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Spatially and taxonomically explicit characterisation factors for greenhouse gas emission impacts on biodiversity

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ABSTRACT

In life-cycle impact assessment, currently available characterisation factors (CF) for climate change impacts on biodiversity are highly simplified and do not consider spatial and taxonomic differentiation of species or local climate variability. We develop the first spatially and taxonomically specific CFs for the impacts of 20 GHGs on biodiversity considering 26,648 species across terrestrial and marine ecosystems. Generally, CFs are higher in the tropics, and marine species are affected more severely than terrestrial ones. When global GHG emissions from 2020 are assessed in a scenario with a global temperature rise of 3 °C by 2100, an average of 0.25%, 0.15% and 0.03% of species are negatively affected in 2100 from CO₂, CH₄, and N₂O emissions, respectively, across the globe. The new CFs can be used at different levels of spatial and taxonomic aggregation to quantify co-benefits for biodiversity of climate change mitigation in tools such as life-cycle assessment, input-output analyses, or integrated assessment models.

1. Introduction

Climate change is amongst the main threats for biodiversity loss (Bongaarts, 2019; Warren et al., 2013) and its effects are expected to accelerate as greenhouse gas (GHG) emissions continue to increase (Masson-Delmotte et al., 2021). About 5% of species are estimated to be at risk of climate-related extinction at 2 °C warming, which rises to 16% at 4 °C warming (Díaz; et al., 2019). To prevent this, global targets and agreements for protecting biodiversity, including those related to climate change, have been developed (Tittensor et al., 2014).

Strategies to achieve biodiversity targets depend on our capacity to measure impacts of human activities on biodiversity. Life cycle assessment (LCA) is a standardised method to quantitatively assess cradle-to-grave environmental impacts of products and processes (Hellweg and Milà i Canals, 2014) and it is commonly used to quantify potential environmental impacts and effects of mitigation strategies (Finnveden et al., 2009).

Currently, available life cycle impact assessment (LCIA) methods for the impacts of GHG emissions on biodiversity are heavily simplified, in terms of both simulated GHG-induced temperature impacts and species

responses (Huijbregts et al., 2017; Joos et al., 2013; Urban, 2015; Verones et al., 2020). Existing characterisation factors (CFs) rely on temperature change estimated using a global average temperature increase that is assumed to be equal for all GHGs, after their conversion to CO₂-equivalents with Global Warming Potentials (GWP100) (Verones et al., 2020). This approach ignores the specific time and spatial dimension of the climate system response to different GHGs, for which the temperature response can vary from a few years to centuries. The response of terrestrial biodiversity to temperature changes is also simplified, as it is estimated with a global average damage factor representing the potentially disappeared fraction (PDF) of species per degree temperature increase (0.037 PDF/°C). This average factor is based on the results of a meta-analysis (Urban, 2015) and does not distinguish vulnerability gradients across species and regions. Further, these CFs are based on data from a limited number of species (i.e., a selection of terrestrial vertebrates, butterflies, and plants) and geographical regions (i.e., Australia, Mexico, South Africa, Brazil and Europe). Marine ecosystems are also vulnerable to climate change (Bongaarts, 2019) but they are not covered by current LCIA models. Local-specific species responses to temperature increases, as well as regional changes in

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near-surface temperature, may differ substantially, making some regions and corresponding species assemblages more vulnerable to climate change than others, and some GHGs more impactful on biodiversity than others (Nunez et al., 2019; Trisos et al., 2020). Very recently, freshwater fishes have been considered in a spatially-explicit model for impacts from increasing river water temperatures (Li et al., 2022).

The inability to capture the regions or species groups that are likely to be impacted first and most severely, as well as the exclusion of certain environments and species groups, limits the capability to accurately quantify effects on biodiversity while assessing the implications of GHG emissions, and to take targeted and effective conservation measures. In LCA, biodiversity impacts from GHG emissions are frequently combined at an endpoint level with other impact categories (exemplified in (Dorber et al., 2020) with land and water use), which are then used to assess the total potential biodiversity impact of a product or process. An incomplete characterization of GHG impacts on biodiversity impedes a comprehensive assessment of global biodiversity footprints. For example, as most of the renewable energy options (solar PV, hydro-power, bioenergy) usually have larger land occupation than fossil fuels, which on the other hand are associated with larger emissions of GHGs, improper characterization of biodiversity impacts from GHGs can lead to unbalanced and suboptimal assessments. Furthermore, incomplete impact characterization may lead to problem-shifting from pressures, species groups, or regions that are comprehensively evaluated to those for which only part of the impacts is considered.

In this study, we present the first set of spatially and taxonomically explicit LCIA CFs for impacts on biodiversity from GHG emissions, covering both terrestrial and marine ecosystems. This new approach integrates effects of 20 different GHG emissions on temperature changes at a grid-level with the grid-specific response of 26,648 species (grouped into nine species groups) to temperature changes to estimate the potentially affected fraction of species per grid cell and kg of GHG emitted. A range of future climate scenarios are considered to explicitly model differences in 2050 and 2100 in terms of background climatic conditions (RCP2.6, 4.5, and 8.5). These CFs are ready for use in footprint studies and made publicly available at different levels of spatial (individual grid, biogeographical realm or global average) and taxonomic (individual or combined species groups) aggregation to facilitate their application in the most common tools used in environmental impact assessments, such as LCA, environmentally extended input output analyses (EEIOA) or integrated assessment models (IAMs).

2. Methods

2.1. Effects of GHG emissions on temperature change

The impact of GHG emissions on temperature change is computed using the Absolute Global Temperature change Potential (AGTP) for 20 GHGs (CO₂, CH₄, N₂O; chlorofluorocarbons: CFC-11, CFC-12, CFC-13, CFC-113, CFC-114, CFC-115; hydrofluorocarbons: HFC-125, HFC-134a, HFC-152a, HFC-23, HFC-32; fluorinated species: NF₃, PFC-116, PFC-14, SF₆, SF₅CF₃, SO₂F₂). AGTP is a commonly used metric to assess instantaneous changes in surface temperature of an emission and is measured in K per kg GHG emitted (Myhre et al., 2013; Shine et al., 2005). AGTPs until a time horizon (TH) of 100 years are computed according to the method used in the IPCC Assessment Report (Joos et al., 2013; Myhre et al., 2013) (more information in Supplementary Information (SI) Eq. S1–4). First, the fraction of the pulse of a GHG remaining in the atmosphere at a certain time after emission is calculated using the perturbation lifetimes of each gas (see the coefficients used in Table S1 and S2 in SI) (Boucher and Reddy, 2008; Joos et al., 2013). The associated radiative forcing (RF) profile is computed according to the specific radiative efficiencies of the gas, typically assumed to be time-invariant in the calculation of emission metrics (Amaas et al., 2012). Then, the effect of each specific emission on the global temperature is estimated by combining the RF profile with a temperature

response function until the intended TH (2050 or 2100, in our study).

Annual-average near-surface temperature data (2-m air temperature for terrestrial species and surface ocean temperature for marine species) are produced as the mean of five climate models (CESM1(CAM5), HadGEM2-ES, IPSL-CM5A-MR, MIROC5, and MPI-ESM-MR) (Collins et al., 2008; Dufresne et al., 2013; Jungclaus et al., 2013; Kay et al., 2015; Watanabe et al., 2010) at a 1.875° resolution (~200 km at the equator) for the years 2010–2100 (5-year intervals) for three future climate scenarios (i.e., RCP2.6, RCP4.5, and RCP8.5). These temperature changes are used to calculate the number of species affected per grid cell due to the temperature change in a specific year and climate scenario (Section 2.2). The proportion of the AGTP for each GHG emission is then used to estimate how much of the temperature change (and species affected) for each grid cell at the given year in the different RCPs can be attributed to each specific GHG emitted (Section 2.3).

2.2. Effects of near-surface temperature change on biodiversity

The effect of temperature change on biodiversity is defined as the fraction of a species group whose realised near-surface temperature niche limit has been exceeded in a climate scenario. Realised species temperature niche limits are obtained from a study (Trisos et al., 2020) that overlaid species ranges with historical (annual-average) near-surface temperature data to estimate niche limits, defined as the maximum temperature a species has experienced across its range over the period 1850–2005.

We overlay species spatial range maps with maps of near-surface temperature projections (per year, y) and identify parts of the species range in grid cell k where the species temperature niche limit has been exceeded for at least five consecutive years. This results in maps of species with surpassed temperature niche limits per grid cell and year. These maps of species with surpassed niche limits are grouped into species groups g and are subsequently aggregated to quantify the number of species whose niche limit has been surpassed in grid cell k and year y ($S_{k,y,g,niche\ surpassed}$), where the number of species increases over time as temperatures increase as a result of cumulative CO₂ emissions to the atmosphere. We used six climate scenarios for future temperature projections in 2050 and 2100 (RCP2.6, RCP4.5, and RCP8.5). The analysis includes 26,648 species, considering various terrestrial and marine species groups, such as birds ($n = 7177$), terrestrial mammals ($n = 5160$), terrestrial reptiles ($n = 4599$), amphibians ($n = 5998$), marine mammals ($n = 117$), marine reptiles ($n = 61$), marine fish ($n = 1822$), benthic marine invertebrates ($n = 916$), and corals and seagrasses ($n = 798$). We calculate at the grid cell level the potentially affected fractions of species (PAF) per year for each group separately, before aggregating them to the marine or terrestrial (including freshwater) groups. The PAF per grid cell is defined as the number of the species (S) whose niche limit has been exceeded relative to the total number of species in the grid cell (based on species spatial range maps without considering surpassed temperature niches):

$$PAF_{k,y,g} = \frac{S_{k,y,g,niche\ surpassed}}{S_{k,g}} \quad (1)$$

The PAF per species group (g) is aggregated to terrestrial and marine PAFs by considering all species groups within the realm r (i.e., r : terrestrial or marine):

$$PAF_{k,y,r} = \frac{\sum_g S_{k,y,g,niche\ surpassed}}{\sum_g S_{k,g,r}} \quad (2)$$

The global average PAF is calculated as the species-richness-weighted mean of all grid cells:

$$PAF_{y,g} = \frac{\sum_k PAF_{k,y,g} \cdot S_{k,g}}{\sum_k S_{k,g}} \quad (3)$$

The PAF/ ΔT is then calculated by dividing the global average PAF by

the global mean temperature change. The PAF per unit global temperature change ($PAF/\Delta T$) is calculated by dividing the PAF by the increase in temperature between the global average near-surface temperature in 2010 and the global average near-surface temperature in the respective climate scenario (global average temperatures are calculated based on the area-weighted mean of the grid cells across the globe).

Species ranges are obtained from the International Union for Conservation of Nature (Oliver, 2019) and BirdLife International (Allinson, 2018). Extinct species were omitted from the analysis, as well as parts of the species ranges where presence is uncertain, species have been introduced, or that are used as passages or during non-breeding seasons only. Species temperature niche limits are defined as the multi-model mean of niche limits estimated by (Trisos et al., 2020). Species for which no niche limits have been estimated were omitted from the analysis. Species are considered affected in locations where their realised temperature niche limit (i.e., highest historical temperature in their range) is exceeded for five consecutive years. In LCIA methodology, impacts on biodiversity are assessed based on species richness losses (Huijbregts et al., 2017) and the same modelling approach is followed here. LCA is a tool that traditionally assesses the negative environmental impacts of anthropogenic activities. Hence, positive impacts (such as larger ranges for certain species) are not assessed and are also disregarded here.

2.3. CFs for GHG impacts on biodiversity

We calculated the CFs across the nine marine and terrestrial species groups for 2050 and 2100 in PAF/kg GHG by multiplying the temperature response to GHG emissions, namely the AGTP (measured in K/kg GHG) from Section 2.1 with the PAF per unit global temperature change ($PAF/\Delta T$) from Section 2.2 (Eq. (4)). This results in CFs indicating the PAF per kg GHG emitted (PAF/kg GHG). This can be interpreted as the fraction of species that will be affected by warmed climate conditions due to the emission of a kg of a GHG. We use the AGTP40 and AGTP90 to compute the impacts on biodiversity in the years 2050 and 2100.

$$CF_{k,y,g,x} = PAF_{k,y,g} / kg\ GHG_x = (PAF_{k,y,g} / \Delta T_y) \cdot (\Delta T_y / kg\ GHG_x) \quad (4)$$

We calculated CFs for impacts for each marine and terrestrial species group separately and for all species groups combined (based on sums of cell-level number of affected species and cell-level species richness across the species groups), similar to calculating realm aggregated PAFs (Eq. (2)) (Olson et al., 2001) (see Figure S1 in SI). We also developed biogeographical realm and global aggregated CFs, based on the spatially aggregated PAFs (Eq. (3)). Regional averages are calculated as the richness-weighted CFs of the grid cells within the region.

3. Results and discussion

3.1. Spatially explicit characterization factors

The spatially explicit PAF in 2050 and 2100 per Gt CO₂ emitted under RCP4.5 for all nine species groups combined are shown in Fig. 1 (a and b). There is a spatial heterogeneity in the number of potentially affected species. The highest impacts are generally located in the tropical band and are larger in 2100 than 2050, as the number of species affected by global warming cumulates over time. The difference between 2050 and 2100 concerns both an increase in intensity and spatial expansion of the potentially affected regions, especially in the North and across the oceans in the tropical band (Fig. 1c). In 2050, mid- and high-latitude areas of the boreal hemisphere have a lower number of affected terrestrial species than the rest of the globe. For a global average temperature increase of 3 °C (which is the mean projected global temperature change in 2100 in RCP4.5), about one out of every 357 species in the most impacted areas can be potentially affected by the emission of 1 Gt CO₂.

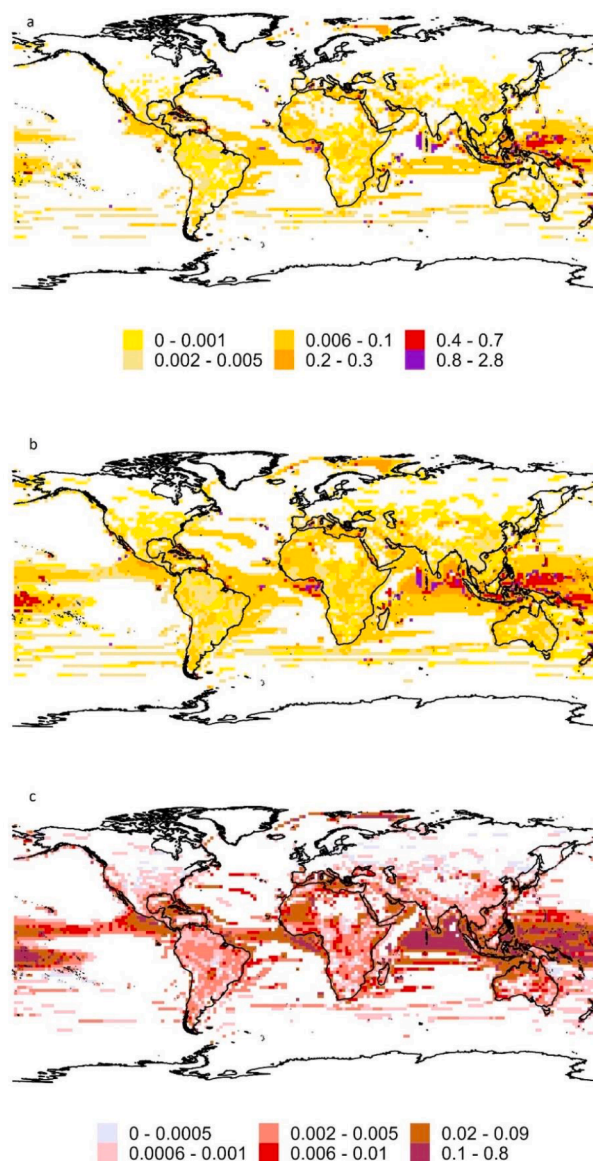


Fig. 1. Global potentially affected fraction of species (PAF) in 2050 (a), 2100 (b), and the difference between 2050 and 2100 (c) per Mt CO₂ emitted under RCP4.5, averaged over all species groups. In (c), positive values indicate that PAF is larger in 2100 than 2050.

Figures S2-S4 in the SI show the spatially explicit number of affected species in 2100 for the major GHGs (CO₂, CH₄ and N₂O) emitted under RCP4.5 scenario for all nine individual species groups (and all species groups combined). Corals and seagrasses are the group with the largest number of species affected for all three GHGs, while marine reptiles show the lowest number of species affected on a global scale. In general, terrestrial and marine mammals are most vulnerable in the tropics. Birds, amphibians and terrestrial reptiles are also primarily sensitive around the equator, while the vulnerability of benthic invertebrates, corals and seagrasses, marine reptiles and fishes is the highest in South-East Asia and North Oceania. Owing to the larger warming efficiency, impacts per unit of emissions are higher for N₂O and CH₄ than CO₂.

3.2. Aggregated characterization factors

CFs of combined species groups (e.g., terrestrial species) are calculated based on the sum of the cell-level number of affected species and cell-level species richness of combined species groups (see Table S3 in

SI). In 2050, global average affected fractions of species differ by a factor of two between different climate scenarios. This increases to about a factor of four in 2100, indicating that over time the differences between climate scenarios become more pronounced (i.e., climate impacts on species increase less steeply in RCP2.6 than RCP8.5). For example, under mitigation (RCP4.5 versus RCP8.5), we find the largest potential reductions of the PAF per kg GHG emitted in 2100 to be of a factor of 1.58 for N₂O, while with more stringent mitigation (RCP2.6 versus RCP8.5), the largest potential reductions are for CO₂ with a factor of 3.31 (Table S3 in SI). Being successful in mitigating climate change thus leads to significantly smaller biodiversity impacts.

For each GHG, marine species show a larger relative increase in PAF from 2050 to 2100 than terrestrial species. While terrestrial species are more affected in the years up to 2050, marine species will be more affected after that. As most of the GHGs increase more than 100% between 2050 and 2100, and the oceans need more time than land areas to increase its temperature due to the thermal inertia, this indicates the larger sensitivity of the marine species to long term warming. From Table S3 in SI, a difference in the temporal evolution of PAF between short-lived (i.e., CH₄ and HFC32) and long-lived gases (all the others) emerges. Short-lived climate pollutants have a much lower percent increase in PAF values between 2050 and 2100 than long-lived gases. For example, for terrestrial species the increase is between 7% (HFC32,

lifetime: 5.2 years) and 14% (CH₄, lifetime: 12.4 years) for short-lived GHGs, and between 74% (CFC12, lifetime: 100 years) and 101% (SF₆, lifetime: 3200 years) for long-lived GHGs. The same is valid for marine species, although increases are slightly higher. As the number of potentially affected species increases over time, this indicates that the powerful but (relatively) time-limited effect of short-lived GHGs mostly influences the rate of climate change and it has a large effect on species groups by 2050. As the climate forcing from short-lived GHGs remarkably declines over time, lower additional effects are registered by 2100.

3.3. Trends across species groups and geographic realms

In general, there are species groups that are relatively resilient to climate change (i.e., marine mammals, birds, terrestrial mammals, and marine reptiles) and groups that are relatively vulnerable (i.e., marine fish, amphibians, benthic-invertebrates, corals and seagrasses, and reptiles) (Fig. 2a, b, c). Amongst the terrestrial species groups, amphibians and reptiles are the most vulnerable to emissions of GHGs. Amongst the marine groups, higher CFs are typically associated with corals and seagrasses and marine fish. This is consistent with previous research showing that these species groups are the most affected by global temperature changes (Carvalho et al., 2010; Gibbons et al., 2000; Urban, 2015; Wake, 2007). This may be due to their lower long-term

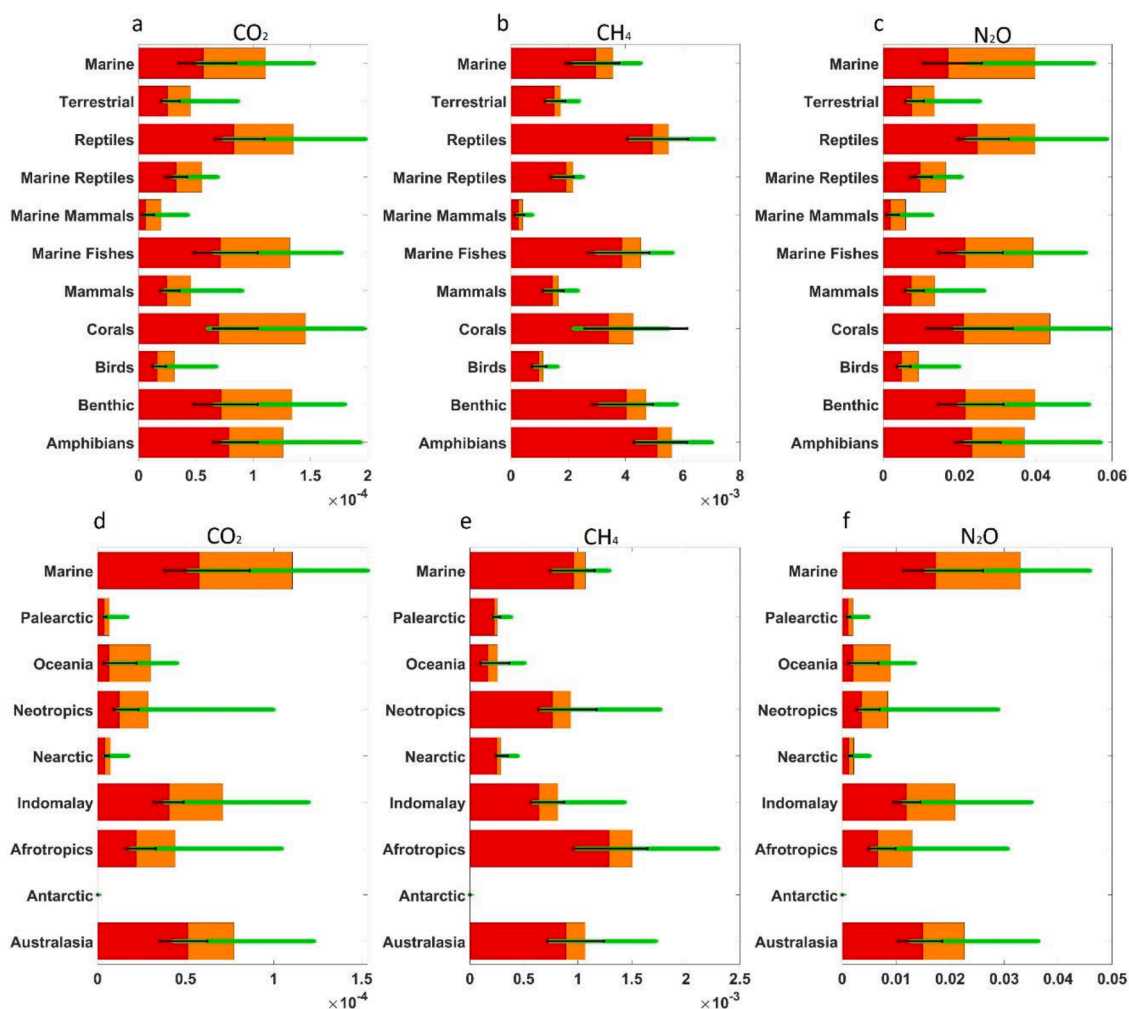


Fig. 2. Average potentially affected fraction (PAF) of species per group (a, b, c) and geographic realm (d, e, f) in 2050 (red bars) and 2100 (red plus orange bars) per Gt GHG for the three main gases (CO₂, CH₄ and N₂O) emitted under RCP4.5. The PAF per Gt GHG for RCP 2.6 (lower end) and RCP 8.5 (higher end) are presented as error bars in black for 2050 and in green for 2100. For the PAF per Gt GHG for CO₂, CH₄ and N₂O per species groups see Table S3–5 in SI (here we shorten the names of the species groups Corals and seagrasses to Corals, Benthic invertebrates to Benthic, and Terrestrial/Freshwater to Terrestrial). For the PAF per Gt GHG for CO₂, CH₄ and N₂O for geographic realms see Table S6 in SI.

dispersal rates relative to the speed of temperature increases (Warren et al., 2013). The relative difference amongst the species groups does not change substantially between 2050 and 2100, but the increase in the average affected fraction of species over time is more pronounced for some groups (e.g., corals and seagrasses) than others (e.g., amphibians) (Table S4 and S5 in SI).

For CO₂, the average PAF impact per unit of emission nearly doubles between 2050 and 2100 for almost all the species. In the case of CH₄, which contrarily to CO₂ is a short-lived GHG, the number of potentially affected species shows relatively smaller differences between 2050 and 2100, as most of the CH₄-induced warming occurs in the couple of decades following the emission. In the case of N₂O, which is a long-lived GHG (lifetime: 128 years), the temporal distribution of potentially affected species is more similar to that of CO₂, with an impact that increases over time.

On average, species in Antarctic, Palearctic, and Nearctic biogeographical realms are the least affected, followed by those in the Neotropics, Oceania, and Afrotropics (Fig. 2d, e, f). Species in the Indomalay and Australasia are the most affected amongst the terrestrial realms by the temperature increases due to CO₂ and N₂O emissions while in the case of CH₄, the Afrotropics is the most impacted realm, as it includes the species that are more vulnerable to short-term changes in temperature (Table S6 in SI). Even if the temperature increase is higher in the Arctic area than the global average due to the polar amplification effect, the species living in the Arctic regions generally have larger ranges when compared to the species at lower latitudes, resulting in larger temperature tolerances. The temperature niches are derived from overlaying the species ranges with historical temperature maps, and Arctic species can cover a larger temperature range compared to small-ranged species. Larger temperature tolerances make species more resilient to climate change, resulting in lower general impacts in the Arctic region (although individual species can be more vulnerable, but when normalized to the number of species per grid cells they become a small fraction).

Species in the marine environment are on average more vulnerable than their terrestrial counterparts when it comes to impacts from long-lived GHGs like CO₂ and N₂O, which tend to cumulate over time.

The latitudinal distribution of potentially affected fractions of species normalized to the unit of temperature changes in the different RCPs is shown in Figure S5 in SI, which summarizes the ratio of species affected by temperature change per grid cell at each latitudinal step. Impacts in the RCP2.6 climate scenario are lower compared to the other scenarios, with only a few species groups slightly affected in the tropics. The situation differs for the other two RCP scenarios. As previously mentioned, the species most severely affected are those in tropical regions, but communities are also affected at higher latitudes (both northern and southern hemisphere). We also find that the number of affected species per degree temperature change and latitudinal step is generally the highest for RCP8.5, but there are evident exceptions. For example, some species groups (e.g., benthic invertebrates and marine fish) reach their maximum normalized impact per temperature change with RCP4.5. This means that for these groups further temperature increases do not remarkably affect new species, so that the denominator (temperature change) increases more than the nominator (number of species affected), thereby making the normalized score smaller for RCP8.5 than RCP4.5. This aspect is mainly observed in the tropics rather than at high latitudes. One of the reasons behind this could be that a large share of the species in these groups have a narrow temperature niche in the tropics, which is exceeded already with the temperature increase projected for RCP4.5. These results are generally in line with previously reported trends, which show the high sensitivity of tropical areas to climate warming (Román-Palacios and Wiens, 2020; Urban, 2015). Similarly, marine species in the tropics have been previously indicated to be the most vulnerable to temperature increases (Comte and Olden, 2017), due to their lower physiological thermal tolerances (Deutsch et al., 2008; Tewksbury et al., 2008).

3.4. Biodiversity impacts of GHG emissions in 2020

The CFs produced in this study are applied to global emissions in 2020 of the three most important GHGs, i.e., CO₂ (34 Gt), N₂O (12 Mt) and CH₄ (570 Mt), to appreciate their relative contributions. When looking at the gridded impacts in 2100 from the combined effect of the three gases (Fig. 3a), on average 0.4% of the species will be negatively affected across the globe, with a maximum of 13% in the most sensitive locations in the tropics (concentrated around the central Indo-Pacific). When considering different evolutions of the background climate system (Figure S6 in SI), areas affected, and intensity of the impacts increase under RCP8.5 and decrease in RCP2.6. The resulting impacts and the benefits of stringent mitigation actions are not geographically uniform, indicating the inherent limitations of using global average values. With no mitigation (RCP8.5), high PAF scores are found across Central Africa, Central and South America and the Indonesian hotspot, and marine areas in the tropics are severely affected.

The breakdown of total potentially affected species from global emissions in 2020 of CO₂, CH₄ and N₂O under all RCPs is shown in Fig. 3b (computed using the values in Table S3 in SI). The mean global PAF over the grid cells are 0.14%, 0.13%, and 0.01% for CO₂, CH₄ and N₂O under RCP4.5 in 2050. In 2100, the global average PAFs are 0.25%, 0.15% and 0.03%, respectively. The spread in the results due to different RCP scenarios increases over time. Under RCP2.6 and RCP4.5, CH₄ has the same contribution to the potentially affected terrestrial species in 2050, and slightly smaller for marine species. In 2100, the relative importance attributed to CH₄ emissions declines to about 40% for terrestrial species and to 34% for marine species (under RCP4.5). As observed with the individual CFs, the longer TH increases the relative importance of long-lived gases more than that of short-lived gases (contributions from CO₂ and N₂O nearly double from 2050 to 2100, while those from CH₄ remain relatively stable).

Such dynamics and relatively high proportion of CH₄ impacts differ from what is typically observed when aggregating climate effects of annual emissions for these three gases with common indicators such as GWP100 or GTP100, which usually highlight a large predominant role of CO₂ when assessing climate impacts of today's emissions. The results observed for biodiversity rather resemble those obtained by applying climate metrics with shorter time-horizons, e.g., GWP20 or GTP20, which attribute more weight to short-lived gases (Allen et al., 2016; Jolliet et al., 2018). Species affected can be regarded as a cumulative indicator that keeps memory of the time evolution of the impact, which accumulates over time and do not decrease while the atmospheric concentration following an emission of a gas declines and its temperature impact gradually fades. There is a high sensitivity of the species to the rate of climate change, which in turn is highly sensitive to emissions of powerful (although short-lived) gases like CH₄, which lead to irreversible impacts on biodiversity. If from a climate change perspective abating emissions of CO₂ is a clear priority for long-term temperature stabilization, from a biodiversity point of view reducing CH₄ emissions is also key to prevent near-term extinction risks.

4. Limitations

With increased magnitude and speed of global warming, better tools are needed to quantify the impacts of climate change on biodiversity at the taxonomic and regional level. In this study, we develop the first set of spatially and taxonomically differentiated CFs to assess the impact of GHG emissions on biodiversity. The produced outcomes are in the form of tabularized values for biogeographic realm or global-average CFs or spatially gridded data. The CFs are made publicly available in a format that is suitable for integration in existing impact assessment frameworks and can be used to better represent effects of GHG emissions on biodiversity in LCA, EEIO or IAMs. The large diversity of CFs availability is suitable to match different research questions and allows to explore how results can differ across different levels of aggregation. LCA practitioners

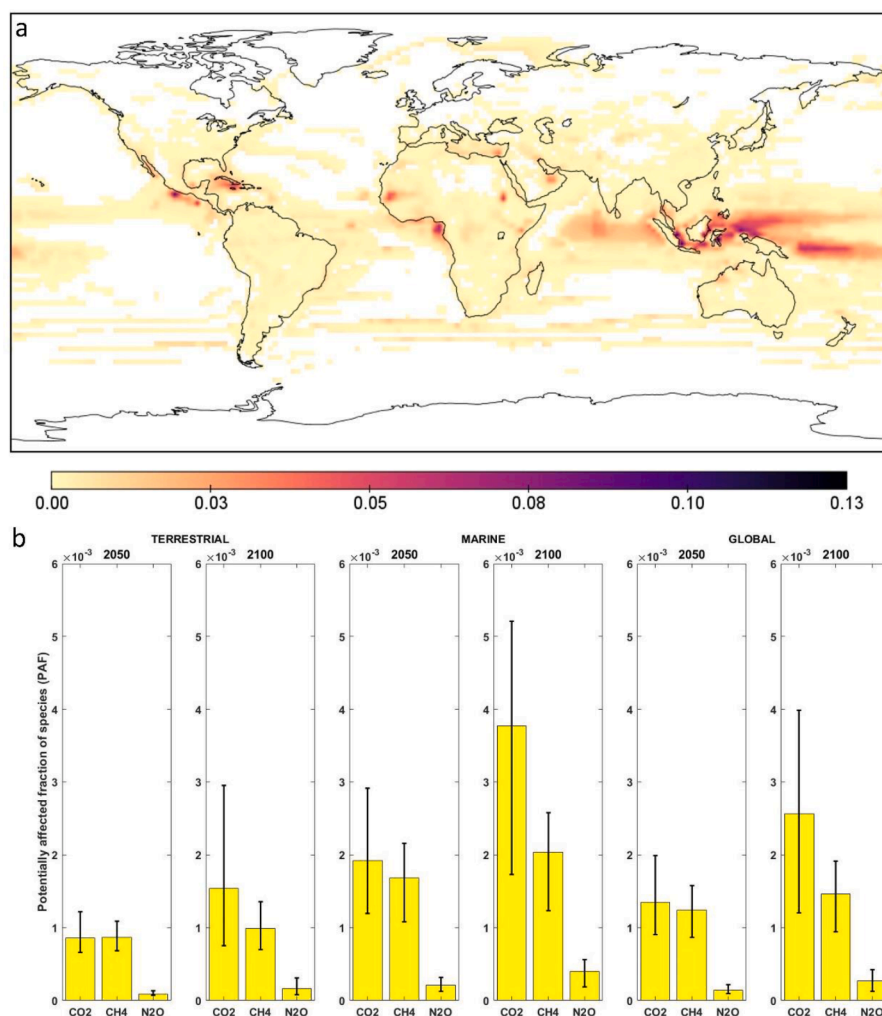


Fig. 3. Characterized potentially affected fraction of species (PAF) due to global CO₂, CH₄ and N₂O emissions in 2020. a) spatially explicit characterized PAF for all species groups combined under RCP4.5 in year 2100. b) characterized PAF using the global aggregated PAFs for each realm: terrestrial (amphibians, birds, mammals, reptiles), marine (benthic invertebrate, corals and seagrasses, marine mammals, marine fish, marine reptiles) and global averages (all species groups combined) under RCP4.5 (main bar plots in yellow) with the error-bars showing results under RCP2.6 (lower end) and RCP8.5 (higher end).

now have the opportunity to evaluate the biodiversity impacts in terms of impact on both terrestrial/freshwater species and marine species separately and across different locations, spatial scales, and time horizons, rather than using a single aggregated global value. Depending on the objectives of the individual study, each analyst has the flexibility to use different levels of spatial resolution and species group. Given the sensitivity of the CFs to different climate scenarios, the extent to which the results depend on the type of RCPs considered for the CFs should be explored and, if significant, results for different RCPs should be reported in a sensitivity analysis.

A direct comparison of our CFs with those previously available in the literature is hindered by a variety of factors. Table 1 shows a summary of the comparison, highlighting the main differences in terms of methodological approach and data coverage. From a numerical point of view, our values are generally lower by one order of magnitude, but the comparison can only be done for impacts aggregated as global averages for terrestrial species, as the previous method lacks both a characterization of marine species and a higher resolution on species responses and climate impacts (Table S7 in SI). There are large methodological differences between the approaches, and our analysis specifically aimed to overcome the limitations and simplifications in the previous LCIA method using more sophisticated methods and higher spatial and temporal resolution. For example, we calculated grid-specific temperature impacts using AGTP for each GHG and under different RCPs instead of converting all GHGs to CO₂-equivalents with GWP100 and then consider a global average temperature increase from CO₂; or we estimated species affected using PAF/°C for each of the 26,648 species at the grid level,

instead of using a global average factor for terrestrial ecosystems only. The spatial patterns of species responses that emerged from this analysis show the large variations in both regions and species groups, which cannot be properly represented by an average global factor.

Our analysis is not exempt from limitations and uncertainties, mostly associated with the integration of varying datasets and models into a common framework. Assessing the uncertainty level of the CFs is only possible to a limited extent, mostly because it depends on the original data for the species niche limits (Trisos et al., 2020), for which uncertainty ranges are not available, and to the computation of the climate metric. For the latter, we consider a multi-model mean to represent future temperature projections and alternative background climate scenarios as described by the RCPs. In addition, there are other qualitative uncertainties that can be considered. The uncertainty in the AGTP is determined by the uncertainties in the perturbation lifetimes and radiative efficiency of the GHGs, as well as from the ocean heat uptake and climate sensitivity (Stocker, 2014). Impulse response functions and radiative efficiencies are based on a constant background climate, in line with the approach used in the IPCC reports to secure a transparent comparison (Forster et al., 2021; Myhre et al., 2013). The climate sensitivity used is 3.9 °C for a doubling of CO₂ concentration. The latest IPCC assessment report has a best estimate of 3 °C, with a likely range of 2.5 °C to 4 °C (Masson-Delmotte et al., 2021). Uncertainty is also found in the time evolution of the temperature response function, which has been shown to be model-dependant. We have used a function from the HadCM3 climate model (Boucher and Reddy, 2008; Masson-Delmotte et al., 2021) that is amongst the most applied in the emission metric

Table 1

Comparison of the main characteristics of the previous method (LC-Impact), referred as “Current”, and our new approach, referred to as “New”. An example of how characterized results of biodiversity impacts differ between the two methods is shown in Table S7 in SI.

Main characteristic	Current	New
Coverage of species	Marine	None
	Terrestrial/ Freshwater	168 species
Species response to temperature	A single global average value is used	3714 species 22934 species
Species specific	None (only one generic group for terrestrial species)	Based on species-specific ranges and individual temperature niche limits 9 species groups (5 marine and 4 terrestrial)
Sensitivity to future climate	No	Yes 3 RCPs: 2.6, 4.5, 8.5
GHG specific	No (all GHGs are first converted to CO ₂ eq.)	Yes, method applicable for each GHG
Temperature response	Simple factor scaling CO ₂ emissions with temperature change	Response function with multiple timescales and climate sensitivity
Spatial resolution	Single global average CF, no spatial resolution	Gridded CFs, and aggregated by species groups and realms
Uncertainty	None	Alternative background climatic conditions (RCPs)
Time horizon	100 years	Here for 2050 and 2100 (but others are possible)

literature (Aamaas et al., 2016, 2012), and it falls within the range of various response functions tested in a multi-model intercomparison study (Oliví and Peters, 2012). Future climate change projections are also sensitive to individual model settings, but we used multi-model means of future temperature changes at a grid level to mitigate risks of dependence on specific model biases.

The PAF is estimated as the fraction of species for which the temperature in a grid cell has exceeded for at least five consecutive years the maximum temperature that a species has experienced throughout its range. However, it is unclear whether all species will be affected by temperatures warmer than what they have experienced historically, so these results should be interpreted in terms of uncertainty about their persistence and potential risks to biodiversity. Data on the distribution of species is also associated with uncertainty and constant historical ranges were assumed for deriving the niche limits (Trisos et al., 2020), and possibilities of species adaptation at increasing warming levels are not taken into account. We use in this study species niche limits based on sea surface temperature which is a proxy for temperature effects on all marine species.

Overall, this is a first attempt to quantify improved and more representative CFs for biodiversity impacts from emissions of GHGs, advancing the multiple limitations and low-resolution of the existing method. Future research can better explore how CFs are sensitive to the possible multiple sources of uncertainties and progressively refine the estimates when new datasets and approaches become available.

5. Conclusions

This study makes a step forward in modelling the impact of climate change on biodiversity. For the first time, it estimates characterization factors of biodiversity impacts from different GHGs in a spatially explicit way and for marine species, which were never covered before. Developing advanced models to better include biodiversity impacts in tools used to support the decision-making process is an urgent priority to facilitate addressing the climate and biodiversity crises simultaneously, and to make sure that actions are taken where most needed. By explicitly

linking GHG emissions to biodiversity impacts, we produced new indicators to estimate the temporal dynamics of climate-driven damages to biodiversity that contribute to better knowledge on region- and species-specific impacts of adaptation and mitigation measures. Reducing emissions and the rate of exposure to dangerous climate conditions contributes to reducing the risks of losses in ecological diversity. However, temperature changes are not the only threat to biodiversity, which is also highly sensitive to habitat loss, pollution, invasive species and overexploitation (Harfoot et al., 2021). Advances in the characterization of these threats, and their consistent integration into impact assessment models, is key for the realization of a set of indicators for species response to multiple stressors simultaneously, thereby improving our capacity to develop strategies for a sustainable development that is not at the costs of species diversity.

CRediT authorship contribution statement

Cristina-Maria Jordan: Data curation, Conceptualization, Methodology, Software, Investigation, Visualization, Writing – review & editing. **Koen J.J. Kuipers:** Data curation, Conceptualization, Methodology, Software, Investigation, Visualization, Writing – review & editing. **Bo Huang:** Data curation. **Xiangping Hu:** Visualization. **Francesca Verones:** Conceptualization, Methodology, Validation, Writing – review & editing. **Francesco Cherubini:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known financial interests/personal relationships which may be considered as potential competing interests.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.resconrec.2023.107159](https://doi.org/10.1016/j.resconrec.2023.107159). In addition, gridded PAFs are made available on Zenodo at [10.5281/zenodo.8238659](https://doi.org/10.5281/zenodo.8238659).

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