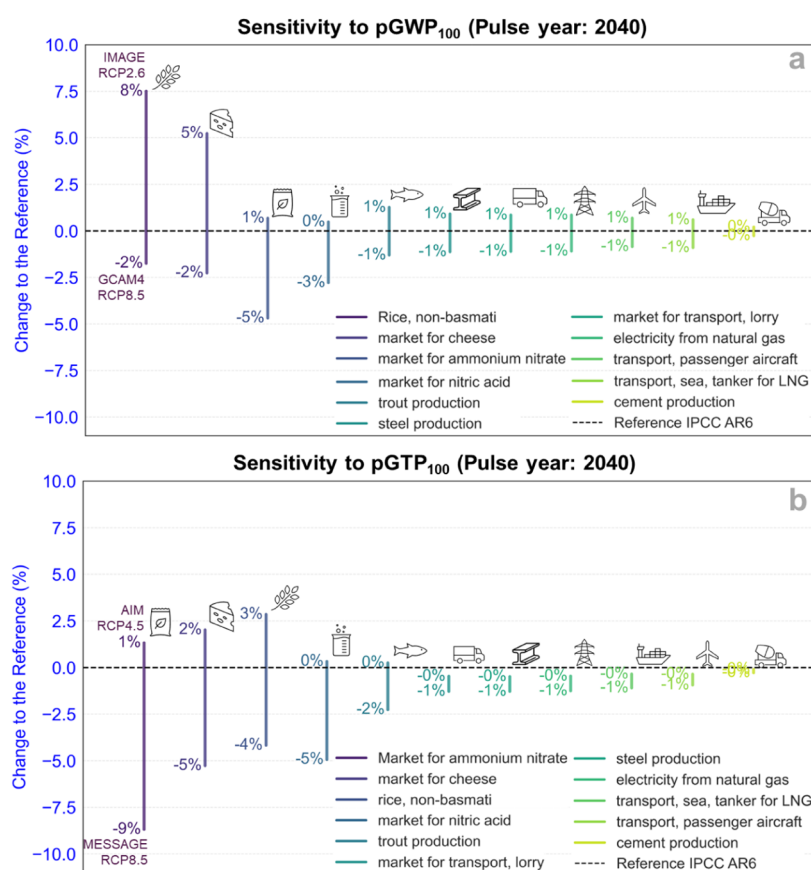


Figure 4. Ranking sensitivity to pCFs for the life-cycle climate change impacts of the selected ecoinvent 3.9 activities in the year 2040. Panel (a) illustrates the sensitivity of activities to global warming potential over 100 years (pGWP₁₀₀) while panel (b) shows the sensitivity to global temperature change potential 100 years after emission (pGTP₁₀₀). Colored bars represent the percentage change relative to the present-day characterization factors from the IPCC Sixth Assessment Report (AR6),²⁶ indicated by dashed lines. Activities are arranged from left to right in order of decreasing sensitivity.

Figure 4 shows the sensitivity to pCFs of a group of activities, including power generation, transport, food, materials, and chemicals production. The most affected by the changes in CFs are rice and cheese production, which show the highest sensitivity to both metrics. For pGWP₁₀₀ (Figure 4a), cheese can achieve life cycle impacts up to 8% higher than the reference, largely driven by CH₄ (27%) and N₂O (13%) impacts originating from ruminant digestion and the production of feed used in cow milk production. Within the food sector, trout farming in semi-intensive systems ranks fifth, as it is particularly impacted by upstream N₂O emissions (which represent 6% of total life cycle impacts) linked to soybean cultivation for trout feed. The chemical sector, represented by ammonium nitrate and nitric acid production, is among the activities with the largest sensitivities represented in Figure 4a. The nitrogen-based fertilizer has the highest contribution of N₂O to total life cycle impacts (35%) among all activities investigated in this study. Such a value is reflected in the lowest change relative to the reference to pGWP₁₀₀ (−3.6%), as the prospective N₂O CFs used to calculate pGWP₁₀₀ can fall below the present-day CF. As CH₄ emissions are practically zero in this activity, the sensitivity profile of ammonium nitrate is dominated by the uncertainty of CFs associated with N₂O. For other activities such as transport, power generation, and cement production, the sensitivity to pGWP₁₀₀ is much lower because CO₂ impacts are predominant.

With pGTP₁₀₀ (Figure 4b), ammonium nitrate shows the largest potential decrease (−9% relative to the present-day value). This is primarily due to the dominant role of N₂O in its life cycle impacts combined with CFs that are lower than the reference. Rice production, which ranked highest in sensitivity under pGWP₁₀₀, decreases its sensitivity under pGTP₁₀₀. This shift reflects the higher CH₄-to-N₂O ratio in its life cycle emissions. Since CH₄ is a short-lived greenhouse gas, its relative importance decreases when using a metric like GTP, which captures the instantaneous impact at a specific time horizon rather than integrating effects over time as GWP does. In contrast, activities dominated by fossil CO₂ emissions—such as transport, power generation, steel, and cement production—exhibit sensitivity even lower under pGTP₁₀₀ than under pGWP₁₀₀. This aligns with their emission profiles, which are largely unaffected by non-CO₂ GHGs. As discussed in detail elsewhere,³⁸ the differences between Figure 4a and b highlight how the choice of the climate metric can affect the estimated climate impact of a given product, especially when there is a high share of non-CO₂ GHG emissions.

3.4. Combination of Prospective Inventories and Prospective CFs

Figure 5 shows the sensitivity of the estimated climate change impacts to changes in the background database by adapting ecoinvent v.3.9 to the prospective REMIND-SSP5 scenarios RCP 2.6 and RCP for the year 2040, in comparison to the cases where the background database is not transformed and

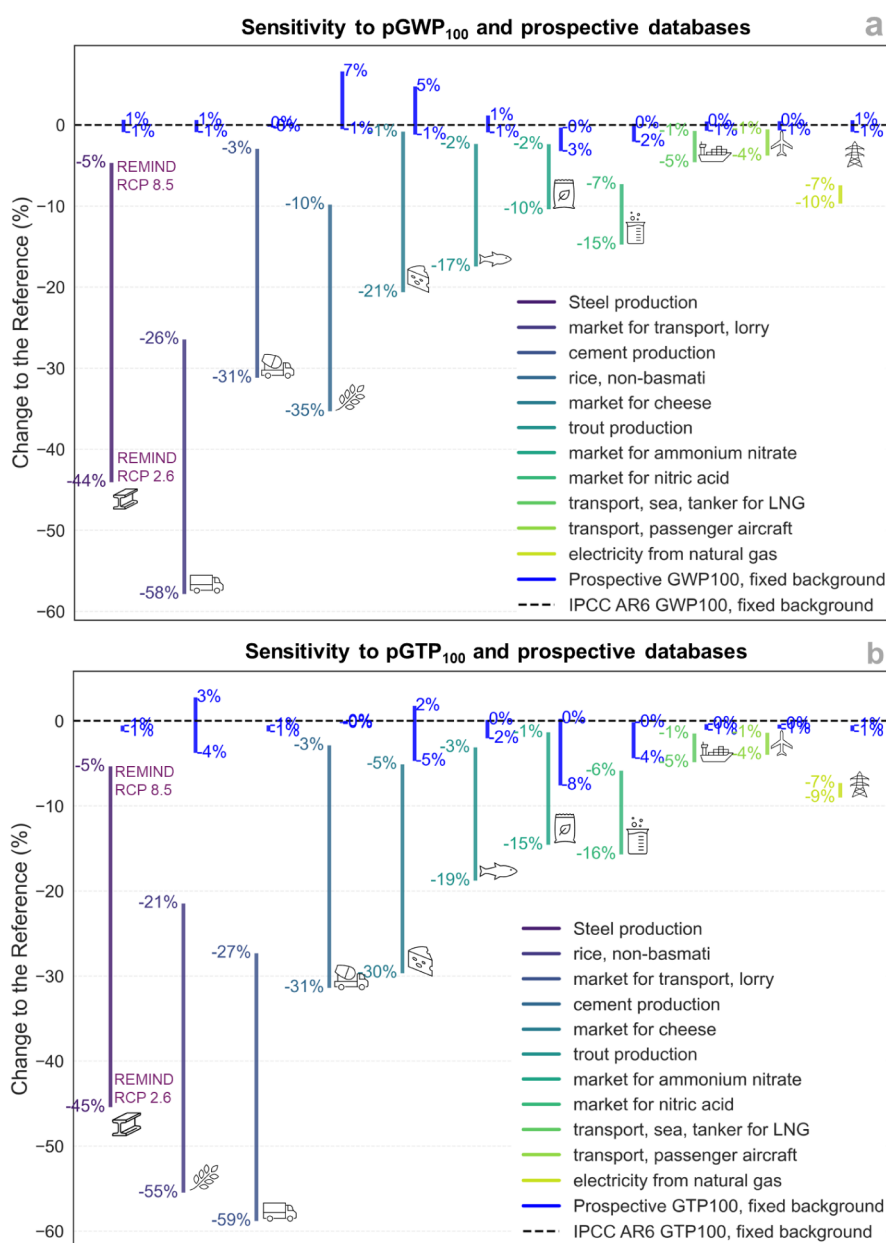


Figure 5. Sensitivity of activities to prospective climate change characterization factors (CFs) and prospective ecoinvent 3.9 data under REMIND-SSP2-2.6 and REMIND-SSP5-8.5 scenarios for the year 2040. Panel (a) illustrates the sensitivity of activities to global warming potential over 100 years ($pGWP_{100}$) while panel (b) shows the sensitivity to global temperature change potential 100 years after emission ($pGTP_{100}$). Activities are ordered from left to right by decreasing the sensitivity. The bars indicate the percentage deviation from the reference case, which is based on the fixed ecoinvent 3.9 database⁴³ and present-day CFs²⁶ (represented by the dashed line). Blue bars isolate the effect of changing only the CFs, i.e., keeping the present-day background database.

only the CFs are prospective. These REMIND-RCP scenarios were chosen because they are the only ones currently available in the Premise tool²¹ that fully align with the IIASA marker scenarios, and they represent the two extremes of the RCP range examined in this study. When only the pCFs are modified, represented by the blue bars, there is a general trend of net increases in climate impacts assessed with GWP_{100} for CH_4 -emission dominated activities and net decreases when GTP_{100} is used for activities dominated by N_2O emissions compared to the reference case (i.e., no prospective inventories nor pCFs). However, adding changes in the background database significantly alters the outcomes, as indicated by the colored bars in Figure 5.

Steel production emerges as the most affected activity by changes in the background scenario under $pGWP_{100}$ (Figure 5a), representing a significant shift in sensitivity compared to the fixed background analysis (Figure 4a) where it ranked sixth. In steel production, net reductions in impacts range from -5% to -44% . These reductions are driven by progressive improvements in energy efficiency and declining direct emissions from both steel and pig iron production.²¹ The maximum reduction corresponds to the RCP 2.6 scenario, which aligns with the adoption of technologies such as carbon capture and storage (CCS). Similarly, road transport is significantly influenced by changes in the prospective databases, reflecting shifts in fleet composition such as the

introduction of electric trucks and enhanced energy efficiency as well as a growing share of renewable fuels in internal combustion engines by 2040. Relative to the fixed background analysis, road transport achieves the largest reduction in impacts across all assessed activities, reaching -58% under the RCP 2.6 scenario. Other CO_2 -intensive activities, such as cement production, also become increasingly responsive to changes in process inventories, showing consistent reductions in pGWP_{100} across all RCP scenarios. For Portland cement, projected decreases in fuel consumption (e.g., coke) and associated CO_2 emissions reflect ongoing improvements in the foreground system, particularly in clinker production. In the RCP 2.6 scenario, the adoption of CCS further amplifies these reductions, potentially lowering the impacts by up to 31% . By contrast, maritime transport and aviation exhibit lower sensitivity to changes in background scenarios due to the limited representation of future developments in fleet composition and fuel mix for ships and aircraft in current prospective scenario modeling.

In terms of pGTP_{100} (Figure 5b), steel production also experiences the highest sensitivity, primarily due to the reduction in fossil- CO_2 emissions driven by cleaner production technologies, with the variability of the impacts ranging from -5% to -45% . When compared with the use of pGWP_{100} , rice production is the activity that shows the most pronounced change in sensitivity when shifting to the pGTP_{100} . The relative contributions of CH_4 and N_2O to the total direct emissions (from rice cultivation and fertilizer use) increase alongside the significant reduction of fossil CO_2 from background activities (such as fuel mixes, road transport, and fertilizer production). As a result, the variability associated with CFs becomes even more impactful under REMIND-SSP5 RCP 2.6, which represents the scenario with the greatest level of decarbonization in the supply chain.

We further exemplify how pCFs can influence LCA outcomes for similar products but produced from different value chains, a perspective that is relevant when LCA is used as a decision support tool by assessing rice production in 2040 in the United States and India using pGTP_{100} under the REMIND-SSP5-RCP 8.5 scenario. With conventional pCFs, the U.S. rice production has higher impacts (758 vs 750 kg of $\text{CO}_2\text{-eq/ton}$). When applying prospective CFs, the results reverse, and rice production in India exhibits higher impacts (704 vs 714 kg $\text{CO}_2\text{-eq/ton}$). A similar trend is found for “market for nitric acid, without water” when comparing Rest of the World (RoW) and UN-Oceania. Without pCFs, UN-Oceania shows higher impacts (1,840 vs 1,709 kg $\text{CO}_2\text{-eq/ton}$ for RoW), but applying pCFs reverses the results (1,604 vs 1,595 kg $\text{CO}_2\text{-eq/ton}$). This occurs because the use of pGTP_{100} makes results particularly sensitive when relatively high emissions of N_2O are present. The results of both examples can be found in Figures S31 and S32 in the SI.

4. DISCUSSION

Comparing the pCFs estimated in this study with those available in the literature is challenging, as no previous publication has projected pCFs across multiple climate metrics using the IAM-SSP marker scenarios. Our results for CH_4 pGWP_{100} for the period 2030–2050 range from 25.6 to 34.5, and slightly differ from the projections by Lan and Yao (2022),²⁹ who reported values between 29 and 41. For N_2O , their estimated range of 280–380 is broader than our findings, which fall between 232 and 292. Although their method

accounts for changes in REs, they do not clearly specify the IAM model or SSP scenario used in their analysis, limiting the comparability of their results. Moreover, unlike our approach, their study does not incorporate variations in the CO_2 IRFs across RCPs, a factor that likely contributes to the observed differences. To our knowledge, no studies have examined other climate metrics (e.g., GTP_{100}) in this context under such conditions.

Potential future changes in GWPs were originally modeled by Reisinger et al. (2011),²⁴ who incorporated both changes in REs and climate–carbon cycle feedback under different RCPs. Although their study provided projections for the GWP of N_2O and CH_4 , a direct comparison with our quantitative results is not feasible, as their analysis did not link their data directly to specific IAM outputs. Nevertheless, some trends in their findings align with ours. For instance, our results for methane’s projected GWP_{100} also lead to the lowest GWP_{100} values under the RCP 8.5 scenario. This outcome is primarily attributed to the rapid increase in CH_4 concentrations in the near term, which reduces its RE and, consequently, its marginal climate impact over a 100-year horizon. Their analysis of the 2030–2050 period further identified the highest GWP_{100} values under RCP 2.6, which is in line with our finding.

A key limitation in our analysis is the absence of a multimodel mean for the IRFs of CO_2 across different RCP scenarios, which led us to adopt an indirect approach to address this gap. It is also important to note that the IRF used by the IPCC for estimating metric values in its last assessment report (dated 2019)²⁶ is the one from Joos et al., which is based on a background atmospheric concentration of CO_2 of 389 ppm, which refers to the year 2010.²² This is lower than the current concentration of 427 ppm. As such, there is an inconsistency as the IRF available for CO_2 becomes progressively outdated and does not reflect present-day conditions nor align with updated RE values. Addressing this issue requires simulations from complex climate models to replicate experiments such as those in Joos et al., requiring competencies and tools that go beyond the current capabilities of the LCA community. Given the importance of IPCC climate metrics for LCA, establishing a collaborative dialog with climate scientists can stimulate the development of an updated set of IRFs that reflect current climate conditions and span multiple future RCPs. Although future changes in the IRFs for CH_4 and N_2O are expected to only have a minor influence on our results given the relative stability of their lifetimes across the historical IPCC assessment reports, the future availability of more refined and time-dependent IRFs could improve the accuracy of the estimated pCFs.

The radiative forcings and GHG concentrations from the IAM-SSP-RCP marker scenarios used in this study are based on the best available data from the IIASA Legacy Database.³² Incorporating other or more recent IAM results could potentially enrich the pCFs and affect the mean statistics elaborated in this paper.

The coupling between pCFs and prospective background databases is hindered by the limited number of IAM scenarios that are currently available within existing prospective tools. In the current version of Premise (v. 2.2.7), only the REMIND-MagPIE-SSP5 scenario is available in more than one RCP. Extending the availability of prospective databases to match other IAM marker scenarios can be beneficial for prospective LCA studies aiming at combining changing CFs with changes in background databases. As the Premise framework is open to

add more IAM scenarios, this gap can be covered by future studies such as the one that coupled the TIAM-UCL model with Premise and ecoinvent.⁵⁴

This study focuses on the three primary GHGs (CO₂, CH₄, and N₂O) with the goal of introducing and demonstrating a consistent methodological approach for estimating pCFs. These gases are a logical starting point to showcase the method to compute pCFs, and they dominate most of the LCA applications. The same approach can be reiterated to estimate pCFs of other GHGs, including chlorinated and fluorinated compounds, for which data are available. Expanding the method to include short-lived climate forcers such as carbon monoxide (CO), nitrogen oxides (NO_x), and sulfur oxides (SO_x) will require additional consideration due to their complex atmospheric behavior and indirect effects. Future research should aim to adapt and refine the framework to accommodate these substances, supported by more comprehensive data sets and modeling tools.

The pCFs computed in this study are timely given the increasing number of pLCAs conducted in recent years.² Unlike previous studies, we provide analytically derived and updatable CFs tailored to LCA that include multiple metrics and align with IPCC methods and IAM scenarios used in pLCA. These features ensure consistency with frameworks for modifying background databases²¹ and enable straightforward integration into existing pLCA tools using tabulated values (Tables S.2–S.9 of the SI). The provided REs, IRFs, and Python codes for AGWP, AGTP, pGWP₁₀₀, pGWP₂₀, pGTP₅₀, and pGTP₁₀₀ enable extended calculations of pCFs of up to 2100. Emission inventories can be adapted to the year at which the emission occurs, a procedure that can be facilitated by integrating these pCFs with dynamic LCA tools that are becoming increasingly available.^{55,56} For more generic applications or uncertainty considerations aiming to provide insights on how alternative scenarios influence LCA results, mean CFs per RCP with the associated standard deviations can be used. This approach enables the exploration of how a single climate target can be met through different pathways, offering insights into the variability arising from alternative socioeconomic and technological assumptions. In cases in which a specific future climate target is not specified, the average and ranges from all of the available CFs for each given pulse year can be considered. Conversely, averaging CFs across SSPs for different RCPs is likely less meaningful, given the substantial variability in impacts that can occur across SSPs. In all cases, the aggregation method used for pCFs should be consistent with the type of IAM-RCP combination considered for projecting process inventories. This variety of applications can be enhanced by uploading individual and aggregated pCFs (for pGWP₁₀₀, pGWP₂₀, pGTP₅₀, and pGTP₁₀₀) into existing LCA tools such as Brightway2. Ultimately, we emphasize the need for a harmonized framework that integrates prospective metrics across impact categories beyond climate change, thereby supporting the broader implementation of pLCA.

As presented in the sensitivity analysis, the use of pCFs can result in significant variations in life-cycle climate change impacts across activities, even for identical products sourced from different regions or supply chains. As exemplified by rice and nitric acid production, pCFs can exert a greater influence on decision-making involving value chains in which nitrous oxide emissions play a larger role.

The outcomes of this study are primarily intended for the LCA community, aiming to strengthen the methodological

consistency of pLCA and apply the prospective analysis to both the inventory and the LCIA phase. The availability of pGWPs and pGTPs is a step forward in developing dynamic, time-dependent climate impact assessment, where CFs vary with the emission year and evolving background conditions. By integrating pulse-year-specific CFs into temporally explicit modeling frameworks, our approach enhances the accuracy, consistency, and policy relevance of future-oriented climate impact evaluations. The prospective CFs developed here are presented in table format in the SI, together with the code to generate them, and as such, they can be readily implemented in pLCA tools to be consistently coupled with the IAM scenarios used to produce future background databases. Alternatively, CFs averaged by a specific RCP can be used in more streamlined applications to reflect a range of plausible futures or to explore scenario-induced variability in an uncertainty analysis. While this study focuses on CH₄ and N₂O, future work can extend this framework to generate pCFs for the remaining GHGs, enabling the creation of complete and harmonized data sets for other climate forcers. This research ultimately supports a robust evolution of pLCA approaches toward greater alignment with forward-looking climate policies and decision-making contexts.

■ ASSOCIATED CONTENT

SI Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.5c12391>.

(XLSX)GTP100_CH4_table
(XLSX)GTP100_N2O_table
(XLSX)GWP100_CH4_table
(XLSX)GWP100_N2O_table
(XLSX)IPCC2021 GTP100
(XLSX)IPCC2021 GTP50
(XLSX)IPCC2021 GWP100
(XLSX)IPCC2021 GWP20
(XLSX)pIRF_CH4
(XLSX)pIRF_CO2
(XLSX)pIRF_N2O
(XLSX)pRE_CH4_AIM
(XLSX)pRE_CH4_GCAM4
(XLSX)pRE_CH4_IMAGE
(XLSX)pRE_CH4_MESSAGE
(XLSX)pRE_CH4_REMIND
(XLSX)pRE_CO2_AIM
(XLSX)pRE_CO2_GCAM4
(XLSX)pRE_CO2_IMAGE
(XLSX)pRE_CO2_MESSAGE
(XLSX)pRE_CO2_REMIND
(XLSX)pRE_N2O_AIM
(XLSX)pRE_N2O_GCAM4
(XLSX)pRE_N2O_IMAGE
(XLSX)pRE_N2O_MESSAGE
(XLSX)pRE_N2O_REMIND
(XLSX)selected_flows

This file provides complementary results, supporting figures, supporting pGWP and pGTP tables, and supporting files and codes (PDF)

AUTHOR INFORMATION

Corresponding Author

Marcos D. Barbosa Watanabe – Industrial Ecology Programme, Department of Energy and Process Engineering, Norwegian University of Science and Technology (NTNU), Trondheim 7034, Norway; orcid.org/0000-0001-9818-7405; Email: marcos.d.b.watanabe@ntnu.no

Author

Francesco Cherubini – Industrial Ecology Programme, Department of Energy and Process Engineering, Norwegian University of Science and Technology (NTNU), Trondheim 7034, Norway

Complete contact information is available at: <https://pubs.acs.org/10.1021/acs.est.5c12391>

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

We acknowledge the support of the Horizon Europe projects LCA4Bio (number 101135371) and ALIGNED (number 101059430).

ABBREVIATIONS:

AGTP, absolute global temperature change potential; AGWP, absolute global warming potential; AR4, IPCC Fourth Assessment Report; AR5, IPCC Fifth Assessment Report; AR6, IPCC Sixth Assessment Report; CCS, carbon capture and storage; CFs, characterization factors; CH₄, methane; CO₂, carbon dioxide; ESMs, Earth system models; GTP, global temperature change potential; GWP, global warming potential; IAMs, integrated assessment models; IPCC, Intergovernmental Panel on Climate Change; IRF, impulse response function; LCI, life cycle inventory; LCIA, life cycle impact assessment; N₂O, nitrous oxide; ODPs, ozone depletion potentials; pGTP₁₀₀, prospective global temperature change potential over 100 years; pGTP₅₀, prospective global temperature change potential over 50 years; pGWP₁₀₀, prospective global warming potential over 100 years; pGWP₂₀, prospective global warming potential over 20 years; pLCA, prospective life cycle assessment; PREMISE, PROspective EnvironMental Impact AsSEssment; RCPs, representative concentration pathways; RE, radiative efficiency; SSPs, shared socioeconomic pathways; SI, [Supporting Information](#); TAR, IPCC Third Assessment Report

REFERENCES

- (1) Cucurachi, S.; Steubing, B.; Siebler, F.; Navarre, N.; Caldeira, C.; Sala, S. *Prospective LCA Methodology for Novel and Emerging Technologies for BIO-Based Products - The PLANET BIO project*; Publications Office of the European Union: Luxembourg, 2022.
- (2) Bisinella, V.; Christensen, T. H.; Astrup, T. F. Future Scenarios and Life Cycle Assessment: Systematic Review and Recommendations. *Int. J. Life Cycle Assess.* **2021**, *26*, 2143–2170.
- (3) Marson, A.; Benozzi, A.; Manzardo, A. Looking to the Future: Prospective Life Cycle Assessment of Emerging Technologies. *Chem.—Eur. J.* **2025**, *31* (25), No. e202500304.
- (4) Arvidsson, R.; Svanström, M.; Sandén, B. A.; Thonemann, N.; Steubing, B.; Cucurachi, S. Terminology for Future-Oriented Life Cycle Assessment: Review and Recommendations. *Int. J. Life Cycle Assess.* **2024**, *29* (4), 607–613.

- (5) Junior, H. J. E.; de Melo, R. X.; Sartori, M. M. P.; Guerra, S. P. S.; Ballarin, A. W. Sustainable Use of Eucalypt Biomass Grown on Short Rotation Coppice for Bioenergy. *Biomass Bioenergy* **2016**, *90*, 15–21.
- (6) Nurdawati, A.; Mir, B. A.; Al-Ghamdi, S. G. Recent Advancements in Prospective Life Cycle Assessment: Current Practices, Trends, and Implications for Future Research. *Resour. Environ. Sustain.* **2025**, *20*, 100203.
- (7) Thonemann, N.; Schulte, A.; Maga, D. How to Conduct Prospective Life Cycle Assessment for Emerging Technologies? A Systematic Review and Methodological Guidance. *Sustainability* **2020**, *12* (3), 1192.
- (8) van der Giesen, C.; Cucurachi, S.; Guinée, J.; Kramer, G. J.; Tukker, A. A Critical View on the Current Application of LCA for New Technologies and Recommendations for Improved Practice. *J. Clean. Prod.* **2020**, *259*, 120904.
- (9) de Souza, N. R. D.; Matt, L.; Sedrik, R.; Vares, L.; Cherubini, F. Integrating Ex-Ante and Prospective Life-Cycle Assessment for Advancing the Environmental Impact Analysis of Emerging Bio-Based Technologies. *Sustainability Prod. Consumption* **2023**, *43*, 319–332.
- (10) Piccinno, F.; Hirsch, R.; Seeger, S.; Som, C. From Laboratory to Industrial Scale: A Scale-up Framework for Chemical Processes in Life Cycle Assessment Studies. *J. Clean. Prod.* **2016**, *135*, 1085–1097.
- (11) Tsoy, N.; Steubing, B.; van der Giesen, C.; Guinée, J. Upscaling Methods Used in Ex Ante Life Cycle Assessment of Emerging Technologies: A Review. *Int. J. Life Cycle Assess.* **2020**, *25* (9), 1680–1692.
- (12) van der Hulst, M. K.; Huijbregts, M. A. J.; van Loon, N.; Theelen, M.; Kootstra, L.; Bergesen, J. D.; Hauck, M. A Systematic Approach to Assess the Environmental Impact of Emerging Technologies: A Case Study for the GHG Footprint of CIGS Solar Photovoltaic Laminates. *J. Ind. Ecol.* **2020**, *24* (6), 1234–1249.
- (13) Bruhn, S.; Sacchi, R.; Cimpan, C.; Birkved, M. Ten Questions Concerning Prospective LCA for Decision Support for the Built Environment. *Build. Environ.* **2023**, *242*, 110535.
- (14) Gibon, T.; Wood, R.; Arvesen, A.; Bergesen, J. D.; Suh, S.; Hertwich, E. G. A Methodology for Integrated, Multiregional Life Cycle Assessment Scenarios under Large-Scale Technological Change. *Environ. Sci. Technol.* **2015**, *49* (18), 11218–11226.
- (15) Pehl, M.; Arvesen, A.; Humpenöder, F.; Popp, A.; Hertwich, E. G.; Luderer, G. Understanding Future Emissions from Low-Carbon Power Systems by Integration of Life-Cycle Assessment and Integrated Energy Modelling. *Nat. Energy* **2017**, *2* (12), 939–945.
- (16) Arvesen, A.; Luderer, G.; Pehl, M.; Bodirsky, B. L.; Hertwich, E. G. Deriving Life Cycle Assessment Coefficients for Application in Integrated Assessment Modelling. *Environ. Model. Software* **2018**, *99*, 111–125.
- (17) Mendoza Beltran, A.; Cox, B.; Mutel, C.; van Vuuren, D. P.; Font Vivanco, D.; Deetman, S.; Edelenbosch, O. Y.; Guinée, J.; Tukker, A. When the Background Matters: Using Scenarios from Integrated Assessment Models in Prospective Life Cycle Assessment. *J. Ind. Ecol.* **2018**, *24*, 64–79.
- (18) Luderer, G.; Pehl, M.; Arvesen, A.; Gibon, T.; Bodirsky, B. L.; de Boer, H. S.; Fricko, O.; Hejazi, M.; Humpenöder, F.; Iyer, G.; et al. Environmental Co-Benefits and Adverse Side-Effects of Alternative Power Sector Decarbonization Strategies. *Nat. Commun.* **2019**, *10* (1), 5229.
- (19) Cox, B.; Mutel, C. L.; Bauer, C.; Beltran, A. M.; Van Vuuren, D. P. Uncertain Environmental Footprint of Current and Future Battery Electric Vehicles. *Environ. Sci. Technol.* **2018**, *52* (8), 4989–4995.
- (20) Cox, B.; Bauer, C.; Beltran, A. M.; Van Vuuren, D. P.; Mutel, C. L. Life Cycle Environmental and Cost Comparison of Current and Future Passenger Cars under Different Energy Scenarios. *Appl. Energy* **2020**, *269*, 115021.
- (21) Sacchi, R.; Terlouw, T.; Siala, K.; Dirnacher, A.; Bauer, C.; Cox, B.; Mutel, C.; Daioglou, V.; Luderer, G. PROspective EnvironMental Impact AsSEment (Premise): A Streamlined Approach to Producing Databases for Prospective Life Cycle

Assessment Using Integrated Assessment Models. *Renewable Sustainable Energy Rev.* **2022**, *160*, 112311.

- (22) Joos, F.; Roth, R.; Fuglestad, J. S.; Peters, G. P.; Enting, I. G.; Von Bloh, W.; Brovkin, V.; Burke, E. J.; Eby, M.; Edwards, N. R.; et al. Carbon Dioxide and Climate Impulse Response Functions for the Computation of Greenhouse Gas Metrics: A Multi-Model Analysis. *Atmos. Chem. Phys.* **2013**, *13* (5), 2793–2825.
- (23) Lang-Quantendorff, L.; Beermann, M. Time-differentiating Methods for Life Cycle Assessment of the Industry Transition toward Climate Neutrality: A Review. *J. Ind. Ecol.* **2025**, *29* (5), 1523–1550.
- (24) Reisinger, A.; Meinshausen, M.; Manning, M. Future Changes in Global Warming Potentials under Representative Concentration Pathways. *Environ. Res. Lett.* **2011**, *6* (2), 024020.
- (25) Myhre, G.; Shindell, D.; Bréon, F.-M.; Collins, W.; Fuglestad, J.; Huang, J.; Koch, D.; Lamarque, J.-F.; Lee, D.; M, B.; Nakajima, T.; et al. 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* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y.; Cambridge University Press, Cambridge: United Kingdom, 2013].
- (26) Forster, P.; Storelvmo, T.; Armour, K.; Collins, W.; Dufresne, J. L.; Frame, D.; Lunt, D. J.; Mauritsen, T.; Palmer, M. D.; Watanabe, M., et al. IPCC AR6 WGI Chapter 7- The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity. In *Climate Change 2021: the Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Masson-Delmotte, V.; Zhai, A.P.; Pirani, S.L.; Connors, C.; Péan, S.; Berger, N.; Caud, Y.; Chen, L.; Goldfarb, M.I.; Gomis, M., Eds.; Cambridge University Press: Cambridge, 2021, p. 210. DOI: .
- (27) Aamaas, B.; Peters, G. P.; Fuglestad, J. S. A Synthesis of Climate-Based Emission Metrics with Applications. *Earth Syst. Dyn. Discuss.* **2012**, *3*(2).
- (28) Shine, K. P.; Fuglestad, 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* (3), 281–302.
- (29) Lan, K.; Yao, Y. Dynamic Life Cycle Assessment of Energy Technologies under Different Greenhouse Gas Concentration Pathways. *Environ. Sci. Technol.* **2022**, *56* (2), 1395–1404.
- (30) Solomon, S.; Qin, D.; Manning, M.; Chen, Z.; Marquis, M.; Averyt, K. B.; Tignor, M.; Miller, H. L. The Physical Science Basis. *Contribution of Working Group I to the Fourth Assessment Report of the IPCC*. Cambridge University Press, 2007, 996.
- (31) Myhre, G.; Highwood, E. J.; Shine, K. P.; Stordal, F. New Estimates of Radiative Forcing Due to Well Mixed Greenhouse Gases. *Geophys. Res. Lett.* **1998**, *25* (14), 2715–2718.
- (32) Riahi, K.; Van Vuuren, D. P.; Kriegler, E.; Edmonds, J.; O'Neill, B. C.; Fujimori, S.; Bauer, N.; Calvin, K.; Dellink, R.; Fricko, O.; et al. The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview. *Glob. Environ. Change* **2017**, *42*, 153–168.
- (33) Ritz, S. P.; Stocker, T. F.; Joos, F. A Coupled Dynamical Ocean–Energy Balance Atmosphere Model for Paleoclimate Studies. *J. Clim.* **2011**, *24* (2), 349–375.
- (34) Spahni, R.; Joos, F.; Stocker, B. D.; Steinacher, M.; Yu, Z. C. Transient Simulations of the Carbon and Nitrogen Dynamics in Northern Peatlands: From the Last Glacial Maximum to the 21st Century. *Clim. Past Discuss.* **2012**, *8* (6), 5633–5685.
- (35) Houghton, J. T.; Ding, Y.; Griggs, D. J.; Noguera, M.; van der Linden, P. J.; Dai, X.; Maskell, K.; Johnson, C. A. Climate Change 2001: The Scientific Basis. In *Contribution Of Working Group I To The Third Assessment Report Of The Intergovernmental Panel On Climate Change*; Cambridge University Press, 2001.
- (36) Persson, U. M.; Johansson, D. J. A. *Simple Climate Model*; zenodo, 2022.
- (37) Fuglestad, J. S.; Berntsen, T. K.; Godal, O.; Sausen, R.; Shine, K. P.; Skodvin, T. Metrics of Climate Change: Assessing Radiative Forcing and Emission Indices. *Clim. Change* **2003**, *58* (3), 267–331.
- (38) Tanaka, K.; Cavalett, O.; Collins, W. J.; Cherubini, F. Asserting the Climate Benefits of the Coal-to-Gas Shift across Temporal and Spatial Scales. *Nat. Clim. Change* **2019**, *9* (5), 389–396.
- (39) Myhre, G.; Shindell, D.; Bréon, F.-M.; Collins, W.; Fuglestad, J.; Huang, J.; Koch, D.; Lamarque, J.-F.; Lee, D.; Mendoza, B. *IPCC Fifth Assessment Report (AR5) Chapter 8: Anthropogenic and Natural Radiative Forcing*; IPCC, 2013.
- (40) Allen, M. R.; Fuglestad, J. S.; Shine, K. P.; Reisinger, A.; Pierrehumbert, R. T.; Forster, P. M. New Use of Global Warming Potentials to Compare Cumulative and Short-Lived Climate Pollutants. *Nat. Clim. Change* **2016**, *6* (8), 773–776.
- (41) Cherubini, F.; Fuglestad, J.; Gasser, T.; Reisinger, A.; Cavalett, O.; Huijbregts, M. A. J.; Johansson, D. J. A.; Jørgensen, S. V.; Rauei, M.; Schivley, G.; et al. Bridging the Gap between Impact Assessment Methods and Climate Science. *Environ. Sci. Policy* **2016**, *64*, 129–140.
- (42) Levasseur, A.; Cavalett, O.; Fuglestad, J. S.; Gasser, T.; Johansson, D. J. A.; Jørgensen, S. V.; Rauei, M.; Reisinger, A.; Schivley, G.; Strømman, A.; et al. Enhancing Life Cycle Impact Assessment from Climate Science: Review of Recent Findings and Recommendations for Application to LCA. *Ecol. Indic.* **2016**, *71*, 163–174.
- (43) Wernet, G.; Bauer, C.; Steubing, B.; Reinhard, J.; Moreno-Ruiz, E.; Weidema, B. The Ecoinvent Database Version 3 (Part I): Overview and Methodology. *Int. J. Life Cycle Assess.* **2016**, *21* (9), 1218–1230.
- (44) Archer, D.; Eby, M.; Brovkin, V.; Ridgwell, A.; Cao, L.; Mikolajewicz, U.; Caldeira, K.; Matsumoto, K.; Munhoven, G.; Montenegro, A.; et al. Atmospheric Lifetime of Fossil Fuel Carbon Dioxide. *Annu. Rev. Earth Planet. Sci.* **2009**, *37* (1), 117–134.
- (45) Solomon, S.; Plattner, G.-K.; Knutti, R.; Friedlingstein, P. Irreversible Climate Change Due to Carbon Dioxide Emissions. *Proc. Natl. Acad. Sci. U. S. A.* **2009**, *106* (6), 1704–1709.
- (46) Friedlingstein, P.; Andrew, R. M.; Rogelj, J.; Peters, G. P.; Canadell, J. G.; Knutti, R.; Luderer, G.; Raupach, M. R.; Schaeffer, M.; van Vuuren, D. P.; et al. Persistent Growth of CO₂ Emissions and Implications for Reaching Climate Targets. *Nat. Geosci.* **2014**, *7* (10), 709–715.
- (47) Stocker, T. F. The Closing Door of Climate Targets. *Science* **2013**, *339* (6117), 280–282.
- (48) Knutti, R.; Rugenstein, M. A. A. Feedbacks, Climate Sensitivity and the Limits of Linear Models. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2015**, *373*, 20150146.
- (49) Mackey, B.; Prentice, I. C.; Steffen, W.; House, J. I.; Lindenmayer, D.; Keith, H.; Berry, S. Untangling the Confusion around Land Carbon Science and Climate Change Mitigation Policy. *Nat. Clim. Change* **2013**, *3* (6), 552–557.
- (50) Gasser, T.; Peters, G. P.; Fuglestad, J. S.; Collins, W. J.; Shindell, D. T.; Ciais, P. Accounting for the Climate–Carbon Feedback in Emission Metrics. *Earth Syst. Dynam.* **2017**, *8* (2), 235–253.
- (51) Millar, R. J.; Nicholls, Z. R.; Friedlingstein, P.; Allen, M. R. A Modified Impulse-Response Representation of the Global Response to Carbon Dioxide Emissions. *Atmos. Chem. Phys. Discuss.* **2016**, *1*–20.
- (52) Pierrehumbert, R. T. Short-Lived Climate Pollution. *Annu. Rev. Earth Planet. Sci.* **2014**, *42*, 341–379.
- (53) Bowerman, N. H. A.; Frame, D. J.; Huntingford, C.; Lowe, J. A.; Smith, S. M.; Allen, M. R. The Role of Short-Lived Climate Pollutants in Meeting Temperature Goals. *Nat. Clim. Change* **2013**, *3* (12), 1021–1024.
- (54) Šimaitis, J.; Butnar, I.; Sacchi, R.; Lupton, R.; Vagg, C.; Allen, S. Expanding Scenario Diversity in Prospective LCA: Coupling the TIAM-UCL Integrated Assessment Model with Premise and Ecoinvent. *Renewable Sustainable Energy Rev.* **2025**, *211*, 115298.
- (55) Cardellini, G.; Mutel, C. L.; Vial, E.; Muys, B. Temporalis, a Generic Method and Tool for Dynamic Life Cycle Assessment. *Sci. Total Environ.* **2018**, *645*, 585–595.

(56) Pigné, Y.; Gutiérrez, T. N.; Gibon, T.; Schaubroeck, T.; Popovici, E.; Shimako, A. H.; Benetto, E.; Tiruta-Barna, L. A Tool to Operationalize Dynamic LCA, Including Time Differentiation on the Complete Background Database. *Int. J. Life Cycle Assess.* **2020**, 25 (2), 267–279.