Global Carbon Budget 2023


1 Faculty of Environment, Science and Economy, University of Exeter, Exeter EX4 4QF, UK
2 Laboratoire de Météorologie Dynamique / Institut Pierre-Simon Laplace, CNRS, Ecole Normale Supérieure / Université PSL, Sorbonne Université, Ecole Polytechnique, Paris, France
3 Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich Research Park, Norwich NR4 7TJ, UK
4 CICERO Center for International Climate Research, Oslo 0349, Norway
5 School of Environmental Sciences, University of East Anglia, Norwich NR4 7TJ, UK
6 Alfred-Wegener-Institut, Helmholtz-Zentrum für Polar- und Meeresforschung, Am Handelshafen 12, 27570 Bremerhaven
7 VLIZ Flanders Marine Institute, Jacobsenstraat 1, 8400, Ostend, Belgium
38 Environmental Physics Group, ETH Zürich, Institute of Biogeochemistry and Pollutant Dynamics and Center for Climate Systems Modeling (C2SM)

39 NCAS-Climate, Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich Research Park, Norwich, NR4 7TJ, UK

40 Research Institute for Environment, Energy, and Economics, Appalachian State University, Boone, North Carolina, USA

41 Potsdam Institute for Climate Impact Research (PIK), member of the Leibniz Association, P.O. Box 60 12 03, 14412 Potsdam, Germany

42 Woodwell Climate Research Center, Falmouth, MA 02540, USA

43 Department of Geographical Sciences, University of Maryland, College Park, Maryland 20742, USA

44 Cooperative Institute for Research in Environmental Sciences (CIREs), University of Colorado, Boulder, CO 80305, USA

45 National Oceanic and Atmospheric Administration, Global Monitoring Laboratory (NOAA/GML), 325 Broadway R/GML, Boulder, CO 80305, USA

46 Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61821, USA

47 School of Environmental Sciences, University of East Anglia, Norwich Research Park, Norwich NR4 7TJ, UK

48 Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, International Institute for Earth System Science, Nanjing University, Nanjing, 210023, China

49 State Key Laboratory of Tibetan Plateau Earth System and Resource Environment, Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing 100101, China

50 Institute of Carbon Neutrality, Peking University, Beijing 100871, China

51 Climate and Environmental Physics, Physics Institute, University of Bern, Bern, Switzerland

52 Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland

53 Institute of Applied Energy (IAE), Minato-ku, Tokyo 105-0003, Japan

54 University of California, San Diego, Scripps Institution of Oceanography, La Jolla, CA 92093-0244, USA

55 National Center for Atmospheric Research, Climate and Global Dynamics, Terrestrial Sciences Section, Boulder, CO 80305, USA

56 Utrecht University, Faculty of Geosciences, Department IMEW, Copernicus Institute of Sustainable Development, Heidelberglaan 2, P.O. Box 80115, 3508 TC, Utrecht, the Netherlands

57 Hawkesbury Institute for the Environment, Western Sydney University, Penrith, New South Wales, Australia

58 GEOMAR Helmholtz Centre for Ocean Research, Wischhofstr. 1-3, 24148 Kiel, Germany

59 LOCEAN/IPSL laboratory, Sorbonne Université, CNRS/IRD/MNHN, Paris, France

60 NASA JPL

61 Caltech

62 CMA Key Open Laboratory of Transforming Climate Resources to Economy, Chongqing Institute of Meteorological Sciences, Chongqing 401147, China
Abstract

Accurate assessment of anthropogenic carbon dioxide (CO$_2$) emissions and their redistribution among the atmosphere, ocean, and terrestrial biosphere in a changing climate is critical to better understand the global carbon cycle, support the development of climate policies, and project future climate change. Here we describe and synthesise data sets and methodology to quantify the five major components of the global carbon budget and their uncertainties. Fossil CO$_2$ emissions (E$_{FOS}$) are based on energy statistics and cement production data, while emissions from land-use change (E$_{LUC}$), mainly deforestation, are based on land-use and land-use change data and bookkeeping models. Atmospheric CO$_2$ concentration is measured directly, and its growth rate (G$_{ATM}$) is computed from the annual changes in concentration. The ocean CO$_2$ sink (S$_{OCEAN}$) is estimated with global ocean biogeochemistry models and observation-based fCO$_2$-products. The terrestrial CO$_2$ sink (S$_{LAND}$) is estimated with dynamic global vegetation models. Additional lines of evidence on land and ocean sinks are provided by atmospheric inversions, atmospheric oxygen measurements and Earth System Models. The resulting carbon budget imbalance (B$_{IM}$), the difference between the estimated total emissions and the estimated changes in the atmosphere, ocean, and terrestrial biosphere, is a measure of imperfect data and incomplete understanding of the contemporary carbon cycle. All uncertainties are reported as ±1σ.

For the year 2022, E$_{FOS}$ increased by 0.9% relative to 2021, with fossil emissions at 9.9 ± 0.5 GtC yr$^{-1}$ (10.2 ± 1.8 GtC yr$^{-1}$ when the cement carbonation sink is not included), E$_{LUC}$ was 1.2 ± 0.7 GtC yr$^{-1}$, for a total anthropogenic CO$_2$ emission (including the cement carbonation sink) of 11.1 ± 0.8 GtC yr$^{-1}$ (40.7 ± 3.2 GtCO$_2$ yr$^{-1}$). Also, for 2022, G$_{ATM}$ was 4.6 ± 0.2 GtC yr$^{-1}$ (2.18 ± 0.1 ppm yr$^{-1}$), S$_{OCEAN}$ was 2.8 ± 0.4 GtC yr$^{-1}$ and S$_{LAND}$ was 3.8 ± 0.8 GtC yr$^{-1}$, with a B$_{IM}$ of -0.1 GtC yr$^{-1}$ (i.e. total estimated sources marginally too low or sinks marginally too high). The global atmospheric CO$_2$ concentration averaged over 2022 reached 417.1 ± 0.1 ppm. Preliminary data for 2023, suggest an increase in E$_{FOS}$ relative to 2022 of +1.1% (0.1% to 2.2%) globally, and atmospheric CO$_2$ concentration reaching 419.3 ppm, 51% above pre-industrial level (around 278 ppm in 1750). Overall, the mean and trend in the components of the global carbon budget are consistently estimated
over the period 1959-2022, with a near-zero overall budget imbalance, although discrepancies of up to around 1 GtC yr\(^{-1}\) persist for the representation of annual to semi-decadal variability in CO\(_2\) fluxes. Comparison of estimates from multiple approaches and observations shows: (1) a persistent large uncertainty in the estimate of land-use changes emissions, (2) a low agreement between the different methods on the magnitude of the land CO\(_2\) flux in the northern extra-tropics, and (3) a discrepancy between the different methods on the strength of the ocean sink over the last decade.

This living data update documents changes in methods and data sets applied to this most-recent global carbon budget as well as evolving community understanding of the global carbon cycle. The data presented in this work are available at https://doi.org/10.18160/GCP-2023 (Friedlingstein et al., 2023).

**Executive Summary**

**Global fossil CO\(_2\) emissions (including cement carbonation) are expected to further increase in 2023, to 1.4% above their pre-COVID-19 pandemic 2019 level.** The 2022 emission increase was 0.09 GtC yr\(^{-1}\) (0.33 GtCO\(_2\) yr\(^{-1}\)) relative to 2021, bringing 2022 fossil CO\(_2\) emissions to 9.9 ± 0.5 GtC yr\(^{-1}\) (36.4 ± 1.8 GtCO\(_2\) yr\(^{-1}\)), virtually equal to the emissions level of 2019. Preliminary estimates based on data available suggest fossil CO\(_2\) emissions to increase further in 2023, by 1.1% relative to 2022 (0.1% to 2.2%), bringing emissions to 10.0 GtC yr\(^{-1}\) (36.8 GtCO\(_2\) yr\(^{-1}\)), 1.4% above the 2019 level.

Emissions from coal, oil, and gas in 2023 are all expected to be slightly above their 2022 levels (by 1.3%, 1.5% and 0.2% respectively). Regionally, fossil emissions in 2022 are expected to decrease by 7.4% in the European Union (0.7 GtC, 2.6 GtCO\(_2\)), and by 3.0% in the United States (1.3 GtC, 4.9 GtCO\(_2\)), but to increase by 4.0% in China (3.2 GtC, 11.9 GtCO\(_2\)), 8.7% in India (0.8 GtC, 3.1 GtCO\(_2\)) and 0.5% for the rest of the world (4.2 GtC, 15.2 GtCO\(_2\)).

**Fossil CO\(_2\) emissions decreased in 18 countries during the decade 2013-2022.** Altogether, these 18 countries contribute about 1.9 GtC yr\(^{-1}\) (7.1 GtCO\(_2\)) fossil fuel CO\(_2\) emissions over the last decade, representing about 20% of world CO\(_2\) fossil emissions.

**Global CO\(_2\) emissions from land-use, land-use change, and forestry (LULUCF) averaged 1.3 ± 0.7 GtC yr\(^{-1}\) (4.7 ± 2.6 GtCO\(_2\) yr\(^{-1}\)) for the 2013-2022 period with a preliminary projection for 2023 of 1.1 ± 0.7 GtC yr\(^{-1}\) (4.0 ± 2.6 GtCO\(_2\) yr\(^{-1}\)). A small decrease over the past two decades is not robust given the large model uncertainty.** Emissions from deforestation, the main driver of global gross sources, remain high at around 1.9 GtC yr\(^{-1}\) over the 2013-2022 period, highlighting the strong potential of halting deforestation for emissions reductions. Sequestration of 1.3 GtC yr\(^{-1}\) through re-/afforestation and forestry offsets two third of the deforestation emissions. Emissions from other land-use transitions and from peat drainage and peat fire add further, smaller contributions. The highest emitters during 2013-2022 in descending order were Brazil, Indonesia, and the Democratic Republic of the Congo, with these 3 countries contributing more than half of global land-use CO\(_2\) emissions.
Total anthropogenic emissions were 11.1 GtC yr\(^{-1}\) (40.7 GtCO\(_2\) yr\(^{-1}\)) in 2022, with a similar preliminary estimate of 11.2 GtC yr\(^{-1}\) (40.9 GtCO\(_2\) yr\(^{-1}\)) for 2023.

The remaining carbon budget for a 50% likelihood to limit global warming to 1.5°C, 1.7°C and 2°C has respectively reduced to 75 GtC (275 GtCO\(_2\)), 175 GtC (625 GtCO\(_2\)) and 315 GtC (1150 GtCO\(_2\)) from the beginning of 2024, equivalent to around 7, 15 and 28 years, assuming 2023 emissions levels.

The concentration of CO\(_2\) in the atmosphere is set to reach 419.3 ppm in 2023, 51% above pre-industrial levels. The atmospheric CO\(_2\) growth was 5.2 ± 0.02 GtC yr\(^{-1}\) during the decade 2013-2022 (47% of total CO\(_2\) emissions) with a preliminary 2023 growth rate estimate of around 5.1 GtC (2.4 ppm).

The ocean CO\(_2\) sink resumed a more rapid growth in the past two decades after low or no growth during the 1991-2002 period, overlaid with imprints of climate variability. The estimates based on /CO\(_2\)-products and models diverge with the growth of the ocean CO\(_2\) sink in the past decade being a factor 2.5 larger than in the models. This discrepancy in the trend originates from all latitudes but is largest in the Southern Ocean. The ocean CO\(_2\) sink was 2.9 ± 0.4 GtC yr\(^{-1}\) during the decade 2013-2022 (26% of total CO\(_2\) emissions), and did not grow since 2019 due to a triple La Niña event. A similar value of 2.9 GtC yr\(^{-1}\) is preliminarily estimated for 2023, which marks an increase in the sink compared to the last two years due to the transition from La Niña to El Niño conditions in 2023.

The land CO\(_2\) sink continued to increase during the 2013-2022 period primarily in response to increased atmospheric CO\(_2\), albeit with large interannual variability. The land CO\(_2\) sink was 3.3 ± 0.8 GtC yr\(^{-1}\) during the 2013-2022 decade (31% of total CO\(_2\) emissions), 0.4 GtC yr\(^{-1}\) larger than during the previous decade (2000-2009), with a preliminary 2023 estimate of around 2.9 GtC yr\(^{-1}\), significantly lower than in 2022, and attributed to the response of the land biosphere to the emerging El Niño in 2023. Year to year variability in the land sink is about 1 GtC yr\(^{-1}\) and dominates the year-to-year changes in the global atmospheric CO\(_2\) concentration, implying that small annual changes in anthropogenic emissions (such as the fossil fuel emission decrease in 2020) are hard to detect in the atmospheric CO\(_2\) observations.
The concentration of carbon dioxide (CO$_2$) in the atmosphere has increased from approximately 278 parts per million (ppm) in 1750 (Gulev et al., 2021), the beginning of the Industrial Era, to 417.1 ± 0.1 ppm in 2022 (Lan et al., 2023; Figure 1). The atmospheric CO$_2$ increase above pre-industrial levels was, initially, primarily caused by the release of carbon to the atmosphere from deforestation and other land-use change activities (Canadell et al., 2021). While emissions from fossil fuels started before the Industrial Era, they became the dominant source of anthropogenic emissions to the atmosphere from around 1950 and their relative share has continued to increase until present. Anthropogenic emissions occur on top of an active natural carbon cycle that circulates carbon between the reservoirs of the atmosphere, ocean, and terrestrial biosphere on time scales from sub-daily to millennia, while exchanges with geologic reservoirs occur at longer timescales (Archer et al., 2009).

The global carbon budget (GCB) presented here refers to the mean, variations, and trends in the perturbation of CO$_2$ in the environment, referenced to the beginning of the Industrial Era (defined here as 1750). This paper describes the components of the global carbon cycle over the historical period with a stronger focus on the recent period (since 1958, onset of robust atmospheric CO$_2$ measurements), the last decade (2013-2022), the last year (2022) and the current year (2023). Finally, it provides cumulative emissions from fossil fuels and land-use change since the year 1750 (the pre-industrial period), and since the year 1850 (the reference year for historical simulations in IPCC AR6) (Eyring et al., 2016).

We quantify the input of CO$_2$ to the atmosphere by emissions from human activities, the growth rate of atmospheric CO$_2$ concentration, and the resulting changes in the storage of carbon in the land and ocean reservoirs in response to increasing atmospheric CO$_2$ levels, climate change and variability, and other anthropogenic and natural changes (Figure 2). An understanding of this perturbation budget over time and the underlying variability and trends of the natural carbon cycle is necessary to understand the response of natural sinks to changes in climate, CO$_2$ and land-use change drivers, and to quantify emissions compatible with a given climate stabilisation target.

The components of the CO$_2$ budget that are reported annually in this paper include separate and independent estimates for the CO$_2$ emissions from (1) fossil fuel combustion and oxidation from all energy and industrial processes; also including cement production and carbonation (E$_{FOS}$; GtC yr$^{-1}$) and (2) the emissions resulting from deliberate human activities on land, including those leading to land-use change (E$_{LUC}$; GtC yr$^{-1}$); and their partitioning among (3) the growth rate of atmospheric CO$_2$ concentration (G$_{ATM}$; GtC yr$^{-1}$), and the uptake of CO$_2$ (the ‘CO$_2$ sinks’) in (4) the ocean (S$_{OCEAN}$; GtC yr$^{-1}$) and (5) on land (S$_{LAND}$; GtC yr$^{-1}$). The CO$_2$ sinks as defined here conceptually include the response of the land (including inland waters and estuaries) and ocean (including coastal and marginal seas) to elevated CO$_2$ and changes in climate and other environmental conditions, although in practice not all processes are fully accounted for (see Section 2.10). Global emissions and their partitioning among the atmosphere, ocean and land are in balance in the real world. Due to the combination of imperfect spatial and/or temporal data coverage, errors in each estimate, and smaller terms not included in our budget estimate (discussed in Section 2.10), the independent estimates (1) to (5) above do not
necessarily add up to zero. We therefore assess a set of additional lines of evidence derived from global atmospheric inversion system results (Section 2.7), observed changes in oxygen concentration (Section 2.8) and Earth System Models (ESMs) simulations (Section 2.9), all of which closing the global carbon balance. We also estimate a budget imbalance ($B_{IM}$), which is a measure of the mismatch between the estimated emissions and the estimated changes in the atmosphere, land and ocean, as follows:

$$B_{IM} = E_{FOS} + E_{LUC} - (G_{ATM} + S_{OCEAN} + S_{LAND}) \quad (1)$$

$G_{ATM}$ is usually reported in ppm yr$^{-1}$, which we convert to units of carbon mass per year, GtC yr$^{-1}$, using 1 ppm $= 2.124$ GtC (Ballantyne et al., 2012; Table 1). All quantities are presented in units of gigatonnes of carbon (GtC, $10^{15}$ gC), which is the same as petagrams of carbon (PgC; Table 1). Units of gigatonnes of CO$_2$ (or billion tonnes of CO$_2$) used in policy are equal to 3.664 multiplied by the value in units of GtC.

We also quantify $E_{FOS}$ and $E_{LUC}$ by country, including both territorial and consumption-based accounting for $E_{FOS}$ (see Section 2), and discuss missing terms from sources other than the combustion of fossil fuels (see Section 2.10, Supplement S1 and S2).

We now assess carbon dioxide removal (CDR) (see Sect. 2.2 and 2.3). Land-based CDR is significant, but already accounted for in $E_{LUC}$ in equation (1) (Sect 3.2.2). Other CDR methods, not based on vegetation, are currently several orders of magnitude smaller than the other components of the budget (Sect. 3.3), hence these are not included in equation (1), or in the global carbon budget tables or figures (with the exception of Figure 2 where CDR is shown primarily for illustrative purpose).

The global CO$_2$ budget has been assessed by the Intergovernmental Panel on Climate Change (IPCC) in all assessment reports (Prentice et al., 2001; Schimel et al., 1995; Watson et al., 1990; Denman et al., 2007; Ciais et al., 2013; Canadell et al., 2021), and by others (e.g. Ballantyne et al., 2012). The Global Carbon Project (GCP, www.globalcarbonproject.org, last access: 9 November 2023) has coordinated this cooperative community effort for the annual publication of global carbon budgets for the year 2005 (Raupach et al., 2007; including fossil emissions only), year 2006 (Canadell et al., 2007), year 2007 (GCP, 2008), year 2008 (Le Quéré et al., 2009), year 2009 (Friedlingstein et al., 2010), year 2010 (Peters et al., 2012a), year 2012 (Le Quéré et al., 2013; Peters et al., 2013), year 2013 (Le Quéré et al., 2014), year 2014 (Le Quéré et al., 2015a; Friedlingstein et al., 2014), year 2015 (Jackson et al., 2016; Le Quéré et al., 2015b), year 2016 (Le Quéré et al., 2016), year 2017 (Le Quéré et al., 2018a; Peters et al., 2017), year 2018 (Le Quéré et al., 2018b; Jackson et al., 2018), year 2019 (Friedlingstein et al., 2019; Jackson et al., 2019; Peters et al., 2020), year 2020 (Friedlingstein et al., 2020; Le Quéré et al., 2021), year 2021 (Friedlingstein et al., 2022a; Jackson et al., 2022) and most recently the year 2022 (Friedlingstein et al., 2022b). Each of these papers updated previous estimates with the latest available information for the entire time series.

We adopt a range of ±1 standard deviation (σ) to report the uncertainties in our global estimates, representing a likelihood of 68% that the true value will be within the provided range if the errors have a gaussian distribution, and no bias is assumed. This choice reflects the difficulty of characterising the uncertainty in the CO$_2$ fluxes.
between the atmosphere and the ocean and land reservoirs individually, particularly on an annual basis, as well as the difficulty of updating the CO₂ emissions from land-use change. A likelihood of 68% provides an indication of our current capability to quantify each term and its uncertainty given the available information. The uncertainties reported here combine statistical analysis of the underlying data, assessments of uncertainties in the generation of the data sets, and expert judgement of the likelihood of results lying outside this range. The limitations of current information are discussed in the paper and have been examined in detail elsewhere (Ballantyne et al., 2015; Zscheischler et al., 2017). We also use a qualitative assessment of confidence level to characterise the annual estimates from each term based on the type, amount, quality, and consistency of the different lines of evidence as defined by the IPCC (Stocker et al., 2013).

This paper provides a detailed description of the data sets and methodology used to compute the global carbon budget estimates for the industrial period, from 1750 to 2023, and in more detail for the period since 1959. This paper is updated every year using the format of ‘living data’ to keep a record of budget versions and the changes in new data, revision of data, and changes in methodology that lead to changes in estimates of the carbon budget. Additional materials associated with the release of each new version will be posted at the Global Carbon Project (GCP) website (http://www.globalcarbonproject.org/carbonbudget, last access: 9 November 2023), with fossil fuel emissions also available through the Global Carbon Atlas (http://www.globalcarbonatlas.org, last access: 9 November 2023). All underlying data used to produce the budget can also be found at https://globalcarbonbudget.org/ (last access: 9 November 2023). With this approach, we aim to provide the highest transparency and traceability in the reporting of CO₂, the key driver of climate change.

### 2 Methods

Multiple organisations and research groups around the world generated the original measurements and data used to complete the global carbon budget. The effort presented here is thus mainly one of synthesis, where results from individual groups are collated, analysed, and evaluated for consistency. We facilitate access to original data with the understanding that primary data sets will be referenced in future work (see Table 2 for how to cite the data sets, and Section on data availability). Descriptions of the measurements, models, and methodologies follow below, with more detailed descriptions of each component provided as Supplementary Information (S1 to S5).

This is the 18th version of the global carbon budget and the 12th revised version in the format of a living data update in Earth System Science Data. It builds on the latest published global carbon budget of Friedlingstein et al. (2022b). The main changes this year are: the inclusion of (1) data to year 2022 and a projection for the global carbon budget for year 2023; (2) CO₂ uptake from Carbon Dioxide Removal (CDR); (3) land and ocean net carbon fluxes estimates from changes in atmospheric oxygen concentration; (4) land and ocean net carbon fluxes estimates from ESMs; and (5) revised method to estimate the current year (2023) atmospheric CO₂. The main methodological differences between recent annual carbon budgets (2019 to 2023) are summarised in Table 3 and previous changes since 2006 are provided in Table S8.
2.1 Fossil CO\textsubscript{2} emissions (E\textsubscript{FOS})

2.1.1 Historical period 1850-2022

The estimates of global and national fossil CO\textsubscript{2} emissions (E\textsubscript{FOS}) include the oxidation of fossil fuels through both combustion (e.g., transport, heating) and chemical oxidation (e.g. carbon anode decomposition in aluminium refining) activities, and the decomposition of carbonates in industrial processes (e.g. the production of cement). We also include CO\textsubscript{2} uptake from the cement carbonation process. Several emissions sources are not estimated or not fully covered: coverage of emissions from lime production are not global, and decomposition of carbonates in glass and ceramic production are included only for the “Annex 1” countries of the United Nations Framework Convention on Climate Change (UNFCCC) for lack of activity data. These omissions are considered to be minor. Short-cycle carbon emissions - for example from combustion of biomass - are not included here but are accounted for in the CO\textsubscript{2} emissions from land use (see Section 2.2).

Our estimates of fossil CO\textsubscript{2} emissions rely on data collection by many other parties. Our goal is to produce the best estimate of this flux, and we therefore use a prioritisation framework to combine data from different sources that have used different methods, while being careful to avoid double counting and undercounting of emissions sources. The CDIAC-FF emissions dataset, derived largely from UN energy data, forms the foundation, and we extend emissions to year Y-1 using energy growth rates reported by the Energy Institute (a dataset formally produced by BP). We then proceed to replace estimates using data from what we consider to be superior sources, for example Annex 1 countries’ official submissions to the UNFCCC. All data points are potentially subject to revision, not just the latest year. For full details see Andrew and Peters (2022).

Other estimates of global fossil CO\textsubscript{2} emissions exist, and these are compared by Andrew (2020a). The most common reason for differences in estimates of global fossil CO\textsubscript{2} emissions is a difference in which emissions sources are included in the datasets. Datasets such as those published by the energy company BP, the US Energy Information Administration, and the International Energy Agency’s ‘CO\textsubscript{2} emissions from fuel combustion’ are all generally limited to emissions from combustion of fossil fuels. In contrast, datasets such as PRIMAP-hist, CEDS, EDGAR, and GCP’s dataset aim to include all sources of fossil CO\textsubscript{2} emissions. See Andrew (2020a) for detailed comparisons and discussion.

Cement absorbs CO\textsubscript{2} from the atmosphere over its lifetime, a process known as ‘cement carbonation’. We estimate this CO\textsubscript{2} sink, from 1931, onwards as the average of two studies in the literature (Cao et al., 2020; Guo et al., 2021). Both studies use the same model, developed by Xi et al. (2016), with different parameterisations and input data, with the estimate of Guo and colleagues being a revision of Xi et al. (2016). The trends of the two studies are very similar. Since carbonation is a function of both current and previous cement production, we extend these estimates to 2022 by using the growth rate derived from the smoothed cement emissions (10-year smoothing) fitted to the carbonation data. In the present budget, we always include the cement carbonation carbon sink in the fossil CO\textsubscript{2} emission component (E\textsubscript{FOS}).
We use the Kaya Identity for a simple decomposition of CO₂ emissions into the key drivers (Raupach et al., 2007). While there are variations (Peters et al., 2017), we focus here on a decomposition of CO₂ emissions into population, GDP per person, energy use per GDP, and CO₂ emissions per energy. Multiplying these individual components together returns the CO₂ emissions. Using the decomposition, it is possible to attribute the change in CO₂ emissions to the change in each of the drivers. This method gives a first-order understanding of what causes CO₂ emissions to change each year.

2.1.2 2023 projection

We provide a projection of global fossil CO₂ emissions in 2022 by combining separate projections for China, USA, EU, India, and for all other countries combined. The methods are different for each of these. For China we combine monthly fossil fuel production data from the National Bureau of Statistics and trade data from the Customs Administration, giving us partial data for the growth rates to date of natural gas, petroleum, and cement, and of the apparent consumption itself for raw coal. We then use a regression model to project full-year emissions based on historical observations. For the USA our projection is taken directly from the Energy Information Administration’s (EIA) Short-Term Energy Outlook (EIA, 2023), combined with the year-to-date growth rate of cement clinker production. For the EU we use monthly energy data from Eurostat to derive estimates of monthly CO₂ emissions through July, with coal emissions extended through September using a statistical relationship with reported electricity generation from coal and other factors. For natural gas we use Holt-Winters to project the last four months of the year. EU emissions from oil are derived using the EIA’s projection of oil consumption for Europe. EU cement emissions are based on available year-to-date data from three of the largest producers, Germany, Poland, and Spain. India’s projected emissions are derived from estimates through August (July for coal) using the methods of Andrew (2020b) and extrapolated assuming seasonal patterns from before 2019. Emissions for the rest of the world are derived using projected growth in economic production from the IMF (2023) combined with extrapolated changes in emissions intensity of economic production. More details on the EFOS methodology and its 2023 projection can be found in Supplement S.1.

2.2 CO₂ emissions from land-use, land-use change and forestry (ELUC)

2.2.1 Historical period 1850-2022

The net CO₂ flux from land-use, land-use change and forestry (ELUC, called land-use change emissions in the rest of the text) includes CO₂ fluxes from deforestation, afforestation, logging and forest degradation (including harvest activity), shifting cultivation (cycle of cutting forest for agriculture, then abandoning), and regrowth of forests (following wood harvest or agriculture abandonment). Emissions from peat burning and peat drainage are added from external datasets, peat drainage being averaged from three spatially explicit independent datasets (see Supplement S.2.1).

Three bookkeeping approaches (updated estimates each of BLUE (Hansis et al., 2015), OSCAR (Gasser et al., 2020), and H&C2023 (Houghton and Castanho, 2023)) were used to quantify gross emissions and gross
removals and the resulting net $E_{\text{LUC}}$. Uncertainty estimates were derived from the Dynamic Global Vegetation Models (DGVMs) ensemble for the time period prior to 1960, and using for the recent decades an uncertainty range of $\pm 0.7 \text{ GtC yr}^{-1}$, which is a semi-quantitative measure for annual and decadal emissions and reflects our best value judgement that there is at least 68% chance ($\pm 1\sigma$) that the true land-use change emission lies within the given range, for the range of processes considered here.

Our $E_{\text{LUC}}$ estimates follow the definition of global carbon cycle models of CO$_2$ fluxes related to land use and land management and differ from IPCC definitions adopted in National GHG Inventories (NGHGI) for reporting under the UNFCCC, which additionally generally include, through adoption of the IPCC so-called managed land proxy approach, the terrestrial fluxes occurring on all land that countries define as managed. This partly includes fluxes due to environmental change (e.g. atmospheric CO$_2$ increase), which are part of $S_{\text{LAND}}$ in our definition. This causes the global emission estimates to be smaller for NGHGI than for the global carbon budget definition (Grassi et al., 2018). The same is the case for the Food Agriculture Organization (FAO) estimates of carbon fluxes on forest land, which include both anthropogenic and natural sources on managed land (Tubiello et al., 2021). We translate the two definitions to each other, to provide a comparison of the anthropogenic carbon budget to the official country reporting to the climate convention.

$E_{\text{LUC}}$ contains a range of fluxes that are related to Carbon Dioxide Removal (CDR). CDR can be defined as the set of anthropogenic activities that remove CO$_2$ from the atmosphere and store it in durable form, such as in forest biomass and soils, long-lived products, or in geological or ocean reservoirs. We quantify vegetation-based CDR that is implicitly or explicitly captured by land-use fluxes consistent with our updated model estimates (CDR not based on vegetation is discussed in Section 2.3; IPCC, 2023). We quantify re/afforestation from the three bookkeeping estimates by separating forest regrowth in shifting cultivation cycles from permanent increases in forest cover (see Supplement C.2.1). The latter count as CDR, but it should be noted that the permanence of the storage under climate risks such as fire is increasingly questioned. Other CDR activities contained in $E_{\text{LUC}}$ include the transfer of carbon to harvested wood products (HWP), which is represented by the bookkeeping models with varying details concerning product usage and their lifetimes; bioenergy with carbon capture and storage (BECCS); and biochar production. Bookkeeping and TRENDY models currently only represent BECCS and biochar with regard to the CO$_2$ removal through photosynthesis, but not for the durable storage. HWP, BECCS, and biochar are typically counted as CDR when the transfer to the durable storage site occurs and not when the CO$_2$ is removed from the atmosphere, which complicates a direct comparison to the global carbon budgets approach to quantify annual fluxes to and from the atmosphere. Estimates for CDR through HWP, BECCS, and biochar are thus not indicated in this budget, but can be found elsewhere (see Section 3.2.2).

### 2.2.2 2023 Projection

We project the 2023 land-use emissions for BLUE, H&C2023, and OSCAR based on their $E_{\text{LUC}}$ estimates for 2022 and adding the change in carbon emissions from peat fires and tropical deforestation and degradation fires (2023 emissions relative to 2022 emissions) estimated using active fire data (MCD14ML; Giglio et al., 2016).
Peat drainage is assumed to be unaltered as it has low interannual variability. More details on the $E_{\text{LUC}}$ methodology can be found in Supplement S.2.

### 2.3 Carbon Dioxide Removal (CDR) not based on vegetation

CDR not based on terrestrial vegetation currently relies on enhanced rock weathering and Direct Air Carbon Capture and Storage (DACCS) projects. The majority of this (58%) derives from a single project: Climeworks’ Orca DACCS plant based in Hellisheidi, Iceland. The remainder is generated by 13 small-scale projects including, for example, 500 tons of carbon dioxide sequestered through the spreading of crushed olivine on agricultural areas by Eion Carbon. We use data from the State of CDR Report (Smith et al., 2023), which quantifies all currently deployed CDR methods, including the land-use related activities already covered by Section 2.2. The State of CDR Report (Smith et al., 2023) combines estimates of carbon storage in managed land derived from NGHGI data with project-by-project storage rates obtained through 20 extant CDR databases and registries (status as of mid-year 2022) by Powis et al. (2023). They assessed the data quality on existing CDR projects to be poor, suffering from fragmentation, different reporting standards, limited geographical coverage, and inclusion of a number of pilot plants with uncertain lifespans. As a consequence, these numbers could change substantially from year-to-year in the near-term.

### 2.4 Growth rate in atmospheric CO$_2$ concentration ($G_{\text{ATM}}$)

#### 2.4.1 Historical period 1850-2022

The rate of growth of the atmospheric CO$_2$ concentration is provided for years 1959-2022 by the US National Oceanic and Atmospheric Administration Global Monitoring Laboratory (NOAA/GML; Lan et al., 2023), which includes recent revisions to the calibration scale of atmospheric CO$_2$ measurements (Hall et al., 2021).

For the 1959-1979 period, the global growth rate is based on measurements of atmospheric CO$_2$ concentration averaged from the Mauna Loa and South Pole stations, as observed by the CO$_2$ Program at Scripps Institution of Oceanography (Keeling et al., 1976). For the 1980-2021 time period, the global growth rate is based on the average of multiple stations selected from the marine boundary layer sites with well-mixed background air (Ballantyne et al., 2012), after fitting a smooth curve through the data for each station as a function of time, and averaging by latitude band (Masarie and Tans, 1995). The annual growth rate is estimated by Lan et al. (2023) from atmospheric CO$_2$ concentration by taking the average of the most recent December-January months corrected for the average seasonal cycle and subtracting this same average one year earlier. The growth rate in units of ppm yr$^{-1}$ is converted to units of GtC yr$^{-1}$ by multiplying by a factor of 2.124 GtC per ppm, assuming instantaneous mixing of CO$_2$ throughout the atmosphere (Ballantyne et al., 2012; Table 1).

Since 2020, NOAA/GML provides estimates of atmospheric CO$_2$ concentrations with respect to a new calibration scale, referred to as WMO-CO2-X2019, in line with a recalibration agreed by the World Meteorological Organization (WMO) Global Atmosphere Watch (GAW) community (Hall et al., 2021). The recalibrated data were first used to estimate $G_{\text{ATM}}$ in the 2021 edition of the global carbon budget (Friedlingstein et al., 2022a). Friedlingstein et al. (2022a) verified that the change of scales from WMO-CO2-X2007 to WMO-
CO2-X2019 made a negligible difference to the value of $G_{\text{ATM}}$ (-0.06 GtC yr$^{-1}$ during 2010-2019 and -0.01 GtC yr$^{-1}$ during 1959-2019, well within the uncertainty range reported below).

The uncertainty around the atmospheric growth rate is due to four main factors. First, the long-term reproducibility of reference gas standards (around 0.03 ppm for 1σ from the 1980s; Lan et al., 2023). Second, small unexplained systematic analytical errors that may have a duration of several months to two years come and go. They have been simulated by randomising both the duration and the magnitude (determined from the existing evidence) in a Monte Carlo procedure. Third, the network composition of the marine boundary layer with some sites coming or going, gaps in the time series at each site, etc (Lan et al., 2023). The latter uncertainty was estimated by NOAA/GML with a Monte Carlo method by constructing 100 "alternative" networks (Masarie and Tans, 1995; NOAA/GML, 2019). The second and third uncertainties, summed in quadrature, add up to 0.085 ppm on average (Lan et al., 2023). Fourth, the uncertainty associated with using the average CO$_2$ concentration from a surface network to approximate the true atmospheric average CO$_2$ concentration (mass-weighted, in 3 dimensions) as needed to assess the total atmospheric CO$_2$ burden. In reality, CO$_2$ variations measured at the stations will not exactly track changes in total atmospheric burden, with offsets in magnitude and phasing due to vertical and horizontal mixing. This effect must be very small on decadal and longer time scales, when the atmosphere can be considered well mixed. The CO2 increase in the stratosphere lags the increase (meaning lower concentrations) that we observe in the marine boundary layer, while the continental boundary layer (where most of the emissions take place) leads the marine boundary layer with higher concentrations. These effects nearly cancel each other. In addition, the growth rate is nearly the same everywhere (Ballantyne et al, 2012). We therefore maintain an uncertainty around the annual growth rate based on the multiple stations data set ranges between 0.11 and 0.72 GtC yr$^{-1}$, with a mean of 0.61 GtC yr$^{-1}$ for 1959-1979 and 0.17 GtC yr$^{-1}$ for 1980-2022, when a larger set of stations were available as provided by Lan et al. (2023). We estimate the uncertainty of the decadal averaged growth rate after 1980 at 0.02 GtC yr$^{-1}$ based on the calibration and the annual growth rate uncertainty but stretched over a 10-year interval. For years prior to 1980, we estimate the decadal averaged uncertainty to be 0.07 GtC yr$^{-1}$ based on a factor proportional to the annual uncertainty prior and after 1980 (0.02 * [0.61/0.17] GtC yr$^{-1}$).

We assign a high confidence to the annual estimates of $G_{\text{ATM}}$ because they are based on direct measurements from multiple and consistent instruments and stations distributed around the world (Ballantyne et al., 2012; Hall et al., 2021).

To estimate the total carbon accumulated in the atmosphere since 1750 or 1850, we use an atmospheric CO$_2$ concentration of 278.3 ± 3 ppm or 285.1 ± 3 ppm, respectively (Gulev et al., 2021). For the construction of the cumulative budget shown in Figure 3, we use the fitted estimates of CO$_2$ concentration from Joos and Spahni (2008) to estimate the annual atmospheric growth rate using the conversion factors shown in Table 1. The uncertainty of ±3 ppm (converted to ±1σ) is taken directly from the IPCC’s AR5 assessment (Ciais et al., 2013). Typical uncertainties in the growth rate in atmospheric CO$_2$ concentration from ice core data are equivalent to ±0.1-0.15 GtC yr$^{-1}$ as evaluated from the Law Dome data (Etheridge et al., 1996) for individual 20-year intervals over the period from 1850 to 1960 (Bruno and Joos, 1997).
We provide an assessment of $G_{\text{ATM}}$ for 2023 as the average of two methods. The GCB regression method models monthly global-average atmospheric CO$_2$ concentrations and derives the increment and annual average from these. The model uses lagged observations of concentration (Lan et al., 2023): both a 12-month lag, and the lowest lag that will allow model prediction to produce an estimate for the following January, recalling that the $G_{\text{ATM}}$ increment is derived from December/January pairs. The largest driver of interannual changes is the ENSO signal (Betts et al., 2016), so the monthly ENSO 3.4 index (Huang et al., 2023) is included in the model. Given the natural lag between sea-surface temperatures and effects on the biosphere, and in turn effects on globally mixed atmospheric CO$_2$ concentration, a lagged ENSO index is used, and we use both a 5-month and a 6-month lag. The combination of the two lagged ENSO values helps reduce possible effects of noise in a single month. To help characterise the seasonal variation, we add month as a categorical variable. Finally, we flag the period affected by the Pinatubo eruption (August 1991 - November 1993) as a categorical variable. Note that while emissions of CO$_2$ are the largest driver of the trend in atmospheric CO$_2$ concentration, our goal here is to predict divergence from that trend. Because changes in emissions from year to year are relatively minor, this has little effect on the variation of concentration from the trend line. Even the relatively large drop in emissions in 2020 due to the COVID-19 pandemic does not cause any problems for the model.

For the first time this year, we also use the multi-model mean and uncertainty of the 2023 $G_{\text{ATM}}$ estimated by the ESMs prediction system (see Section 2.9). We then take the average of the GCB regression and ESMs $G_{\text{ATM}}$ estimates, with their respective uncertainty combined quadratically.

Similarly, the projection of the 2023 global average CO$_2$ concentration (in ppm), is calculated as the average of the estimates from the two methods. For the GCB regression method, it is the annual average of global concentration over the 12 months of 2023; for the ESMs, it is the observed global average CO$_2$ concentration for 2022 plus the annual increase in 2023 of the global average CO$_2$ concentration predicted by the ESMs multi-model mean.

2.5 Ocean CO$_2$ sink

2.5.1 Historical period 1850-2022

The reported estimate of the global ocean anthropogenic CO$_2$ sink $S_{\text{OCEAN}}$ is derived as the average of two estimates. The first estimate is derived as the mean over an ensemble of ten global ocean biogeochemistry models (GOBMs, Table 4 and Table S2). The second estimate is obtained as the mean over an ensemble of seven surface ocean /CO$_2$-observation-based data-products (Table 4 and Table S3). An eighth /CO$_2$-product (Watson et al., 2020) is shown, but is not included in the ensemble average as it differs from the other products by adjusting the flux to a cool, salty ocean surface skin (see Supplement S.3.1 for a discussion of the Watson product). The GOBMs simulate both the natural and anthropogenic CO$_2$ cycles in the ocean. They constrain the anthropogenic air-sea CO$_2$ flux (the dominant component of $S_{\text{OCEAN}}$) by the transport of carbon into the ocean interior, which is also the controlling factor of present-day ocean carbon uptake in the real world. They cover
the full globe and all seasons and were recently evaluated against surface ocean carbon observations, suggesting they are suitable to estimate the annual ocean carbon sink (Hauck et al., 2020). The fCO₂-products are tightly linked to observations of fCO₂ (fugacity of CO₂, which equals pCO₂ corrected for the non-ideal behaviour of the gas; Pfeil et al., 2013), which carry imprints of temporal and spatial variability, but are also sensitive to uncertainties in gas-exchange parameterizations and data-sparcity (Gloege et al., 2021, Hauck et al., 2023). Their asset is the assessment of the mean spatial pattern of variability and its seasonality (Hauck et al., 2020, Gloege et al. 2021, Hauck et al., 2023). We further use two diagnostic ocean models to estimate SOCEAN over the industrial era (1781-1958).

The global fCO₂-based flux estimates were adjusted to remove the pre-industrial ocean source of CO₂ to the atmosphere of 0.65 ± 0.3 GtC yr⁻¹ from river input to the ocean (Regnier et al., 2022), to satisfy our definition of SOCEAN (Hauck et al., 2020). The river flux adjustment was distributed over the latitudinal bands using the regional distribution of Lacroix et al. (2020; North: 0.14 GtC yr⁻¹, Tropics: 0.42 GtC yr⁻¹, South: 0.09 GtC yr⁻¹). Acknowledging that this distribution is based on only one model, the advantage is that a gridded field is available, and the river flux adjustment can be calculated for the three latitudinal bands and the RECCAP regions (REgional Carbon Cycle Assessment and Processes (RECCAP2; Ciais et al., 2020, Poulter et al., 2022, DeVries et al., 2023). This data set suggests that more of the riverine outgassing is located in the tropics than in the Southern Ocean and is thus opposed to the previously used data set of Aumont et al. (2001). Accordingly, the regional distribution is associated with a major uncertainty in addition to the large uncertainty around the global estimate (Crisp et al., 2022; Gruber et al., 2023). Anthropogenic perturbations of river carbon and nutrient transport to the ocean are not considered (see Section 2.10 and Supplement S.6.3).

We derive SOCEAN from GOBMs by using a simulation (sim A) with historical forcing of climate and atmospheric CO₂, accounting for model biases and drift from a control simulation (sim B) with constant atmospheric CO₂ and normal year climate forcing. A third simulation (sim C) with historical atmospheric CO₂ increase and normal year climate forcing is used to attribute the ocean sink to CO₂ (sim C minus sim B) and climate (sim A minus sim C) effects. A fourth simulation (sim D; historical climate forcing and constant atmospheric CO₂) is used to compare the change in anthropogenic carbon inventory in the interior ocean (sim A minus sim D) to the observational estimate of Gruber et al. (2019) with the same flux components (steady state and non-steady state anthropogenic carbon flux). The fCO₂-products are adjusted with respect to their original publications to represent the full ice-free ocean area, including coastal zones and marginal seas, when the area coverage is below 99%. This is done by either area filling following Fay et al. (2021) or a simple scaling approach. GOBMs and fCO₂-products fall within the observational constraints over the 1990s (2.2 ± 0.7 GtC yr⁻¹, Ciais et al., 2013) after applying adjustments.

SOCEAN is calculated as the average of the GOBM ensemble mean and the fCO₂-product ensemble mean from 1990 onwards. Prior to 1990, it is calculated as the GOBM ensemble mean plus half of the offset between GOBMs and fCO₂-products ensemble means over 1990-2001.

We assign an uncertainty of ± 0.4 GtC yr⁻¹ to the ocean sink based on a combination of random (ensemble standard deviation) and systematic uncertainties (GOBMs bias in anthropogenic carbon accumulation,
previously reported uncertainties in \( f_{CO_2} \)-products; see Supplement S.3.4). We assess a medium confidence level to the annual ocean CO\(_2\) sink and its uncertainty because it is based on multiple lines of evidence, it is consistent with ocean interior carbon estimates (Gruber et al., 2019, see Section 3.6.5) and the interannual variability in the GOBMs and data-based estimates is largely consistent and can be explained by climate variability. We refrain from assigning a high confidence because of the systematic deviation between the GOBM and \( f_{CO_2} \)-product trends since around 2002. More details on the \( S_{OCEAN} \) methodology can be found in Supplement S.3.

2.5.2 2023 Projection

The ocean CO\(_2\) sink forecast for the year 2023 is based on the annual historical (Lan et al., 2023) and our estimated 2023 atmospheric CO\(_2\) concentration growth rate, the historical and our estimated 2023 annual global fossil fuel emissions from this year’s carbon budget, and the spring (March, April, May) Oceanic Niño Index (ONI) (NCEP, 2023). Using a non-linear regression approach, i.e., a feed-forward neural network, atmospheric CO\(_2\), ONI, and the fossil fuel emissions are used as training data to best match the annual ocean CO\(_2\) sink (i.e. combined \( S_{OCEAN} \) estimate from GOBMs and data products) from 1959 through 2022 from this year’s carbon budget. Using this relationship, the 2023 \( S_{OCEAN} \) can then be estimated from the projected 2022 input data using the non-linear relationship established during the network training. To avoid overfitting, the neural network was trained with a variable number of hidden neurons (varying between 2-5) and 20% of the randomly selected training data were withheld for independent internal testing. Based on the best output performance (tested using the 20% withheld input data), the best performing number of neurons was selected. In a second step, we trained the network 10 times using the best number of neurons identified in step 1 and different sets of randomly selected training data. The mean of the 10 trainings is considered our best forecast, whereas the standard deviation of the 10 ensembles provides a first order estimate of the forecast uncertainty. This uncertainty is then combined with the \( S_{OCEAN} \) uncertainty (0.4 GtC yr\(^{-1}\)) to estimate the overall uncertainty of the 2023 projection. As an additional line of evidence, we also assess the 2023 atmosphere-ocean carbon flux from the ESM prediction system (see Section 2.9).

2.6 Land CO\(_2\) sink

2.6.1 Historical Period 1850-2022

The terrestrial land sink (\( S_{LAND} \)) is thought to be due to the combined effects of fertilisation by rising atmospheric CO\(_2\) and N inputs on plant growth, as well as the effects of climate change such as the lengthening of the growing season in northern temperate and boreal areas. \( S_{LAND} \) does not include land sinks directly resulting from land-use and land-use change (e.g., regrowth of vegetation) as these are part of the land-use flux (\( E_{LUC} \)), although system boundaries make it difficult to attribute exactly CO\(_2\) fluxes on land between \( S_{LAND} \) and \( E_{LUC} \) (Erb et al., 2013).

\( S_{LAND} \) is estimated from the multi-model mean of 20 DGVMs (Table S1) with an additional comparison of DGVMs with a data-driven, carbon data model framework (CARDAMOM) (Bloom and Williams, 2015; Bloom
et al., 2016), see Supplement S4. DGVMs simulations include all climate variability and CO\textsubscript{2} effects over land. In addition to the carbon cycle represented in all DGVMs, 14 models also account for the nitrogen cycle and hence can include the effect of N inputs on S\textsubscript{LAND}. The DGVMs estimate of S\textsubscript{LAND} does not include the export of carbon to aquatic systems or its historical perturbation, which is discussed in Supplement S.6.3. DGVMs need to meet several criteria to be included in this assessment. In addition, we use the International Land Model Benchmarking system (ILAMB; Collier et al., 2018) for the DGVMs evaluation (see Supplement S.4.2). The uncertainty on S\textsubscript{LAND} is taken from the GGVMs standard deviation (see Supplement S.4.3). More details on the S\textsubscript{LAND} methodology can be found in Supplement S.4.

2.6.2 2023 Projection

Like for the ocean forecast, the land CO\textsubscript{2} sink (S\textsubscript{LAND}) forecast is based on the annual historical (Lan et al., 2023) and our estimated 2023 atmospheric CO\textsubscript{2} concentration, historical and our estimated 2023 annual global fossil fuel emissions from this year’s carbon budget, and the summer (June, July, August) ONI (NCEP, 2022). All training data are again used to best match S\textsubscript{LAND} from 1959 through 2022 from this year’s carbon budget using a feed-forward neural network. To avoid overfitting, the neural network was trained with a variable number of hidden neurons (varying between 2-15), larger than for S\textsubscript{OCEAN} prediction due to the stronger land carbon interannual variability. As done for S\textsubscript{OCEAN}, a pre-training selects the optimal number of hidden neurons based on 20% withheld input data, and in a second step, an ensemble of 10 forecasts is produced to provide the mean forecast plus uncertainty. This uncertainty is then combined with the S\textsubscript{LAND} uncertainty for 2022 (0.9 GtC yr\textsuperscript{-1}) to estimate the overall uncertainty of the 2023 projection.

2.7 Atmospheric inversion estimate

The world-wide network of in-situ atmospheric measurements and satellite derived atmospheric CO\textsubscript{2} column (xCO\textsubscript{2}) observations put a strong constraint on changes in the atmospheric abundance of CO\textsubscript{2}. This is true globally (hence our large confidence in G\textsubscript{ATM}), but also regionally in regions with sufficient observational density found mostly in the extra-tropics. This allows atmospheric inversion methods to constrain the magnitude and location of the combined total surface CO\textsubscript{2} fluxes from all sources, including fossil and land-use change emissions and land and ocean CO\textsubscript{2} fluxes. The inversions assume E\textsubscript{FOS} to be well known, and they solve for the spatial and temporal distribution of land and ocean fluxes from the residual gradients of CO\textsubscript{2} between stations that are not explained by fossil fuel emissions. By design, such systems thus close the carbon balance (B\textsubscript{IM} = 0) and thus provide an additional perspective on the independent estimates of the ocean and land fluxes.

This year’s release includes fourteen inversion systems that are described in Table S4, of which thirteen are included in the ensemble of inverse estimates presented in the text and figures. Each system is rooted in Bayesian inversion principles but uses different methodologies. These differences concern the selection of atmospheric CO\textsubscript{2} data or xCO\textsubscript{2}, and the choice of a-priori fluxes to refine. They also differ in spatial and temporal resolution, assumed correlation structures, and mathematical approach of the models (see references in Table S4 for details). Importantly, the systems use a variety of transport models, which was demonstrated to be a driving factor behind differences in atmospheric inversion-based flux estimates, and specifically their
distribution across latitudinal bands (Gaubert et al., 2019; Schuh et al., 2019). Six inversion systems (CAMS-FT23r1, CMS-flux, GONGGA, THU, COLA, GCASv2) used satellite xCO₂ retrievals from GOSAT and/or OCO-2, scaled to the WMO 2019 calibration scale. Two inversions this year (CMS-Flux, COLA) used these xCO₂ datasets in addition to the in-situ observational CO₂ mole fraction records.

The original products delivered by the inverse modellers were modified to facilitate the comparison to the other elements of the budget, specifically on two accounts: (1) global total fossil fuel emissions including cement carbonation CO₂ uptake, and (2) riverine CO₂ transport. Details are given below. We note that with these adjustments the inverse results no longer represent the net atmosphere-surface exchange over land/ocean areas as sensed by atmospheric observations. Instead, for land, they become the net uptake of CO₂ by vegetation and soils that is not exported by fluvial systems, similar to the DGVMs estimates. For oceans, they become the net uptake of anthropogenic CO₂, similar to the GOBMs estimates.

The inversion systems prescribe global fossil fuel emissions based on e.g. the GCP’s Gridded Fossil Emissions Dataset versions 2023.1 (GCP-GridFED; Jones et al., 2023), which are updates to GCP-GridFEDv2021 presented by Jones et al. (2021b). GCP-GridFEDv2023 scales gridded estimates of CO₂ emissions from EDGARv4.3.2 (Janssens-Maenhout et al., 2019) within national territories to match national emissions estimates provided by the GCB for the years 1959-2022, which were compiled following the methodology described in Section 2.1. Small differences between the systems due to for instance regridding to the transport model resolution, or use of different fossil fuel emissions, are adjusted in the latitudinal partitioning we present, to ensure agreement with the estimate of E_FOS in this budget. We also note that the ocean fluxes used as prior by 8 out of 14 inversions are part of the suite of the ocean process model or f/CO₂-products listed in Section 2.5. Although these fluxes are further adjusted by the atmospheric inversions, it makes the inversion estimates of the ocean fluxes not completely independent of S_OCEAN assessed here.

To facilitate comparisons to the independent S_OCEAN and S_LAND, we used the same corrections for transport and outgassing of carbon transported from land to ocean, as done for the observation-based estimates of S_OCEAN (see Supplement S.3).

The atmospheric inversions are evaluated using vertical profiles of atmospheric CO₂ concentrations (Figure S4). More than 30 aircraft programs over the globe, either regular programs or repeated surveys over at least 9 months (except for SH programs), have been used to assess system performance (with space-time observational coverage sparse in the SH and tropics, and denser in NH mid-latitudes; Table S7). The fourteen systems are compared to the independent aircraft CO₂ measurements between 2 and 7 km above sea level between 2001 and 2022. Results are shown in Figure S4 and discussed in Supplement S.5.2. One inversion was flagged for concerns after quality control with these observations, as well as assessment of their global growth rate. This makes the number of systems included in the ensemble to be N=13.

With a relatively small ensemble of systems that cover at least one full decade (N=9), and which moreover share some a-priori fluxes used with one another, or with the process-based models, it is difficult to justify using their mean and standard deviation as a metric for uncertainty across the ensemble. We therefore report their full range
(min-max) without their mean. More details on the atmospheric inversions methodology can be found in Supplement S.5.

2.8 Atmospheric oxygen based estimate

Long-term atmospheric O$_2$ and CO$_2$ observations allow estimation of the global ocean and land carbon sinks, due to the coupling of O$_2$ and CO$_2$ with distinct exchange ratios for fossil fuel emissions and land uptake, and uncoupled O$_2$ and CO$_2$ ocean exchange (Keeling and Manning, 2014). The global ocean and net land carbon sinks were calculated following methods and constants used in Keeling and Manning (2014), modified to include the effective O$_2$ source from metal refining (Battle et al., 2023), and using a value of 1.05 for the exchange ratio of the net land sink, following Resplandy et al. (2019). Atmospheric O$_2$ is observed as δ(O$_2$/N$_2$) and combined with CO$_2$ mole fraction observations into Atmospheric Potential Oxygen (APO, Stephens et al., 1998). The APO observations from 1990 to 2022 were taken from a weighted average of flask records from the three stations in the Scripps O$_2$ program network (Alert, Canada (ALT), La Jolla, California (LJO), and Cape Grim, Australia (CGO), weighted per Keeling and Manning (2014). Observed CO$_2$ was taken from the globally averaged marine surface annual mean growth rate from the NOAA/GML Global Greenhouse Gas Reference Network (Lan et al., 2023). The O$_2$ source from ocean warming is based on ocean heat content from updated data from NOAA/NCEI (Levitus et al., 2012). The effective O$_2$ source from metal refining is based on production data from Bray (2020), Flanagan (2021), and Tuck (2022). Uncertainty was determined through a Monte Carlo approach with 5,000 iterations, using uncertainties prescribed in Keeling and Manning (2014), including observational uncertainties from Keeling et al. (2007) and autoregressive errors in fossil fuel emissions (Ballantyne et al., 2015). The reported uncertainty is 1 standard deviation of the ensemble.

2.9 Earth System Models estimate

Reconstructions and predictions from decadal prediction systems based on Earth system models (ESMs) provide a novel line of evidence in assessing the atmosphere-land and atmosphere-ocean carbon fluxes in the past decades and predicting their changes for the current year. The decadal prediction systems based on ESMs used here consist of three sets of simulations: (i) uninitialized freely evolving historical simulations (1850-2014); (ii) assimilation reconstruction incorporating observational data into the model (1980-2022); (iii) initialized prediction simulations for the 1981-2023 period, starting every year from initial states obtained from the above assimilation simulations. The assimilations are designed to reconstruct the actual evolution of the Earth system by assimilating essential fields from data products. The assimilations’ states, which are expected to be close to observations, are used to start the initialized prediction simulations used for the current year (2023) global carbon budget. Similar initialized prediction simulations starting every year (Nov. 1st or Jan. 1st) over the 1981-2022 period (i.e., hindcasts) are also performed for predictive skill quantification and for bias correction. More details on the illustration of a decadal prediction system based on an ESM can refer to Figure 1 of Li et al. (2023).

By assimilating physical atmospheric and oceanic data products into the ESMs, the models are able to reproduce the historical variations of the atmosphere-sea CO$_2$ fluxes, atmosphere-land CO$_2$ fluxes, and atmospheric CO$_2$
growth rate (Li et al., 2016, 2019; Lovenduski et al., 2019a,b; Ilyina et al., 2021; Li et al., 2023). Furthermore, the ESM-based predictions have proven their skill in predicting the air-sea CO₂ fluxes for up to 6 years, the air-land CO₂ fluxes and atmospheric CO₂ growth for 2 years (Lovenduski et al., 2019a,b; Ilyina et al., 2021; Li et al., 2023). The reconstructions from the fully coupled model simulations ensure a closed budget within the Earth system, i.e., no budget imbalance term.

Four ESMs, i.e., CanESM5 (Swart et al., 2019; Sospedra-Alfonso et al., 2021), IPSL-CM6A-CO2-LR (Boucher et al., 2020), MIROC-ES2L (Watanabe et al., 2020), and MPI-ESM1-2-LR (Mauritsen et al., 2019; Li et al., 2023), have performed the set of prediction simulations. Each ESM uses a different assimilation method and combination of data products incorporated in the system, more details on the models configuration can be found in Table 4.

The ESMs use external forcings from the Coupled Model Intercomparison Project Phase 6 (CMIP6) historical (1980-2014) plus SSP2-4.5 baseline and CovidMIP two-year blip scenario (2015-2023) (Eyring et al., 2016; Jones et al., 2021a). The CO₂ emissions forcing from 2015-2023 are substituted by GCB-GridFED (v2023.1, Jones et al., 2023) to provide a more realistic forcing. Reconstructions of atmosphere-ocean CO₂ fluxes (S\text{OCEAN}) and atmosphere-land CO₂ fluxes (S\text{LAND}-E\text{LUC}) for the time period from 1980-2022 are assessed here. Predictions of the atmosphere-ocean CO₂ flux, atmosphere-land CO₂ flux, and atmospheric CO₂ growth for 2023 are calculated based on the predictions at a lead time of 1 year. The predictions are bias-corrected using the 1985-2014 climatology mean of GCB2022 (Friedlingstein et al., 2022), more details on methods can be found in Boer et al. (2016) and Li et al. (2023). The ensemble size of initialized prediction simulations is 10, and the ensemble mean for each individual model is used here. The ESMs are used here to support the assessment of S\text{OCEAN} and net atmosphere-land CO₂ flux (S\text{LAND} - E\text{LUC}) over the 1980-2022 period, and to provide an estimate of the 2023 projection of \text{GATM}.

2.10 Processes not included in the global carbon budget

The contribution of anthropogenic CO and CH₄ to the global carbon budget is not fully accounted for in Eq. (1) and is described in Supplement S.6.1. The contributions to CO₂ emissions of decomposition of carbonates not accounted for is described in Supplement S.6.2. The contribution of anthropogenic changes in river fluxes is conceptually included in Eq. (1) in S\text{OCEAN} and in S\text{LAND}, but it is not represented in the process models used to quantify these fluxes. This effect is discussed in Supplement S.6.3. Similarly, the loss of additional sink capacity from reduced forest cover is missing in the combination of approaches used here to estimate both land fluxes (E\text{LUC} and S\text{LAND}) and its potential effect is discussed and quantified in Supplement S.6.4.

3 Results

For each component of the global carbon budget, we present results for three different time periods: the full historical period, from 1850 to 2022, the decades in which we have atmospheric concentration records from Mauna Loa (1960-2022), a specific focus on last year (2022), and the projection for the current year (2023). Subsequently, we assess the estimates of the budget components of the last decades against the top-down constraints from inverse modelling of atmospheric observations, the land/ocean partitioning derived from the atmospheric O₂ measurements, and the budget components estimates from the ESMs assimilation simulations.
Atmospheric inversions further allow for an assessment of the budget components with a regional breakdown of land and ocean sinks.

### 3.1 Fossil CO$_2$ Emissions

#### 3.1.1 Historical period 1850-2022

Cumulative fossil CO$_2$ emissions for 1850-2022 were 477 ± 25 GtC, including the cement carbonation sink (Figure 3, Table 8, with all cumulative numbers rounded to the nearest 5GtC). In this period, 46% of global fossil CO$_2$ emissions came from coal, 35% from oil, 15% from natural gas, 3% from decomposition of carbonates, and 1% from flaring. In 1850, the UK stood for 62% of global fossil CO$_2$ emissions. In 1891 the combined cumulative emissions of the current members of the European Union reached and subsequently surpassed the level of the UK. Since 1917 US cumulative emissions have been the largest. Over the entire period 1850-2022, US cumulative emissions amounted to 115GtC (24% of world total), the EU27’s to 80 GtC (17%), China’s to 70 GtC (15%), and India’s to 15 GtC (3%).

In addition to the estimates of fossil CO$_2$ emissions that we provide here (see Methods), there are three global datasets with long time series that include all sources of fossil CO$_2$ emissions: CDIAC-FF (Gilfillan and Marland, 2021), CEDS version v_2021_04_21 (Hoesly et al., 2018; O’Rourke et al., 2021) and PRIMAP-hist version 2.4.2 (Gütschow et al., 2016; Gütschow and Pflüger, 2023), although these datasets are not entirely independent from each other (Andrew, 2020a). CDIAC-FF has the lowest cumulative emissions over 1750-2018 at 440 GtC, GCP has 444 GtC, CEDS 445 GtC, PRIMAP-hist TP 453 GtC, and PRIMAP-hist CR 452 GtC. CDIAC-FF excludes emissions from lime production. CEDS has higher emissions from international shipping in recent years, while PRIMAP-hist has higher fugitive emissions than the other datasets. However, in general these four datasets are in relative agreement as to total historical global emissions of fossil CO$_2$.

#### 3.1.2 Recent period 1960-2022

Global fossil CO$_2$ emissions, $E_{FOS}$ (including the cement carbonation sink), have increased every decade from an average of $3.0 \pm 0.2$ GtC yr$^{-1}$ for the decade of the 1960s to an average of $9.6 \pm 0.5$ GtC yr$^{-1}$ during 2013-2022 (Table 7, Figure 2 and Figure 5). The growth rate in these emissions decreased between the 1960s and the 1990s, from 4.3% yr$^{-1}$ in the 1960s (1960-1969), 3.2% yr$^{-1}$ in the 1970s (1970-1979), 1.6% yr$^{-1}$ in the 1980s (1980-1989), to 1.0% yr$^{-1}$ in the 1990s (1990-1999). After this period, the growth rate began increasing again in the 2000s at an average growth rate of 2.8% yr$^{-1}$, decreasing to 0.5% yr$^{-1}$ for the last decade (2013-2022). China’s emissions increased by +1.6% yr$^{-1}$ on average over the last 10 years dominating the global trend, and India’s emissions increased by +3.5% yr$^{-1}$, while emissions decreased in EU27 by −1.7% yr$^{-1}$, and in the USA by −1.0% yr$^{-1}$. Figure 6 illustrates the spatial distribution of fossil fuel emissions for the 2013-2022 period.

$E_{FOS}$ reported here includes the uptake of CO$_2$ by cement via carbonation which has increased with increasing stocks of cement products, from an average of 18 MtC yr$^{-1}$ (0.018 GtC yr$^{-1}$) in the 1960s to an average of 197 MtC yr$^{-1}$ (0.197 GtC yr$^{-1}$) during 2013-2022 (Figure 5).
3.1.3 Final year 2022

Global fossil CO$_2$ emissions were slightly higher, 0.92%, in 2022 than in 2021, with an increase of less than 0.1 GtC to reach 9.9 ± 0.5 GtC (including the 0.2 GtC cement carbonation sink) in 2022 (Figure 5), distributed among coal (42%), oil (32%), natural gas (21%), cement (4%), flaring (1%), and others (<1%). Compared to the previous year, 2022 emissions from coal and oil increased by 1.6% and 3.2% respectively, while emissions from gas and cement respectively decreased by 2.2% and 5.1%. All growth rates presented are adjusted for the leap year, unless stated otherwise.

In 2022, the largest absolute contributions to global fossil CO$_2$ emissions were from China (31%), the USA (14%), India (8%), and the EU27 (7%). These four regions account for 59% of global fossil CO$_2$ emissions, while the rest of the world contributed 41%, including international aviation and marine bunker fuels (2.6% of the total). Growth rates for these countries from 2021 to 2022 were 0.5% (China), 0.5% (USA), -1.6% (EU27), and 5.8% (India), with +0.9% for the rest of the world. The per-capita fossil CO$_2$ emissions in 2022 were 1.3 tC person$^{-1}$ yr$^{-1}$ for the globe, and were 4.1 (USA), 2.2 (China), 1.7 (EU27) and 0.5 (India) tC person$^{-1}$ yr$^{-1}$ for the four highest emitters (Figure 5).

3.1.4 Year 2023 Projection

Globally, we estimate that global fossil CO$_2$ emissions (including cement carbonation) will grow by 1.1% in 2023 (0.1% to 2.2%) to 10.1 GtC (36.8 GtCO$_2$), exceeding the pre-COVID19 2019 emission levels of 9.9 GtC (36.3 GtCO$_2$). Global increase in 2023 emissions per fuel types are projected to be +1.3% (range 0.0% to 2.6%) for coal, +1.5% (range 0.5% to 2.5%) for oil, +0.2% (range -0.6% to 1.1%) for natural gas, and 1.4% (range -0.3% to 3.0%) for cement.

For China, projected fossil emissions in 2023 are expected to increase by 4% (range 1.9% to 6.2%) compared with 2022 emissions, bringing 2023 emissions for China around 3.2 GtC yr$^{-1}$ (11.9 GtCO$_2$ yr$^{-1}$). Changes in fuel specific projections for China are 3.5% for coal, 7.7% for oil, 6.4% natural gas, and 0.2% for cement.

For the USA, the Energy Information Administration (EIA) emissions projection for 2023 combined with cement clinker data from USGS gives an decrease of 3.0% (range -5.0% to -1.0%) compared to 2022, bringing USA 2023 emissions to around 1.3 GtC yr$^{-1}$ (4.9 GtCO$_2$ yr$^{-1}$). This is based on separate projections for coal -18.3%, oil -0.3%, natural gas +1.4%, and cement -4.0%.

For the European Union, our projection for 2023 is for a decrease of 7.4% (range -9.9% to -4.9%) over 2022, with 2023 emissions around 0.7 GtC yr$^{-1}$ (2.6 GtCO$_2$ yr$^{-1}$). This is based on separate projections for coal of -18.8%, oil -1.5%, natural gas -6.6%, and cement -8.7%.

For India, our projection for 2023 is an increase of 8.7% (range of 7.2% to 10.2%) over 2022, with 2023 emissions around 0.8 GtC yr$^{-1}$ (3.1 GtCO$_2$ yr$^{-1}$). This is based on separate projections for coal of +10.1%, oil +5.3%, natural gas +5.6%, and cement +8.8%.
For the rest of the world, the expected growth rate for 2023 is 0.5% (range -1.2% to 2.2%) with 2023 emissions around 4.2 GtC yr\(^{-1}\) (15.2 GtCO\(_2\) yr\(^{-1}\)). The fuel-specific projected 2023 growth rates for the rest of the world are: +0.8% for coal, +0.8% for oil, -0.4% for natural gas, +2.4% for cement.

### 3.2 Emissions from Land Use Changes

#### 3.2.1 Historical period 1850-2022

Cumulative CO\(_2\) emissions from land-use changes (E\(_{\text{LUC}}\)) for 1850-2022 were 220 ± 65 GtC (Table 8; Figure 3; Figure 15). The cumulative emissions from E\(_{\text{LUC}}\) show a large spread among individual estimates of 150 GtC (H\&C2023), 290 GtC (BLUE), and 215 GtC (OSCAR) for the three bookkeeping models and a similar wide estimate of 210 ± 65 GtC for the DGVMs (all cumulative numbers are rounded to the nearest 5 GtC). These estimates are broadly consistent with indirect constraints from vegetation biomass observations, giving cumulative emissions of 155 ± 50 GtC over the 1901-2012 period (Li et al., 2017). However, given the large spread, a best estimate is difficult to ascertain.

#### 3.2.2 Recent period 1960-2022

In contrast to growing fossil emissions, CO\(_2\) emissions from land-use, land-use change, and forestry remained relatively constant over the 1960-1999 period. Since then, they have shown a slight decrease of about 0.1 GtC per decade, reaching 1.3 ± 0.7 GtC yr\(^{-1}\) for the 2013-2022 period (Table 7), but with large spread across estimates (Table 5, Figure 7). Different from the bookkeeping average, the DGVMs average grows slightly larger over the 1970-2022 period and shows no sign of decreasing emissions in the recent decades (Table 5, Figure 7). This is, however, expected as DGVM-based estimates include the loss of additional sink capacity, which grows with time, while the bookkeeping estimates do not (Supplement S.6.4).

We separate net E\(_{\text{LUC}}\) into five component fluxes to gain further insight into the drivers of net emissions:

- deforestation, forest (re-)growth, wood harvest and other forest management, peat drainage and peat fires, and
- all other transitions (Figure 7c; Sec. C.2.1). We further decompose the deforestation and the forest (re-)growth term into contributions from shifting cultivation vs permanent forest cover changes (Figure 7d). Averaged over the 2013-2022 period and over the three bookkeeping estimates, fluxes from deforestation amount to 1.9 [1.5 to 2.4] GtC yr\(^{-1}\) (Table 5), of which 1.1 [1.0, 1.2] GtC yr\(^{-1}\) are from permanent deforestation. Fluxes from forest (re-)growth amount to -1.3 [-1.5, -0.9] GtC yr\(^{-1}\) (Table 5), of which -0.5 [-0.8 to -0.2] GtC yr\(^{-1}\) are from re/afforestation and the remainder from forest regrowth in shifting cultivation cycles. Emissions from wood harvest and other forest management (0.2 [0.0, 0.6] GtC yr\(^{-1}\), peat drainage and peat fires (0.3 [0.3, 0.3] GtC yr\(^{-1}\)) and the net flux from other transitions (0.1 [0.0, 0.3] GtC yr\(^{-1}\)) are substantially less important globally (Table 5). However, the small net flux from wood harvest and other forest management contains substantial gross fluxes that largely compensate each other (see Figure S7): 1.3 [0.9, 2.0] GtC yr\(^{-1}\) emissions result from the decomposition of slash and the decay of wood products and -1.1 [-1.3, -0.8] GtC yr\(^{-1}\) removals result from regrowth after wood harvesting. This split into component fluxes clarifies the potentials for emission reduction and carbon dioxide removal: the emissions from permanent deforestation - the largest of our component fluxes -
could be halted (largely) without compromising carbon uptake by forests, contributing substantially to emissions reduction. By contrast, reducing wood harvesting would have limited potential to reduce emissions as it would be associated with less forest regrowth; removals and emissions cannot be decoupled here on long timescales. A similar conclusion applies to removals and emissions from shifting cultivation, which we have therefore separated out. Carbon Dioxide Removal (CDR) in forests could instead be increased by permanently increasing the forest cover through re/afforestation. Our estimate of about -0.5 [-0.8, -0.2] GtC yr\(^{-1}\) (of which about two thirds are located in non-Annex-I countries, in particular in China) removed on average each year during 2013-2022 by re/afforestation is very similar to independent estimates that were derived from NGHGiS for 2022.

Re/afforestation constitutes the vast majority of all current CDR (Powis et al., 2023). Though they cannot be compared directly to annual fluxes from the atmosphere, CDR through transfers between non-atmospheric reservoirs such as in durable HWPs, biochar or BECCS comprise much smaller amounts of carbon. 61 MtC yr\(^{-1}\) have been estimated to be transferred to HWPs in 2022, and BECCS projects have been estimated to store 0.5 MtC yr\(^{-1}\) in geological projects worldwide (Powis et al., 2023). “Blue carbon”, i.e. coastal wetland management such as restoration of mangrove forests, saltmarshes and seagrass meadows, though at the interface of land and ocean carbon fluxes, are counted towards the land-use sector as well. Currently, bookkeeping models do not include blue carbon; however, current CDR deployment in coastal wetlands is small globally, less than 0.003 MtC yr\(^{-1}\) (Powis et al., 2023).

The small declining trend of \(E_{\text{LUC}}\) over the last three decades is a result of total deforestation emissions showing no clear trend, while forest regrowth has provided steadily increasing removals. Since the processes behind gross removals, foremost forest regrowth and soil recovery, are all slow, while gross emissions include a large instantaneous component, short-term changes in land-use dynamics, such as a temporary decrease in deforestation, influences gross emissions dynamics more than gross removals dynamics, which rather are a response to longer-term dynamics. Component fluxes often differ more across the three bookkeeping estimates than the net flux, which is expected due to different process representation; in particular, treatment of shifting cultivation, which increases both gross emissions and removals, differs across models, but also net and gross wood harvest fluxes show high uncertainty. By contrast, models agree relatively well for emissions from permanent deforestation emissions and removals by re/afforestation.

Overall, highest land-use emissions occur in the tropical regions of all three continents. The top three emitters (both cumulatively 1959-2022 and on average over 2013-2022) are Brazil (in particular the Amazon Arc of Deforestation), Indonesia and the Democratic Republic of the Congo, with these 3 countries contributing 0.7 GtC yr\(^{-1}\) or 55% of the global net land-use emissions (average over 2013-2022) (Figure 6b). This is related to massive expansion of cropland, particularly in the last few decades in Latin America, Southeast Asia, and sub-Saharan Africa (Hong et al., 2021), to a substantial part for export of agricultural products (Pendrill et al., 2019). Emission intensity is high in many tropical countries, particularly of Southeast Asia, due to high rates of land conversion in regions of carbon-dense and often still pristine, undegraded natural forests (Hong et al., 2021). Emissions are further increased by peat fires in equatorial Asia (GFED4s, van der Werf et al., 2017). Uptake due to land-use change occurs, particularly in Europe, partly related to expanding forest area as a consequence of the
forest transition in the 19th and 20th century and subsequent regrowth of forest (Figure 6b) (Mather 2001; McGrath et al., 2015).

While the mentioned patterns are robust and supported by independent literature, we acknowledge that model spread is substantially larger on regional than global levels, as has been shown for bookkeeping models (Bastos et al., 2021) as well as DGVMs (Obermeier et al., 2021). Assessments for individual regions will be performed as part of REgional Carbon Cycle Assessment and Processes (RECCAP2; Ciais et al., 2020, Poulter et al., 2022) or already exist for selected regions (e.g., for Europe by Petrescu et al., 2020, for Brazil by Rosan et al., 2021, for 8 selected countries/regions in comparison to inventory data by Schwingshackl et al., 2022).

As mentioned before, the NGHGI data under the LULUCF sector or data submitted by countries to FAOSTAT differ from the global models’ definition of $E_{LUC}$. In the NGHGI reporting, the natural fluxes ($S_{LAND}$) are counted towards $E_{LUC}$ when they occur on managed land (Grassi et al., 2018). To compare our results to the NGHGI approach, we perform a translation of our $E_{LUC}$ estimates by subtracting $S_{LAND}$ in managed forest from the DGVMs simulations (following the methodology described in Grassi et al., 2023) from the bookkeeping $E_{LUC}$ estimate (see Supplement S.2.3). For the 2013-2022 period, we estimate that 2.0 GtC yr$^{-1}$ of $S_{LAND}$ occurred in managed forests. Subtracting this value from $E_{LUC}$ changes $E_{LUC}$ from being a source of 1.3 GtC yr$^{-1}$ to a sink of 0.8 GtC yr$^{-1}$, very similar to the NGHGI estimate that yields a sink of 0.7 GtC yr$^{-1}$ (Table 9). The translation approach has been shown to be generally applicable also on country-level (Grassi et al., 2023; Schwingshackl et al., 2022). Country-level analysis suggests, e.g., that the bookkeeping method estimates higher deforestation emissions than the national report in Indonesia, but less CO$_2$ removal by afforestation than the national report in China. The fraction of the natural CO$_2$ sinks that the NGHGI estimates include differs substantially across countries, related to varying proportions of managed vs total forest areas (Schwingshackl et al., 2022). By comparing $E_{LUC}$ and NGHGI on the basis of the component fluxes used above, we find that our estimates reproduce very closely the NGHGI estimates for emissions from permanent deforestation (1.1 GtC yr$^{-1}$ averaged over 2013-2022). Forest fluxes, that is, (re-)growth from re/afforestation plus the net flux from wood harvesting and other forest management, constitute a large sink in the NGHGI (-1.9 GtC yr$^{-1}$ averaged over 2013-2022), since they also include $S_{LAND}$ in managed forests. Summing up the bookkeeping estimates of (re-)growth from re/afforestation and the net flux from wood harvesting and other forest management and adding $S_{LAND}$ in managed forests yields a flux of -2.3 GtC yr$^{-1}$ (averaged over 2013-2022), which compares well with the NGHGI estimate. Emissions from organic soils in NGHGI are similar to the estimates based on the bookkeeping approach and the external peat drainage and burning datasets. The net flux from other transitions is small in both NGHGI and bookkeeping estimates, but a difference in sign (small source in bookkeeping estimates, small sink in NGHGI) creates a notable difference between NGHGI and bookkeeping estimates. Though estimates between NGHGI, FAOSTAT and the translated budget estimates still differ in value and need further analysis, the approach suggested by Grassi et al. (2023), which we adopt here, provides a feasible way to relate the global models’ and NGHGI approach to each other and thus link the anthropogenic carbon budget estimates of land CO$_2$ fluxes directly to the Global Stocktake, as part of UNFCCC Paris Agreement.
3.2.3 Final year 2022

The global CO\textsubscript{2} emissions from land-use change are estimated as 1.2 ± 0.7 GtC in 2022, similar to the 2020 and 2021 estimates. However, confidence in the annual change remains low. Effects of the COVID-19 pandemic on land-use change have turned out to be country-specific as global market mechanisms, national economics and changes in household income all could act to curb or enhance deforestation (Wunder et al., 2021). Concerns about enhanced deforestation due to weakened environmental protection and monitoring in tropical countries (Brancalion et al., 2020, Vale et al., 2021) have been confirmed only for some countries (Cespedes et al., 2023). For example, a recent study suggests slightly increased deforestation rates for the Democratic Republic of Congo linked in particular to post-pandemic economic recovery in the mining sector, while deforestation trends in Brazil seem to have been unaffected. Land use dynamics may be further altered by the Russian invasion of Ukraine, but scientific evidence related to international dependencies (like a shift to tropical palm oil to alleviate dependencies on sunflower oil) so far is very limited and recent changes will not be reflected by the land-use forcing applied in the global models. High food prices, which preceded but were exacerbated by the war (FAO, 2022), are generally linked to higher deforestation (Angelsen and Kaimowitz, 1999). A new wave of cropland abandonment in the conflict region may increase the substantial Eastern European carbon sink due to land-use changes, but sanctions being placed on trade may also incentivise domestic agricultural production, thus leading to recultivation of abandoned areas in Russia (Winkler et al., 2023).

3.2.4 Year 2023 Projection

In Indonesia, peat fire emissions are below average (12 Tg C through September 29 2023) despite El Niño conditions, which in general lead to more fires. Tropical deforestation and degradation fires in Indonesia are around average (13 Tg C through September 29 2023), but higher than in the previous year, which had a relatively wet dry season (GFED4.1s, van der Werf et al., 2017; see also https://www.geo.vu.nl/~gwerf/GFED/GFED4/tables/GFED4.1s_C.txt). In South America, emissions from tropical deforestation and degradation fires are among the lowest over the last decades (64 Tg C through September 29 2023). Effects of the El Niño in the Amazon, such as droughts, are not expected before 2024. Disentangling the degree to which interannual variability in rainfall patterns and stronger environmental protection measures in both Indonesia after their 2015 high fire season and in Brazil after the change in government in Brazil play a role in this is an important research topic. Cumulative fire emission estimates through September 29 2023 are 155 Tg C for global deforestation and degradation fires and 12 Tg C for peatland fires in Indonesia (https://www.geo.vu.nl/~gwerf/GFED/GFED4/tables/GFED4.1s_C.txt).

Based on these estimates, we expect E\textsubscript{LUC} emissions of around 1.1 GtC (4.1 GtCO\textsubscript{2}) in 2023. Our preliminary estimate of E\textsubscript{LUC} for 2023 is substantially lower than the 2013-2022 average, which saw years of anomalously dry conditions in Indonesia and high deforestation fires in South America (Friedlingstein et al., 2022b). Note that although our extrapolation includes tropical deforestation and degradation fires, degradation attributable to selective logging, edge-effects or fragmentation is not captured. Further, deforestation and fires in deforestation zones may become more disconnected, partly due to changes in legislation in some regions. For example, Van
Wees et al. (2021) found that the contribution from fires to forest loss decreased in the Amazon and in Indonesia over the period of 2003-2018.

3.3 CDR not based on vegetation

Besides the CDR through land-use (Sec. 3.2), the atmosphere to geosphere flux of carbon resulting from carbon dioxide removal (CDR) activity is currently 0.003 MtC/yr, with 0.002 MtC/yr of DACCS and 0.001 MtC/yr of enhanced weathering projects. This is more than a million times smaller than current fossil CO₂ emissions.

3.4 Total anthropogenic emissions

Cumulative anthropogenic CO₂ emissions for 1850-2022 totalled 695 ± 70 GtC (2550 ± 260 GtCO₂), of which 70% (485 GtC) occurred since 1960 and 33% (235 GtC) since 2000 (Table 7 and 8). Total anthropogenic emissions more than doubled over the last 60 years, from 4.6 ± 0.7 GtC yr⁻¹ for the decade of the 1960s to an average of 10.9 ± 0.8 GtC yr⁻¹ during 2013-2022 and reaching 11.1 ± 0.9 GtC (40.7 ± 3.3 GtCO₂) in 2022. For 2023, we project global total anthropogenic CO₂ emissions from fossil and land use changes to be also around 11.2 GtC (40.9 GtCO₂). All values here include the cement carbonation sink (currently about 0.2 GtC yr⁻¹).

During the historical period 1850-2022, 31% of historical emissions were from land use change and 69% from fossil emissions. However, fossil emissions have grown significantly since 1960 while land use changes have not, and consequently the contributions of land use change to total anthropogenic emissions were smaller during recent periods (18% during the period 1960-2022 and down to 12% over the 2013-2022 period).

3.5 Atmospheric CO₂

3.5.1 Historical period 1850-2022

Atmospheric CO₂ concentration was approximately 278 parts per million (ppm) in 1750, reaching 300 ppm in the 1910s, 350 ppm in the late 1980s, and reaching 417.07 ± 0.1 ppm in 2022 (Lan et al., 2023; Figure 1). The mass of carbon in the atmosphere increased by 48% from 590 GtC in 1750 to 886 GtC in 2022. Current CO₂ concentrations in the atmosphere are unprecedented in the last 2 million years and the current rate of atmospheric CO₂ increase is at least 10 times faster than at any other time during the last 800,000 years (Canadell et al., 2021).

3.5.2 Recent period 1960-2022

The growth rate in atmospheric CO₂ level increased from 1.7 ± 0.07 GtC yr⁻¹ in the 1960s to 5.2 ± 0.02 GtC yr⁻¹ during 2013-2022 with important decadal variations (Table 7, Figure 3 and Figure 4). During the last decade (2013-2022), the growth rate in atmospheric CO₂ concentration continued to increase, albeit with large interannual variability (Figure 4).
The airborne fraction (AF), defined as the ratio of atmospheric CO₂ growth rate to total anthropogenic emissions:

\[ AF = \frac{G_{\text{ATM}}}{(E_{\text{FOS}} + E_{\text{LUC}})} \]  

(2)

provides a diagnostic of the relative strength of the land and ocean carbon sinks in removing part of the anthropogenic CO₂ perturbation. The evolution of AF over the last 60 years shows no significant trend, remaining at around 44%, albeit showing a large interannual and decadal variability driven by the year-to-year variability in \( G_{\text{ATM}} \) (Figure 9). The observed stability of the airborne fraction over the 1960-2020 period indicates that the ocean and land CO₂ sinks have been removing on average about 56% of the anthropogenic emissions (see Sections 3.6.2 and 3.7.2).

### 3.5.3 Final year 2022

The growth rate in atmospheric CO₂ concentration was 4.6 ± 0.2 GtC (2.18 ± 0.08 ppm) in 2022 (Figure 4; Lan et al., 2023), below the 2021 growth rate (5.2 ± 0.2 GtC) or the 2013-2022 average (5.2 ± 0.02 GtC).

### 3.5.4 Year 2023 Projection

The 2023 growth in atmospheric CO₂ concentration (\( G_{\text{ATM}} \)) is projected to be about 5.1 GtC (2.4 ppm). This is the average of the GCB regression method (5.07 GtC, 2.39 ppm) and ESMs the multi-model mean (5.11 GtC, 2.41 ppm). The 2023 atmospheric CO₂ concentration, averaged over the year, is expected to reach the level of 419.3 ppm, 51% over the pre-industrial level.

### 3.6 Ocean Sink

#### 3.6.1 Historical period 1850-2022

Cumulated since 1850, the ocean sink adds up to 180 ± 35 GtC, with more than two thirds of this amount (125 GtC) being taken up by the global ocean since 1960. Over the historical period, the ocean sink increased in pace with the anthropogenic emissions exponential increase (Figure 3). Since 1850, the ocean has removed 26% of total anthropogenic emissions.

#### 3.6.2 Recent period 1960-2022

The ocean CO₂ sink increased from 1.1 ± 0.4 GtC yr⁻¹ in the 1960s to 2.8 ± 0.4 GtC yr⁻¹ during 2013-2022 (Table 7), with interannual variations of the order of a few tenths of GtC yr⁻¹ (Figure 10). The ocean-borne fraction (\( S_{\text{OCEAN}} (E_{\text{FOS}} + E_{\text{LUC}}) \)) has been remarkably constant around 25% on average (Figure 9c), with variations around this mean illustrating the decadal variability of the ocean carbon sink. So far, there is no indication of a decrease in the ocean-borne fraction from 1960 to 2022. The increase of the ocean sink is primarily driven by the increased atmospheric CO₂ concentration, with the strongest CO₂ induced signal in the North Atlantic and the Southern Ocean (Figure 11a). The effect of climate change is much weaker, reducing the ocean sink globally.
by 0.16 ± 0.04 GtC yr⁻¹ (-6.7% of \(S_{\text{OCEAN}}\)) during 2013-2022 (all models simulate a weakening of the ocean sink by climate change, range -4.3 to -10.3%), and does not show clear spatial patterns across the GOBMs ensemble (Figure 11b). This is the combined effect of change and variability in all atmospheric forcing fields, previously attributed, in one model, to wind and temperature changes (LeQuéré et al., 2010).

The global net air-sea CO₂ flux is a residual of large natural and anthropogenic CO₂ fluxes into and out of the ocean with distinct regional and seasonal variations (Figure 6 and B1). Natural fluxes dominate on regional scales, but largely cancel out when integrated globally (Gruber et al., 2009). Mid-latitudes in all basins and the high-latitude North Atlantic dominate the ocean CO₂ uptake where low temperatures and high wind speeds facilitate CO₂ uptake at the surface (Takahashi et al., 2009). In these regions, formation of mode, intermediate and deep-water masses transport anthropogenic carbon into the ocean interior, thus allowing for continued CO₂ uptake at the surface. Outgassing of natural CO₂ occurs mostly in the tropics, especially in the equatorial upwelling region, and to a lesser extent in the North Pacific and polar Southern Ocean, mirroring a well-established understanding of regional patterns of air-sea CO₂ exchange (e.g., Takahashi et al., 2009, Gruber et al., 2009). These patterns are also noticeable in the Surface Ocean CO2 Atlas (SOCAT) dataset, where an ocean \(f\text{CO}_2\) value above the atmospheric level indicates outgassing (Figure S1). This map further illustrates the data-sparcity in the Indian Ocean and the southern hemisphere in general.

Interannual variability of the ocean carbon sink is driven by climate variability with a first-order effect from a stronger ocean sink during large El Niño events (e.g., 1997-1998) (Figure 10; Rödenbeck et al., 2014, Hauck et al., 2020; McKinley et al. 2017). The GOBMs show the same patterns of decadal variability as the mean of the \(f\text{CO}_2\)-products, with a stagnation of the ocean sink in the 1990s and a strengthening since the early 2000s (Figure 10; Le Quéré et al., 2007; Landschützer et al., 2015, 2016; DeVries et al., 2017; Hauck et al., 2020; McKinley et al., 2020, Gruber et al., 2023). Different explanations have been proposed for this decadal variability, ranging from the ocean’s response to changes in atmospheric wind and pressure systems (e.g., Le Quéré et al., 2007, Keppler and Landschützer, 2019), including variations in upper ocean overturning circulation (DeVries et al., 2017) to the eruption of Mount Pinatubo and its effects on sea surface temperature and slowed atmospheric CO₂ growth rate in the 1990s (McKinley et al., 2020). The main origin of the decadal variability is a matter of debate with a number of studies initially pointing to the Southern Ocean (see review in Canadell et al., 2021), but also contributions from the North Atlantic and North Pacific (Landschützer et al., 2016, DeVries et al., 2019), or a global signal (McKinley et al., 2020) were proposed.

Although all individual GOBMs and \(f\text{CO}_2\)-products fall within the observational constraint, the ensemble means of GOBMs, and \(f\text{CO}_2\)-products adjusted for the riverine flux diverge over time with a mean offset increasing from 0.30 GtC yr⁻¹ in the 1990s to 0.57 GtC yr⁻¹ in the decade 2013-2022 and reaching 0.61 GtC yr⁻¹ in 2022. The \(S_{\text{OCEAN}}\) positive trend over time diverges by a factor two since 2002 (GOBMs: 0.24 ± 0.07 GtC yr⁻¹ per decade, \(f\text{CO}_2\)-products: 0.48 ± 0.11 GtC yr⁻¹ per decade, \(S_{\text{OCEAN}}\): 0.36 GtC yr⁻¹ per decade) and by a factor of 2.5 since 2010 (GOBMs: 0.16 ± 0.15 GtC yr⁻¹ per decade, \(f\text{CO}_2\)-products: 0.42 ± 0.18 GtC yr⁻¹ per decade, \(S_{\text{OCEAN}}\): 0.29 GtC yr⁻¹ per decade). The \(f\text{CO}_2\)-product estimate is slightly different compared to Friedlingstein et al.
(2022b) as a result of an updated submission of the NIES-ML3 product (previously NIES-NN), however the difference in the integrated mean flux is small.

The discrepancy between the two types of estimates stems from a larger $S_{\text{OCEAN}}$ trend in the northern and southern extra-tropics since around 2002 (Figure 13). Note that the discrepancy in the mean flux, which was located in the Southern Ocean in previous versions of the GCB, has been reduced due to the choice of the regional river flux adjustment (Lacroix et al., 2020 instead of Aumont et al., 2001). This comes at the expense of a new discrepancy in the mean $S_{\text{OCEAN}}$ of about 0.2 GtC yr$^{-1}$ in the tropics. Likely explanations for the discrepancy in the trends in the high-latitudes are data sparsity and uneven data distribution (Bushinsky et al., 2019, Gloege et al., 2021, Hauck et al., 2023). In particular, two $\text{fCO}_2$-products that are part of the GCB ensemble were shown to overestimate the Southern Ocean $\text{CO}_2$ flux trend by 50 and 130% based on current sampling in a model subsampling experiment (Hauck et al., 2023). Another likely contributor to the discrepancy between GOBMs and $\text{fCO}_2$-products are model biases (as indicated by the large model spread in the South, Figure 13, and the larger model-data $\text{fCO}_2$ mismatch, Figure S2).

In previous GCB releases, the ocean sink 1959-1989 was only estimated by GOBMs due to the absence of $\text{fCO}_2$ observations. Now, the first data-based estimates extending back to 1957/58 are becoming available (Jena-MLS, Rödenbeck et al., 2022, LDEO-HPD, Bennington et al., 2022; Gloege et al., 2022). These are based on a multilinear regression of $p\text{CO}_2$ with environmental predictors (Rödenbeck et al., 2022) or on model-data $p\text{CO}_2$ misfits and their relation to environmental predictors (Bennington et al., 2022). The Jena-MLS and LDEO-HPD estimates fall well within the range of GOBM estimates and have a correlation of 0.99 and 0.98 respectively with $S_{\text{OCEAN}}$ for the period 1959-2022 (and 0.98 and 0.97 for the 1959-1989 period). They agree well on the mean $S_{\text{OCEAN}}$ estimate since 1977 with a slightly higher amplitude of variability (Figure 10). Until 1976, Jena-MLS and LDEO-HPD are respectively about 0.25 GtC yr$^{-1}$ and about 0.1 GtC yr$^{-1}$ below the central $S_{\text{OCEAN}}$ estimate. The agreement especially on phasing of variability is impressive in both products, and the discrepancies in the mean flux 1959-1976 could be explained by an overestimated trend of Jena-MLS (Rödenbeck et al., 2022). Bennington et al. (2022) report a larger flux into the pre-1990 ocean than in Jena-MLS, although lower than $S_{\text{OCEAN}}$.

The reported $S_{\text{OCEAN}}$ estimate from GOBMs and $\text{fCO}_2$-products is $2.2 \pm 0.4$ GtC yr$^{-1}$ over the period 1994 to 2007, which is in excellent agreement with the ocean interior estimate of $2.2 \pm 0.4$ GtC yr$^{-1}$, which accounts for the climate effect on the natural $\text{CO}_2$ flux of $\text{flux of } -0.4 \pm 0.24$ GtC yr$^{-1}$ (Gruber et al., 2019) to match the definition of $S_{\text{OCEAN}}$ used here (Hauck et al., 2020). This comparison depends critically on the estimate of the climate effect on the natural $\text{CO}_2$ flux, which is smaller from the GOBMs (-0.1 GtC yr$^{-1}$) than in Gruber et al. (2019). Uncertainties of these two estimates would also overlap when using the GOBM estimate of the climate effect on the natural $\text{CO}_2$ flux.

During 2010-2016, the ocean $\text{CO}_2$ sink appears to have intensified in line with the expected increase from atmospheric $\text{CO}_2$ (McKinley et al., 2020). This effect is slightly stronger in the $\text{fCO}_2$-products (Figure 10, ocean sink 2016 minus 2010, GOBMs: $+0.42 \pm 0.10$ GtC yr$^{-1}$, $\text{fCO}_2$-products: $+0.48 \pm 0.10$ GtC yr$^{-1}$). The reduction of
-0.14 GtC yr\(^{-1}\) (range: -0.39 to +0.01 GtC yr\(^{-1}\)) in the ocean CO\(_2\) sink in 2017 is consistent with the return to normal conditions after the El Niño in 2015/16, which caused an enhanced sink in previous years. After an increasing \(S_{\text{OCEAN}}\) in 2018 and 2019, 2017, the GOBM and /CO\(_2\)-product ensemble means suggest a decrease of \(S_{\text{OCEAN}}\), related to the triple La Niña event 2020-2023.

### 3.6.3 Final year 2022

The estimated ocean CO\(_2\) sink is 2.8 ± 0.4 GtC for 2022. This is a small decrease of 0.05 GtC compared to 2021, in line with the expected sink weakening from persistent La Niña conditions. GOBM and /CO\(_2\)-product estimates consistently result in a near-stagnation of \(S_{\text{OCEAN}}\) (GOBMs: -0.01 ±0.05 GtC, /CO\(_2\)-products: -0.09 ±0.10 GtC). Four models and six /CO\(_2\)-products show a decrease in \(S_{\text{OCEAN}}\) (GOBMs down to -0.09 GtC, /CO\(_2\)-products down to -0.25 GtC), while one model shows no change and five models and two /CO\(_2\)-products show an increase in \(S_{\text{OCEAN}}\) (GOBMs up to 0.07 GtC, /CO\(_2\)-products up to 0.15 GtC; Figure 10). The /CO\(_2\)-products have a larger uncertainty at the end of the reconstructed time series (tail effect, e.g., Watson et al., 2020).

Specifically, the /CO\(_2\)-products’ estimate of the last year is regularly adjusted in the following release owing to the tail effect and an incrementally increasing data availability. While the monthly grid cells covered may have a lag of only about a year (Figure 10 inset), the values within grid cells may change with 1-5 years lag (see absolute number of observations plotted in previous GCB releases).

### 3.6.4 Year 2023 Projection

Using a feed-forward neural network method (see Section 2.5.2) we project an ocean sink of 2.9 GtC for 2023. This is slightly higher than for the year 2022 (2.8 GtC) and could mark a reversal of the slight decrease of \(S_{\text{OCEAN}}\) sink since 2019, due to the transition from persisting La Niña conditions to emerging El Niño conditions in 2023. The new set of ESMs predictions support this estimate with a 2023 ocean sink of around 3.1 [2.9, 3.2] GtC.

### 3.6.5 Ocean Models Evaluation

The process-based model evaluation draws a generally positive picture with GOBMs scattered around the observational values for Southern Ocean sea-surface salinity, Southern Ocean stratification index and surface ocean Revelle factor (Section C3.3 and Table S10). However, the Atlantic Meridional Overturning Circulation at 26°N is underestimated by 8 out of 10 GOBMs. It is planned to derive skill scores for the GOBMs in future releases based on these metrics.

The model simulations allow to separate the anthropogenic carbon component (steady state and non-steady state, sim D - sim A) and to compare the model flux and DIC inventory change directly to the interior ocean estimate of Gruber et al. (2019) without further assumptions (Table S10). The GOBMs ensemble average of anthropogenic carbon inventory changes 1994-2007 amounts to 2.4 GtC yr\(^{-1}\) and is thus lower than the 2.6 ± 0.3 GtC yr\(^{-1}\) estimated by Gruber et al. (2019) although within the uncertainty. Only four models with the highest sink estimate fall within the range reported by Gruber et al. (2019). This suggests that the majority of the
GOBMs underestimate anthropogenic carbon uptake by 10-20%. Analysis of Earth System Models indicate that an underestimation by about 10% may be due to biases in ocean carbon transport and mixing from the surface mixed layer to the ocean interior (Goris et al., 2018, Terhaar et al., 2021, Bourgeois et al., 2022, Terhaar et al., 2022), biases in the chemical buffer capacity (Revelle factor) of the ocean (Vaittinada Ayar et al., 2022; Terhaar et al., 2022) and partly due to a late starting date of the simulations (mirrored in atmospheric CO\(_2\) chosen for the preindustrial control simulation, Table S2, Bronselaer et al., 2017, Terhaar et al., 2022). Interestingly, and in contrast to the uncertainties in the surface CO\(_2\) flux, we find the largest mismatch in interior ocean carbon accumulation in the tropics (96% of the mismatch), with minor contributions from the north (3%) and the south (<1%). These numbers deviate slightly from GCB2021 because of submission of the ACCESS model with a high anthropogenic carbon accumulation, particularly in the Southern Ocean. The large discrepancy in accumulation in the tropics highlights the role of interior ocean carbon redistribution for those inventories (Khatiwala et al., 2009, DeVries et al., 2023).

The evaluation of the ocean estimates with the \(f\)CO\(_2\) observations from the SOCAT v2023 dataset for the period 1990-2022 shows an RMSE from annually detrended data of 0.4 to 2.4 µatm for the seven \(f\)CO\(_2\)-products over the globe (Figure S2). The GOBMs RMSEs are larger and range from 2.9 to 5.4 µatm. The RMSEs are generally larger at high latitudes compared to the tropics, for both the \(f\)CO\(_2\)-products and the GOBMs. The \(f\)CO\(_2\)-products have RMSEs of 0.3 to 2.8 µatm in the tropics, 0.7 to 2.3 µatm in the north, and 0.7 to 2.8 µatm in the south. Note that the \(f\)CO\(_2\)-products are based on the SOCAT v2023 database, hence the SOCAT is not an independent dataset for the evaluation of the \(f\)CO\(_2\)-products. The GOBMs RMSEs are more spread across regions, ranging from 2.5 to 5.0 µatm in the tropics, 3.0 to 7.2 µatm in the North, and 3.7 to 8.5 µatm in the South. The higher RMSEs occur in regions with stronger climate variability, such as the northern and southern high latitudes (poleward of the subtropical gyres). The upper range of the model RMSEs have increased somewhat relative to Friedlingstein et al. (2022b).

3.7 Land Sink

3.7.1 Historical period 1850-2022

Cumulated since 1850, the terrestrial CO\(_2\) sink amounts to 225 ± 55 GtC, 32% of total anthropogenic emissions. Over the historical period, the sink increased in pace with the anthropogenic emissions exponential increase (Figure 3).

3.7.2 Recent period 1960-2022

The terrestrial CO\(_2\) sink \(S_{\text{LAND}}\) increased from 1.3 ± 0.5 GtC yr\(^{-1}\) in the 1960s to 3.3 ± 0.8 GtC yr\(^{-1}\) during 2013-2022, with important interannual variations of up to 2 GtC yr\(^{-1}\) generally showing a decreased land sink during El Niño events (Figure 8), responsible for the corresponding enhanced growth rate in atmospheric CO\(_2\) concentration. The larger land CO\(_2\) sink during 2013-2022 compared to the 1960s is reproduced by all the DGVMs in response to the increase in both atmospheric CO\(_2\), nitrogen deposition, and the changes in climate, and is consistent with constraints from the other budget terms (Table 5).
Over the period 1960 to present the increase in the global terrestrial CO$_2$ sink is largely attributed to the CO$_2$
fertilisation effect (Prentice et al., 2001, Piao et al., 2009, Schimel et al., 2015) and increased nitrogen
deposition (Huntzinger et al., 2017, O’Sullivan et al., 2019), directly stimulating plant photosynthesis and
increased plant water use in water limited systems, with a small negative contribution of climate change (Figure
11). There is a range of evidence to support a positive terrestrial carbon sink in response to increasing
atmospheric CO$_2$, albeit with uncertain magnitude (Walker et al., 2021). As expected from theory, the greatest
CO$_2$ effect is simulated in the tropical forest regions, associated with warm temperatures and long growing
seasons (Hickler et al., 2008) (Figure 11a). However, evidence from tropical intact forest plots indicate an
overall decline in the land sink across Amazonia (1985-2011), attributed to enhanced mortality offsetting
productivity gains (Brienen et al., 2015, Hubau et al., 2020). During 2013-2022 the land sink is positive in all
regions (Figure 6) with the exception of eastern Brazil, Bolivia, Paraguay, northern Venezuela, Southwest USA,
central Europe and Central Asia, North and South Africa, and eastern Australia, where the negative effects of
climate variability and change (i.e. reduced rainfall and/or increased temperature) counterbalance CO$_2$ effects.
This is clearly visible on Figure 11 where the effects of CO$_2$ (Figure 11a) and climate (Figure 11b) as simulated
by the DGVMs are isolated. The negative effect of climate is the strongest in most of South America, Central
America, Southwest US, Central Europe, western Sahel, southern Africa, Southeast Asia and southern China,
and eastern Australia (Figure 11b). Globally, over the 2013-2022 period, climate change reduces the land sink
by 0.68 ± 0.62 GtC yr$^{-1}$ (20% of S$_{LAND}$).

Most DGVMs have similar S$_{LAND}$ averaged over 2013-2022, and 14/20 models fall within the 1σ range of the
residual land sink [2.0-3.8 GtC yr$^{-1}$] (see Table 5), and all but one model are within the 2σ range [1.1-4.7 GtC yr$^{-1}$]. The ED model is an outlier, with a land sink estimate of 5.7 GtC yr$^{-1}$, driven by a strong CO$_2$ fertilisation
effect (6.6 GtC yr$^{-1}$ in the CO$_2$ only (S1) simulation), that is offset by correspondingly high land-use emissions.
There are no direct global observations of the land sink, or the CO$_2$ fertilisation effect, and so we are not yet in a
position to rule out models based on component fluxes if the net land sink (S$_{LAND}$-E$_{LUC}$) is within the
observational uncertainty provided by atmospheric O$_2$ measurements (Table 5). Overall, therefore the spread
among models for the estimate of S$_{LAND}$ over the last decade has increased this year (0.8 GtC yr$^{-1}$) compared to
GCB2022 (0.6 GtC yr$^{-1}$).

Furthermore, DGVMs were compared against a data-constrained intermediate complexity model of the land
carbon cycle (CARDAMOM) (Bloom and Williams, 2015; Bloom et al., 2016). Results suggest good
correspondence between approaches at the interannual timescales, but divergence in the recent trend with
CARDAMOM simulating a stronger trend than the DGVMs (Figure S8).

Since 2020 the globe has experienced La Niña conditions which would be expected to lead to an increased land
carbon sink. A clear peak in the global land sink is not evident in S$_{LAND}$, and we find that a La Niña- driven
increase in tropical land sink is offset by a reduced high latitude extra-tropical land sink, which may be linked to
the land response to recent climate extremes. A notable difference from GCB2022 (2012-2021 S$_{LAND}$ mean) is
the reduced carbon losses across tropical drylands. Further, central Europe has switched from a sink of carbon to
a source, with the summer heatwave of 2022 (and associated drought and wildfire) causing widespread losses
(Peters et al., 2023). In the past years several regions experienced record-setting fire events. While global burned area has declined over the past decades mostly due to declining fire activity in savannas (Andela et al., 2017), forest fire emissions are rising and have the potential to counter the negative fire trend in savannas (Zheng et al., 2021). Noteworthy events include the 2019-2020 Black Summer event in Australia (emissions of roughly 0.2 GtC; van der Velde et al., 2021) and Siberia in 2021 where emissions approached 0.4 GtC or three times the 1997-2020 average according to GFED4s. While other regions, including Western US and Mediterranean Europe, also experienced intense fire seasons in 2021 their emissions are substantially lower.

Despite these regional negative effects of climate change on $S_{\text{LAND}}$, the efficiency of land to remove anthropogenic CO$_2$ emissions has remained broadly constant over the last six decades, with a land-borne fraction ($S_{\text{LAND}}/(E_{\text{FOS}}+E_{\text{LUC}}))$ of around 30% (Figure 9b).

### 3.7.3 Final year 2022

The terrestrial CO$_2$ sink from the DGVMs ensemble was $3.8 \pm 0.8$ GtC in 2022, above the decadal average of $3.3 \pm 0.8$ GtC yr$^{-1}$ (Figure 4, Table 7), and slightly above the 2021 sink of $3.5 \pm 1.0$ GtC, likely driven by the persistent La Niña conditions. We note that the DGVMs estimate for 2022 is similar to the $3.7 \pm 1.0$ GtC yr$^{-1}$ estimate from the residual sink from the global budget ($E_{\text{FOS}}+E_{\text{LUC}}-G_{\text{ATM}}-S_{\text{OCEAN}}$) (Table 5).

### 3.7.4 Year 2023 Projection

Using a feed-forward neural network method we project a land sink of 2.9 GtC for 2023, 0.9 GtC smaller than the 2022 estimate. As for the ocean sink, we attribute this to the emerging El Niño conditions in 2023, leading to a reduced land sink. The ESMs do not provide an additional estimate of $S_{\text{LAND}}$ as they only simulate the net atmosphere-land carbon flux ($S_{\text{LAND}}-E_{\text{LUC}}$).

### 3.7.5 Land Models Evaluation

The evaluation of the DGVMs shows generally high skill scores across models for runoff, and to a lesser extent for vegetation biomass, GPP, and ecosystem respiration. These conclusions are supported by a more comprehensive analysis of DGVM performance in comparison with benchmark data (Seiler et al., 2022). A relative comparison of DGVM performance (Figure S3) suggests several DGVMs (CABLE-Pop, CLASSIC, OCN, ORCHIDEE) may outperform others at multiple carbon and water cycle benchmarks. However, results from Seiler et al., 2022, also show how DGVM differences are often of similar magnitude compared with the range across observational datasets. All models score high enough over the metrics tests to support their use here. There are a few anomalously low scores for individual metrics from a single model, and these can direct the effort to improve models for use in future budgets.
3.8 Partitioning the carbon sinks

3.8.1 Global sinks and spread of estimates

In the period 2013-2022, the bottom-up view of global net ocean and land carbon sinks provided by the GCB, \( S_{OCEAN} \) for the ocean and \( S_{LAND} - E_{ELUC} \) for the land, agrees closely with the top-down global carbon sinks delivered by the atmospheric inversions. This is shown in Figure 12, which visualises the individual decadal mean atmosphere-land and atmosphere-ocean fluxes from each, along with the constraints on their sum offered by the global fossil CO\(_2\) emissions flux minus the atmospheric growth rate (\( E_{FOS} - G_{ATM} \), 4.5 ± 0.5 Gt C yr\(^{-1}\), Table 7, shown as diagonal line on Figure 12). The GCB estimate for net atmosphere-to-surface flux (\( S_{OCEAN} + S_{LAND} - E_{ELUC} \)) during 2013-2022 is 4.9 ± 1.2 Gt C yr\(^{-1}\) (Table 7), with the difference to the diagonal representing the budget imbalance (\( B_{IM} \)) of 0.4 GtC yr\(^{-1}\) discussed in Section 3.9. By virtue of the inversion methodology, the imbalance of the top-down estimates is < 0.1 GtC yr\(^{-1}\) and thus scatter across the diagonal, inverse models trading land for ocean fluxes in their solution. The independent constraint on the net atmosphere-to-surface flux based on atmospheric O\(_2\) is 4.5 ± 1.0 GtC yr\(^{-1}\) over the 2013-2022 period (orange symbol on Figure 12), while the ESMs estimate for the net atmosphere-to-surface flux over that period is 5.0 [4.2, 5.5] Gt C yr\(^{-1}\), consistent with the GCB estimate (Tables 5 and 6).

The distributions based on the individual models and data products reveal substantial spread but converge near the decadal means quoted in Tables 5 to 7. Sink estimates for \( S_{OCEAN} \) and from inverse systems are mostly non-Gaussian, while the ensemble of DGVMs appears more normally distributed justifying the use of a multi-model mean and standard deviation for their errors in the budget. Noteworthy is that the tails of the distributions provided by the land and ocean bottom-up estimates would not agree with the global constraint provided by the fossil fuel emissions and the observed atmospheric CO\(_2\) growth rate. This illustrates the power of the atmospheric joint constraint from \( G_{ATM} \) and the global CO\(_2\) observation network it derives from.

3.8.1.1 Net atmosphere-to-land fluxes

The GCB net atmosphere-to-land fluxes (\( S_{LAND} - E_{ELUC} \)), calculated as the difference between \( S_{LAND} \) from the DGVMs and \( E_{ELUC} \) from the bookkeeping models, amounts to a 2.1 ± 1.1 GtC yr\(^{-1}\) sink during 2013-2022 (Table 5). Estimates of net atmosphere-to-land fluxes (\( S_{LAND} - E_{ELUC} \)) from the DGVMs alone (1.7 ± 0.6 GtC yr\(^{-1}\), Table 5, green symbol on Figure 12) are slightly lower, within the uncertainty of the GCB estimate and also with the global carbon budget constraint from the ocean sink (\( E_{FOS} - G_{ATM} - S_{OCEAN} \), 1.6 ± 0.6 GtC yr\(^{-1}\); Table 7). For the last decade (2013-2022), the inversions estimate the net atmosphere-to-land uptake to be 1.6 [0.5, 2.3] GtC yr\(^{-1}\), similar to the DGVMs estimates (purple symbol on Figure 12). The ESMs estimate for the net atmosphere-to-land uptake during 2013-2022 is 2.4 [1.8, 3.3] GtC yr\(^{-1}\), consistent with the GCB and DGVMs estimates of \( S_{LAND} - E_{ELUC} \) (Figure 13 top row). The independent constraint based on atmospheric O\(_2\) is significantly lower, 1.2 ± 0.8 GtC yr\(^{-1}\), although its relatively high uncertainty range overlaps with the central estimates from other approaches.
3.8.1.2 Net atmosphere-to-ocean fluxes

For the 2013-2022 period, the GOBMs (2.6 ± 0.4 GtC yr⁻¹) produce a lower estimate for the ocean sink than the /CO₂-products (3.1 [2.6, 3.3] GtC yr⁻¹), which shows up in Figure 12 as separate peaks in the distribution from the GOBMs (dark blue symbols) and from the /CO₂-products (light blue symbols). Atmospheric inversions (3.0 [2.4, 4.1] GtC yr⁻¹) suggest an ocean uptake more in line with the /CO₂-products for the recent decade (Table 7), although the inversions range includes both the GOBMs and /CO₂-products estimates (Figure 13 top row). The ESMs 2.6 [2.2, 3.4] GtC yr⁻¹ suggest a moderate estimate for the ocean carbon sink, comparable to the GOBMs estimate with regard to mean and spread. Conversely, the independent constraint based on atmospheric O₂suggests a larger ocean sink (3.3 ± 0.5 GtC yr⁻¹), more consistent with the /CO₂-products and atmospheric inversions. We caution that the riverine transport of carbon taken up on land and outgassing from the ocean is a substantial (0.65 ± 0.3 GtC yr⁻¹) and uncertain term (Crisp et al., 2022; Gruber et al., 2023; DeVries et al., 2023) that separates the GOBMs, ESMs and oxygen-based estimates on the one hand from the /CO₂-products and atmospheric inversions on the other hand. However, the high ocean sink estimate based on atmospheric oxygen that is not subject to river flux adjustment, provides another line of evidence that most GOBMs and ESMs underestimate the ocean sink.

3.8.2 Regional partitioning

Figure 13 shows the latitudinal partitioning of the global atmosphere-to-ocean (SOCEAN), atmosphere-to-land (SLAND – ELUC), and their sum (SOCEAN + SLAND – ELUC) according to the estimates from GOBMs and ocean /CO₂-products (SOCEAN), DGVMs (SLAND – ELUC), and from atmospheric inversions (SOCEAN and SLAND – ELUC).

3.8.2.1 North

Despite being one of the most densely observed and studied regions of our globe, annual mean carbon sink estimates in the northern extra-tropics (north of 30°N) continue to differ. The atmospheric inversions suggest an atmosphere-to-surface sink (SOCEAN+ SLAND – ELUC) for 2013-2022 of 2.8[1.7 to 3.3] GtC yr⁻¹, which is higher than the process models’ estimate of 2.2 ± 0.4 GtC yr⁻¹ (Figure 13). The GOBMs (1.2 ± 0.2 GtC yr⁻¹), /CO₂-products (1.3[1.2-1.4] GtC yr⁻¹), and inversion systems (1.2[0.7 to 1.4] GtC yr⁻¹) produce consistent estimates of the ocean sink. Thus, the difference mainly arises from the net land flux (SLAND – ELUC) estimate, which is 1.0 ± 0.4 GtC yr⁻¹ in the DGVMs compared to 1.6[0.4 to 2.6] GtC yr⁻¹ in the atmospheric inversions (Figure 13, second row). We note that the range among inversions driven by OCO-2 satellite data is smaller though (1.6 - 2.2 GtC yr⁻¹ N=6), supporting the notion that northern extra-tropics land uptake was larger than suggested by the DGVMs at least in the 2015-2022 period covered by this data product.

Discrepancies in the northern land fluxes conforms with persistent issues surrounding the quantification of the drivers of the global net land CO₂ flux (Armth et al., 2017; Huntzinger et al., 2017; O'Sullivan et al., 2022) and the distribution of atmosphere-to-land fluxes between the tropics and high northern latitudes (Baccini et al., 2017; Schimel et al., 2015; Stephens et al., 2007; Ciais et al., 2019; Gaubert et al., 2019).
In the northern extra-tropics, the process models, inversions, and \( /CO_2 \)-products consistently suggest that most of the variability stems from the land (Figure 13). Inversions generally estimate similar interannual variations (IAV) over land to DGVMs (0.28-0.35 vs 0.8-0.64 GtC yr\(^{-1}\), averaged over 1990-2022), and they have higher IAV in ocean fluxes (0.05-0.10 GtC yr\(^{-1}\)) relative to GOBMs (0.02-0.06 GtC yr\(^{-1}\), Figure S2), and \( /CO_2 \)-products (0.03-0.10 GtC yr\(^{-1}\)).

### 3.8.2.2 Tropics

In the tropics (30°S-30°N), both the atmospheric inversions and process models estimate a net carbon balance \((SOCEAN + SLAND - ELUC)\) that is close to neutral over the past decade. The GOBMs (-0.03 ± 0.24 GtC yr\(^{-1}\)), \( /CO_2 \)-products (0.2 [0.2, 0.3] GtC yr\(^{-1}\)), and inversion systems (-0.3 [-0.1, 0.8] GtC yr\(^{-1}\)) all indicate an approximately neutral tropical ocean flux (see Figure S1 for spatial patterns). DGVMs indicate a net land sink \((SLAND - ELUC)\) of 0.6 ±0.4 GtC yr\(^{-1}\), whereas the inversion systems indicate a net land flux of 0.03 [-0.8, 1.1] GtC yr\(^{-1}\), though with high uncertainty (Figure 13, third row).

The tropical lands are the origin of most of the atmospheric CO\(_2\) interannual variability (Ahlström et al., 2015), consistently among the process models and inversions (Figure 13). The interannual variability in the tropics is similar among the ocean \( /CO_2 \)-products (0.07-0.16 GtC yr\(^{-1}\)) and the GOBMs (0.07-0.16 GtC yr\(^{-1}\), Figure S2), which is the highest ocean sink variability of all regions. The DGVMs and inversions indicate that atmosphere-to-land CO\(_2\) fluxes are more variable than atmosphere-to-ocean CO\(_2\) fluxes in the tropics, with interannual variability of 0.35 to 1.61 and 0.77-0.92 GtC yr\(^{-1}\) for DGVMs and inversions, respectively.

### 3.8.2.3 South

In the southern extra-tropics (south of 30°S), the atmospheric inversions suggest a net atmosphere-to-surface sink \((SOCEAN + SLAND - ELUC)\) for 2013-2022 of 1.5 [1.2, 1.9] GtC yr\(^{-1}\), slightly higher than the process models’ estimate of 1.5 ± 0.4 GtC yr\(^{-1}\) (Figure 13). An approximately neutral net land flux \((SLAND - ELUC)\) for the southern extra-tropics is estimated by both the DGVMs (0.05 ± 0.07 GtC yr\(^{-1}\)) and the inversion systems (sink of 0.02 [-0.2, 0.2] GtC yr\(^{-1}\)). This means nearly all carbon uptake is due to oceanic sinks south of 30°S. The Southern Ocean flux in the \( /CO_2 \)-products (1.6 [1.3, 1.7 GtC yr\(^{-1}\)) and inversion estimates (1.5 [1.3, 1.9 GtC yr\(^{-1}\)) is slightly higher than in the GOBMs (1.4 ± 0.3 GtC yr\(^{-1}\)) (Figure 13, bottom row). This discrepancy in the mean flux is smaller this year than in previous releases due to the change in data set of the regional distribution of the river flux adjustment applied to \( /CO_2 \)-products and inverse systems to isolate the anthropogenic \(SOCEAN\) flux.

The data set used (Lacroix et al., 2020) has less river-induced carbon outgassing in the Southern Ocean than the previously used data set (Aumont et al., 2001). Nevertheless, the time-series of atmospheric inversions and \( /CO_2 \)-products diverge from the GOBMs. A substantial overestimation of the trends in the \( /CO_2 \)-products could be explained by sparse and unevenly distributed observations, especially in wintertime (Figure S1; Hauck et al., 2023; Gloege et al., 2021). Model biases may contribute as well, with biases in mode water formation, stratification, and the chemical buffer capacity known to play a role in Earth System Models (Terhaar et al., 2021, Bourgeois et al., 2022, Terhaar et al., 2022).
The interannual variability in the southern extra-tropics is low because of the dominance of ocean areas with low variability compared to land areas. The split between land (S\textsubscript{LAND}-E\textsubscript{LUC}) and ocean (S\textsubscript{OCEAN}) shows a substantial contribution to variability in the south coming from the land, with no consistency between the DGVMs and the inversions or among inversions. This is expected due to the difficulty of separating exactly the land and oceanic fluxes when viewed from atmospheric observations alone. The S\textsubscript{OCEAN} interannual variability was found to be higher in the fCO\textsubscript{2}-products (0.04-0.18 GtC yr\textsuperscript{-1}) compared to GOBMs (0.03 to 0.06 GtC yr\textsuperscript{-1}) in 1990-2022 (Figure S2). Model subsampling experiments recently illustrated that fCO\textsubscript{2}-products may overestimate decadal variability in the Southern Ocean carbon sink by 30% and the trend since 2000 by 50-130% due to data sparsity, based on one and two fCO\textsubscript{2}-products with strong variability (Gloege et al., 2021; Hauck et al., 2023).

3.8.2.4 RECCAP2 regions

Aligning with the RECCAP-2 initiative (Ciais et al., 2022; Poulter et al., 2022; DeVries et al., 2023), we provide a breakdown of this GCB paper estimate of the E\textsubscript{LUC}, S\textsubscript{LAND}, Net land (S\textsubscript{LAND} - E\textsubscript{LUC}), and S\textsubscript{OCEAN} fluxes over the 10 land, and 5 ocean RECCAP-2 regions, averaged over the period 2013-2022. The DGVMs and inversions suggest a positive net land sink in all regions, except for South America and Africa, where the inversions indicate a small net source of respectively -0.1 [-0.5, 0.3] GtC yr\textsuperscript{-1} and -0.3 [-0.6, -0.1] GtC yr\textsuperscript{-1}, compared to a small sink of 0.1±0.3 GtC yr\textsuperscript{-1} and 0.3±0.2 GtC yr\textsuperscript{-1} for the DGVMs. However, for South America, there is substantial uncertainty in both products (ensembles span zero). For the DGVMs, this is driven by uncertainty in both S\textsubscript{LAND} (0.6±0.5 GtC yr\textsuperscript{-1}) and E\textsubscript{LUC} (0.4±0.2 GtC yr\textsuperscript{-1}). The bookkeeping models also suggest an E\textsubscript{LUC} source of around 0.4 GtC yr\textsuperscript{-1} in South America and Africa, in line with the DGVMs estimates. Bookkeeping models and DGVMs similarly estimate a source of 0.4 GtC yr\textsuperscript{-1} in Southeast Asia, with DGVMs suggesting a near neutral net land sink (0.03±0.12 GtC yr\textsuperscript{-1}). This contrasts with the inversion estimate of a 0.2 [-0.3,0.6] GtC yr\textsuperscript{-1} sink, although the inversions spread is substantial. The inversions suggest the largest net land sinks are located in North America (0.5 [-0.1,0.8] GtC yr\textsuperscript{-1}), Russia (0.7 [0.5,1.1] GtC yr\textsuperscript{-1}), and East Asia (0.3 [0.0,0.9] GtC yr\textsuperscript{-1}). This agrees well with the DGVMs in North America (0.4±0.2 GtC yr\textsuperscript{-1}), which indicate a large natural land sink (S\textsubscript{LAND}) of 0.6±0.2 GtC yr\textsuperscript{-1}, being slightly reduced by land-use related carbon losses (0.2±0.1 GtC yr\textsuperscript{-1}). The DGVMs suggest a smaller net land sink in Russia compared to inversions (0.4±0.2 GtC yr\textsuperscript{-1}), and a similar net sink in East Asia (0.2±0.1 GtC yr\textsuperscript{-1}).

There is generally a higher level of agreement in the estimates of regional S\textsubscript{OCEAN} between the different data streams (GOBMs, fCO\textsubscript{2}-products and atmospheric inversions) on decadal scale, compared to the agreement between the different land flux estimates. All data streams agree that the largest contribution to S\textsubscript{OCEAN} stems from the Southern Ocean due to a combination of high flux density and large surface area, but with important contributions also from the Atlantic (high flux density) and Pacific (large area) basins. In the Southern Ocean, GOBMs suggest a sink of 1.0±0.3 GtC yr\textsuperscript{-1}, in line with the fCO\textsubscript{2}-products (1.1 [0.9,1.2] GtC yr\textsuperscript{-1}) and atmospheric inversions (1.0 [0.8,1.4] GtC yr\textsuperscript{-1}). There is similar agreement in the Pacific Ocean, with GOBMs,
/\(f_{CO_2}\)-products, and atmospheric inversions indicating a sink of 0.5±0.1 GtC yr\(^{-1}\), 0.7 [0.5,0.9] GtC yr\(^{-1}\), and 0.6 [0.2,1.0] GtC yr\(^{-1}\), respectively. However, in the Atlantic Ocean, GOBMs simulate a sink of 0.5±0.1 GtC yr\(^{-1}\), noticeably lower than both the /\(f_{CO_2}\)-products (0.8 [0.7,0.9] GtC yr\(^{-1}\)) and atmospheric inversions (0.8 [0.5,1.2] GtC yr\(^{-1}\)). It is important to note the /\(f_{CO_2}\)-products and atmospheric inversions have a substantial and uncertain river flux adjustment in the Atlantic Ocean (0.3 GtC yr\(^{-1}\)) that also leads to a mean offset between GOBMs and /\(f_{CO_2}\)-products/inversions in the latitude band of the tropics (Figure 13). The Indian Ocean due its smaller size and the Arctic Ocean due to its size and sea-ice cover that prevents air-sea gas-exchange are responsible for smaller but non negligible S\(_{\text{OCEAN}}\) fluxes (Indian Ocean: (0.3 [0.2,0.4] GtC yr\(^{-1}\), 0.3 [0.3,0.4] GtC yr\(^{-1}\), and 0.4 [0.3,0.6] GtC yr\(^{-1}\) for GOBMs, /\(f_{CO_2}\)-products, and atmospheric inversions, respectively, and Arctic Ocean: (0.1 [0.1,0.1] GtC yr\(^{-1}\), 0.2 [0.2,0.2] GtC yr\(^{-1}\), and 0.1 [0.1,0.1] GtC yr\(^{-1}\) for GOBMs, /\(f_{CO_2}\)-products, and atmospheric inversions, respectively). Note that the S\(_{\text{OCEAN}}\) numbers presented here deviate from numbers reported in RECCAP-2 where the net air-sea CO\(_2\) flux is reported (i.e. without river flux adjustment for /\(f_{CO_2}\)-products and inversions, and with river flux adjustment subtracted from GOBMs in most chapters, or comparing unadjusted data sets with discussion of uncertain regional riverine fluxes as major uncertainty, e.g. Sarma et al., 2023, DeVries et al., 2023).

3.8.2.5 Tropical vs northern land uptake

A continuing conundrum is the partitioning of the global atmosphere-land flux between the northern hemisphere land and the tropical land (Stephens et al., 2017; Pan et al., 2011; Gaubert et al., 2019). It is of importance because each region has its own history of land-use change, climate drivers, and impact of increasing atmospheric CO\(_2\) and nitrogen deposition. Quantifying the magnitude of each sink is a prerequisite to understanding how each individual driver impacts the tropical and mid/high-latitude carbon balance.

We define the North-South (N-S) difference as net atmosphere-land flux north of 30°N minus the net atmosphere-land flux south of 30°N. For the inversions, the N-S difference ranges from -0.5 GtC yr\(^{-1}\) to +3.0 GtC yr\(^{-1}\) across this year’s inversion ensemble, but with a clear cluster of solutions driven by the OCO-2 satellite product with a NH land sink of 1.6-2.2 GtC yr\(^{-1}\), along with a tropical land flux of -0.6 to +0.2 GtC yr\(^{-1}\), and a dipole between +1.4 and +2.8 GtC yr\(^{-1}\) for the period 2015-2022. Whether this tighter clustering relative to the surface-observation based inversions is driven by (a) additional information on tropical fluxes delivered by tropical retrievals contained in OCO-2, (b) a tighter constraint on the NH land sink from that same product, or (c) a reduced sensitivity to vertical transport differences between models when using CO\(_2\) column integrals, requires further investigation.

In the ensemble of DGVMs the N-S difference is 0.5 ± 0.6 GtC yr\(^{-1}\), a much narrower range than the one from atmospheric inversions. Five DGVMs have a N-S difference larger than 1.0 GtC yr\(^{-1}\), compared to only two from last year’s ensemble. This is still only 25% of DGVMs, compared to most inversion systems simulating a difference at least this large. The smaller spread across DGVMs than across inversions is to be expected as there is no correlation between Northern and Tropical land sinks in the DGVMs as opposed to the inversions where
the sum of the two regions being well-constrained by atmospheric observations leads to an anti-correlation between these two regions. This atmospheric N-S gradient could be used as an additional way to evaluate tropical and NH uptake in DGVMs, if their fluxes were combined with multiple transport models. Vice versa, the much smaller spread in the N-S difference between the DGVMs could help to scrutinise the inverse systems further. For example, a large northern land sink and a tropical land source in an inversion would suggest a large sensitivity to CO$_2$ fertilisation (the dominant factor driving the land sinks) for Northern ecosystems, which would be not mirrored by tropical ecosystems. Such a combination could be hard to reconcile with the process understanding gained from the DGVM ensembles and independent measurements (e.g. Free Air CO$_2$ Enrichment experiments).

3.8.3 Fire Emissions in 2023

Fire emissions so far in 2023 have been above the average of recent decades, due to an extreme wildfire season in North America. Figure S9 shows global and regional emissions estimates for the period 1st Jan-30th September in each year 2003-2023. Estimates derive from two global fire emissions products: the global fire emissions database (GFED, version 4.1s; van der Werf et al., 2017), and the global fire assimilation system (GFAS, operated by the Copernicus Atmosphere Service; Di Giuseppe et al., 2018). The two products estimate that global emissions from fires were 1.9-2.3 GtC yr$^{-1}$ during January-October 2023. These estimates are 19-33% above the 2013-2022 average for the same months (1.6-1.7 GtC yr$^{-1}$) and 10-28% above the 2003-2022 average (1.8 GtC yr$^{-1}$ in both products).

The above-average global fire emissions during January-October 2023 have occurred despite below-average fire emissions from major source regions. On average during 2013-2022, 75-80% of global fire emissions through October occur in the tropics (1.2-1.4 GtC yr$^{-1}$) and around 41-48% of global fire emissions through October occur in Africa (0.7-0.8 GtC yr$^{-1}$). This year, through October, fire emissions in the tropics were approximately equal to the 2013-2022 average and 7-9% below the 2003-2022 average, while in Africa the fire emissions were approximately equal to the 2013-2022 average and 4-13% below the 2003-2022 average.

In contrast, fire emissions from the Northern extra-tropics so far in 2023 have exceeded the values of all previous years. Northern extra-tropical fire emissions during January-October 2023 (0.7-0.9 GtC yr$^{-1}$) were 84-183% above the average for the same months in 2013-2022 (0.3-0.4 GtC yr$^{-1}$) and 76-190% above the average for the same months in 2003-2022 (0.3-0.4 GtC yr$^{-1}$). Fire emissions in North America alone (0.5-0.8 GtC yr$^{-1}$) were 239-438% above the average of 2013-2022 (0.2 GtC yr$^{-1}$ for both products) and 215-410% above the average for 2003-2022 (0.2 GtC yr$^{-1}$ for both products). Extreme fires in Canada were the largest contributor to the anomaly in 2023, with emissions reaching 0.5-0.8 GtC yr$^{-1}$ or 527-874% above the 2013-2022 average (0.1 Gt C yr$^{-1}$ in both products) and 450-709% above the 2003-2022 average (0.1 Gt C yr$^{-1}$ in both products).

While the fire emission fluxes presented above point towards a highly unusual Northern Hemisphere fire season so far in 2023, we caution that the fluxes presented should not be compared directly with other fluxes of the budget (e.g. $S_{LAND}$ or $E_{LUC}$) due to incompatibilities between the observable fire emission fluxes and what is quantified in the $S_{LAND}$ and $E_{LUC}$ components of the budget. The fire emission estimates from global fire
products relate to all fire types that can be observed in Earth Observations (Giglio et al., 2018; Randerson et al., 2012; Kaiser et al., 2012), including (i) fires occurring as part of natural disturbance-recovery cycles that would also have occurred in the pre-industrial period (Yue et al., 2016; Keeley and Pausas, 2019; Zou et al., 2019), (ii) fires occurring above and beyond natural disturbance-recovery cycle due to changes in climate, CO₂ and N fertilisation and to an increased frequency of extreme drought and heatwave events (Abatzoglou et al., 2019; Jones et al., 2022; Zheng et al., 2021; Burton et al., 2023), and (iii) fires occurring in relation to land use and land use change, such as deforestation fires and agricultural fires (van der Werf et al., 2010; Magi et al., 2012). In the context of the global carbon budget, only the portion of fire emissions associated with (ii) should be included in the S_{LAND} component, and fire emissions associated with (iii) should already be accounted for in the E_{LUC} component. Emissions associated with (i) should not be included in the global carbon budget. It is not currently possible to derive specific estimates for fluxes (i), (ii), and (iii) using global fire emission products such as GFED or GFAS. In addition, the fire emissions estimates from global fire emissions products represent a gross flux of carbon to the atmosphere, whereas the S_{LAND} component of the budget is a net flux that should also include post-fire recovery fluxes. Even if emissions from fires of type (ii) could be separated from those of type (i), these fluxes may be partially or wholly offset in subsequent years by post-fire fluxes as vegetation recovers, sequestering carbon from the atmosphere to the terrestrial biosphere (Yue et al., 2016).

3.9 Closing the Global Carbon Cycle

3.9.1 Partitioning of Cumulative Emissions and Sink Fluxes

The global carbon budget over the historical period (1850-2021) is shown in Figure 3.

Emissions during the period 1850-2022 amounted to 695 ± 70 GtC and were partitioned among the atmosphere (280 ± 5 GtC; 40%), ocean (180 ± 35 GtC; 26%), and land (225 ± 55 GtC; 32%). The cumulative land sink is almost equal to the cumulative land-use emissions (220 ± 70 GtC), making the global land nearly neutral over the whole 1850-2022 period.

The use of nearly independent estimates for the individual terms of the global carbon budget shows a cumulative budget imbalance of 15 GtC (2% of total emissions) during 1850-2022 (Figure 3, Table 8), which, if correct, suggests that emissions could be slightly too high by the same proportion (2%) or that the combined land and ocean sinks are slightly underestimated (by about 3%), although these are well within the uncertainty range of each component of the budget. Nevertheless, part of the imbalance could originate from the estimation of a significant increase in E_{FOS} and E_{LUC} between the mid 1920s and the mid 1960s which is unmatched by a similar growth in atmospheric CO₂ concentration as recorded in ice cores (Figure 3). However, the known loss of additional sink capacity of 30-40 GtC (over the 1850-2020 period) due to reduced forest cover has not been accounted for in our method and would exacerbate the budget imbalance (see Section 2.10 and Supplement S.6.4).

For the more recent 1960-2022 period where direct atmospheric CO₂ measurements are available, total emissions (E_{FOS} + E_{LUC}) amounted to 485 ± 50 GtC, of which 395 ± 20 GtC (82%) were caused by fossil CO₂
emissions, and 90 ± 45 GtC (18%) by land-use change (Table 8). The total emissions were partitioned among
the atmosphere (215 ± 5 GtC; 44%), ocean (125 ± 25 GtC; 25%), and the land (150 ± 35 GtC; 31%), with a near
zero (-5 GtC) unattributed budget imbalance. All components except land-use change emissions have
significantly grown since 1960, with important interannual variability in the growth rate in atmospheric CO₂
concentration and in the land CO₂ sink (Figure 4), and some decadal variability in all terms (Table 7).
Differences with previous budget releases are documented in Figure S5.

The global carbon budget averaged over the last decade (2013-2022) is shown in Figure 2, Figure 14 (right
panel) and Table 7. For this period, 88% of the total emissions (E_FOS + E_LUC) were from fossil CO₂ emissions
(E_FOS), and 12% from land-use change (E_LUC). The total emissions were partitioned among the atmosphere
(47%), ocean (26%) and land (31%), with a small unattributed budget imbalance (~4%). For single years, the
budget imbalance can be larger (Figure 4). For 2022, the combination of our estimated sources (11.1 ± 0.9 GtC
yr⁻¹) and sinks (11.2 ± 0.9 GtC yr⁻¹) leads to a B_IM of -0.09 GtC, suggesting a near closure of the global carbon
budget, although there is relatively high uncertainty on B_IM (±1.3 GtC for 2022) as this is calculated as the
residual of the five budget terms.

3.9.2 Trend and Variability in the Carbon Budget Imbalance

The carbon budget imbalance (B_IM; Eq. 1, Figure 4) quantifies the mismatch between the estimated total
emissions and the estimated changes in the atmosphere, land, and ocean reservoirs. The budget imbalance from
1960 to 2022 is very small (-3.0 GtC over the period, i.e. average of 0.05 GtC yr⁻¹) and shows no trend over the
full time series (Figure 4e). The process models (GOBMs and DGVMs) and data-products have been selected to
match observational constraints in the 1990s, but no further constraints have been applied to their representation
of trend and variability. Therefore, the near-zero mean and trend in the budget imbalance is seen as evidence of
a coherent community understanding of the emissions and their partitioning on those time scales (Figure 4).
However, the budget imbalance shows substantial variability of the order of ±1 GtC yr⁻¹, particularly over semi-
decadal time scales, although most of the variability is within the uncertainty of the estimates. The positive
carbon imbalance during the 1960s, and early 1990s, indicates that either the emissions were overestimated, or
the sinks were underestimated during these periods. The reverse is true for the 1970s, and to a lesser extent for
the 1980s and 2013-2022 period (Figure 4, Table 7).

We cannot attribute the cause of the variability in the budget imbalance with our analysis, we only note that the
budget imbalance is unlikely to be explained by errors or biases in the emissions alone because of its large semi-
decadal variability component, a variability that is atypical of emissions and has not changed in the past 60 years
despite a near tripling in emissions (Figure 4). Errors in S_LAND and S_OCEAN are more likely to be the main cause
for the budget imbalance, especially on interannual to semi-decadal timescales. For example, underestimation of
the S_LAND by DGVMs has been reported following the eruption of Mount Pinatubo in 1991 possibly due to
missing responses to changes in diffuse radiation (Mercado et al., 2009). Although since GCB2021 we
accounted for aerosol effects on solar radiation quantity and quality (diffuse vs direct), most DGVMs only used
the former as input (i.e., total solar radiation) (Table S1). Thus, the ensemble mean may not capture the full
effects of volcanic eruptions, i.e., associated with high light scattering sulphate aerosols, on the land carbon sink (O’Sullivan et al., 2021). DGVMs are suspected to overestimate the land sink in response to the wet decade of the 1970s (Sitch et al., 2008). Quasi-decadal variability in the ocean sink has also been reported, with all methods agreeing on a smaller than expected ocean CO$_2$ sink in the 1990s and a larger than expected sink in the 2000s (Figure 10; Landschützer et al., 2016, DeVries et al., 2019, Hauck et al., 2020, McKinley et al., 2020, Gruber et al., 2023) and the climate-driven variability could be substantial but is not well constrained (DeVries et al., 2023, Müller et al., 2023). Errors in sink estimates could also be driven by errors in the climatic forcing data, particularly precipitation for $S_{\text{LAND}}$ and wind for $S_{\text{OCEAN}}$. Also, the $B_{\text{IM}}$ shows substantial departure from zero on yearly time scales (Figure 4e), highlighting unresolved variability of the carbon cycle, likely in the land sink ($S_{\text{LAND}}$), given its large year to year variability (Figure 4d and 8).

Both the budget imbalance ($B_{\text{IM}}$, Table 7) and the residual land sink from the global budget ($E_{\text{FOX}}+E_{\text{LUC}}-G_{\text{ATM}}-S_{\text{OCEAN}}$, Table 5) include an error term due to the inconsistencies that arises from combining $E_{\text{LUC}}$ from bookkeeping models with $S_{\text{LAND}}$ from DGVMs, most notably the loss of additional sink capacity (see Section 2.10 and Supplement S.6.4). Other differences include a better accounting of land use changes practices and processes in bookkeeping models than in DGVMs, or the bookkeeping models error of having present-day observed carbon densities fixed in the past. That the budget imbalance shows no clear trend towards larger values over time is an indication that these inconsistencies probably play a minor role compared to other errors in $S_{\text{LAND}}$ or $S_{\text{OCEAN}}$.

Although the budget imbalance is near zero for the recent decades, it could be due to a compensation of errors. We cannot exclude an overestimation of CO$_2$ emissions, particularly from land-use change, given their large uncertainty, as has been suggested elsewhere (Piao et al., 2018), and/or an underestimate of the sinks. A larger DGVM estimate of the atmosphere-land CO$_2$ flux ($S_{\text{LAND}}+E_{\text{LUC}}$) over the extra-tropics would reconcile model results with inversion estimates for fluxes in the total land during the past decade (Figure 13; Table 5). Likewise, a larger $S_{\text{OCEAN}}$ is also possible given the higher estimates from the $f_{\text{CO}_2}$-products (see Section 3.6.2, Figure 10 and Figure 13), the underestimation of interior ocean anthropogenic carbon accumulation in the GOBMs (Section 3.6.5), and the recently suggested upward adjustments of the ocean carbon sink in Earth System Models (Terhaar et al., 2022), and in $f_{\text{CO}_2}$-products, here related to a potential temperature bias and skin effects (Watson et al., 2020; Dong et al., 2022; Figure 10). If $S_{\text{OCEAN}}$ were to be based on $f_{\text{CO}_2}$-products alone, with all $f_{\text{CO}_2}$-products including this adjustment, this would result in a 2013-2022 $S_{\text{OCEAN}}$ of 3.7 GtC yr$^{-1}$ (Dong et al., 2022) or $>3.9$ GtC yr$^{-1}$ (Watson et al., 2020), i.e., outside of the range supported by the atmospheric inversions and with an implied negative $B_{\text{IM}}$ of more than -1 GtC yr$^{-1}$ indicating that a closure of the budget could only be achieved with either anthropogenic emissions being significantly larger and/or the net land sink being substantially smaller than estimated here. A recent model study suggests that the skin effect is smaller (about 0.1 GtC yr$^{-1}$ or 5%) due to feedbacks with surface carbon concentration (Bellenger et al., 2023), which would nevertheless lead to a larger $S_{\text{OCEAN}}$ even in the GOBMs. More integrated use of observations in the Global Carbon Budget, either on their own or for further constraining model results, should help resolve some of the budget imbalance (Peters et al., 2017).
4 Tracking progress towards mitigation targets

The average growth in global fossil CO₂ emissions peaked at nearly +3% per year during the 2000s, driven by the rapid growth in emissions in China. In the last decade, however, the global growth rate has slowly declined, reaching a low +0.5% per year over 2013-2022. While this slowdown in global fossil CO₂ emissions growth is welcome, global fossil CO₂ emissions continue to grow, far from the rapid emission decreases needed to be consistent with the temperature goals of the Paris Agreement.

Since the 1990s, the average growth rate of fossil CO₂ emissions has continuously declined across the group of developed countries of the Organisation for Economic Co-operation and Development (OECD), with emissions peaking in around 2005 and now declining at around 1% yr⁻¹ (Le Quéré et al., 2021). In the decade 2013-2022, territorial fossil CO₂ emissions decreased significantly (at the 95% confidence level) in 26 countries/economies whose economies grew significantly: Belgium, Brazil, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Israel, Italy, Jamaica, Japan, Luxembourg, Netherlands, Norway, Portugal, Romania, Slovenia, South Africa, Sweden, Switzerland, United Kingdom, USA, Zimbabwe (updated from Le Quéré et al., 2019). Altogether, these 26 countries emitted 2.7 GtC yr⁻¹ (10.0 GtCO₂ yr⁻¹) on average over the last decade, about 28% of world CO₂ fossil emissions. For comparison, 22 countries showed a significant decrease in territorial fossil CO₂ emissions over the previous decade (2003-2012). Figure 16 shows that the emission declines in the USA and the EU27 are primarily driven by slightly weaker economic growth in the last decade compared to the 1990s, sustained declines in energy per GDP (though, weakening in the USA), and sustained declines in CO₂ emissions per unit energy (decarbonisation) with a slight acceleration in the USA in the last decade.

In contrast, fossil CO₂ emissions continue to grow in non-OECD countries, although the growth rate has slowed from more than 6% yr⁻¹ during the 2000s to less than 2% yr⁻¹ in the last decade. Representing 47% of non-OECD emissions in 2022, a large part of this slowdown is due to China, which has seen emissions growth decline from 9% yr⁻¹ in the 2000s to 1.6% yr⁻¹ in the last decade. Excluding China, non-OECD emissions grew at 3.1% yr⁻¹ in the 2000s compared to 1.5% yr⁻¹ in the last decade. China has had weaker economic growth in the 2000s compared to the 2010s and a higher decarbonisation rate from 2005 to 2015 comparable to the highs in the 1990s, though the decarbonisation rate has slowed considerably since 2016 (Figure 16). India and the rest of the world have strong economic growth that is not offset by decarbonisation or declines in energy per GDP, driving up fossil CO₂ emissions. Despite the high deployment of renewables in some countries (e.g., India), fossil energy sources continue to grow to meet growing energy demand (Le Quéré et al., 2019).

Globally, fossil CO₂ emissions growth is slowing, and this is due in part to the emergence of climate policy (Eskander and Fankhauser 2020; Le Quere et al 2019) and technological change, which is leading to a shift from coal to gas and growth in renewable energies, and reduced expansion of coal capacity. At the aggregated global level, decarbonisation shows a strong and growing signal in the last decade, with smaller contributions from lower economic growth and declines in energy per GDP. Altogether, global emissions are still growing (average
of 0.5% per year over the 2013-2022 decade), far from the reductions needed to meet the ambitious climate
goals of the UNFCCC Paris agreement.

This year we updated the remaining carbon budget (RCB) based on two studies, the IPCC AR6 (Canadell et al,
2021) as used in GCB2022, and a recent revision of the IPCC AR6 estimates (Forster et al 2023, Lamboll et al.,
2023). We update the RCB assessed by the IPCC AR6 (Canadell et al., 2021), accounting for the 2020 to 2023
estimated emissions from fossil fuel combustion (E_{FOS}) and land use changes (E_{LUC}). From January 2024, the
IPCC AR6 RCB (50% likelihood) for limiting global warming to 1.5°C, 1.7°C and 2°C is estimated to amount
to 95, 190, and 325 GtC (340, 690, 1190 GtCO_2). The Forster et al. (2023) study proposed a significantly lower
RCB than IPCC AR6, with the largest reduction being due to an update of the climate emulator (MAGICC)
used to estimate the warming contribution of non-CO_2 agents, and to the warming (i.e. emissions) that occurred
over the 2020-2022 period. We update the Forster et al., budget accounting for the 2023 estimated emissions
from fossil fuel combustion (E_{FOS}) and land use changes (E_{LUC}). From January 2024, the Forster et al., (2023)
RCB (50% likelihood) for limiting global warming to 1.5°C, 1.7°C and 2°C is estimated to amount to 55, 155,
and 305 GtC (210, 560, 1110 GtCO_2), significantly smaller than the updated IPCC AR6 estimate. Both the
original IPCC AR6 and Forster et al. (2023) estimates include an uncertainty due to the climate response to
cumulative CO_2 emissions, which is reflected through the percent likelihood of exceeding the given temperature
threshold, an additional uncertainty of 220GtCO_2 due to alternative non-CO_2 emission scenarios, and other
sources of uncertainties (see Canadell et al., 2021). The two sets of estimates overlap when considering all
uncertainties. The IPCC AR6 estimates have the advantage of a consensus building approach, while the Forster
et al. (2023) estimates include significant update estimates but without the backing of the IPCC yet. Here, we
take the average of our update of both IPCC AR6 and Forster et al. (2023) estimates, giving a remaining carbon
(50% likelihood) for limiting global warming to 1.5°C, 1.7°C and 2°C of respectively 75, 175, and 315 GtC
(275, 625, 1150 GtCO_2) starting from January 2024. We emphasise the large uncertainties, particularly when
close to the global warming limit of 1.5°C. These 1.5°C, 1.7°C and 2°C average remaining carbon budgets
correspond respectively to about 7, 15 and 28 years from the beginning of 2024, at the 2023 level of total
anthropogenic CO_2 emissions. Reaching net-zero CO_2 emissions by 2050 entails cutting total anthropogenic
CO_2 emissions by about 0.4 GtC (1.5 GtCO_2) each year on average, comparable to the decrease in E_{FOS}
observed in 2020 during the COVID-19 pandemic. However, this would lead to cumulative emissions over
2024-2050 of 150 GtC (550 GtCO_2), well above the remaining carbon budget of 75 GtC to limit global warming
to 1.5°C, but still below the remaining budget of 175 GtC to limit warming to 1.7°C (in phase with the “well
below 2°C” ambition of the Paris Agreement). Even reaching net zero CO_2 globally by 2040, which would
require annual emissions cuts of 0.7 GtC (2.4 GtCO_2) on average, would still exceed the remaining carbon
budget, with 95 GtC (350 GtCO_2) cumulative emissions over 2024-2050, unless the global emissions trajectory
becomes net negative (i.e. more anthropogenic CO_2 sinks than emissions) after 2040.

5 Discussion

Each year when the global carbon budget is published, each flux component is updated for all previous years to
consider corrections that are the result of further scrutiny and verification of the underlying data in the primary
input data sets. Annual estimates may be updated with improvements in data quality and timeliness (e.g., to eliminate the need for extrapolation of forcing data such as land-use). Of all terms in the global budget, only the fossil CO₂ emissions and the growth rate in atmospheric CO₂ concentration are based primarily on empirical inputs supporting annual estimates in this carbon budget. The carbon budget imbalance, yet an imperfect measure, provides a strong indication of the limitations in observations, in understanding and representing processes in models, and/or in the integration of the carbon budget components.

The persistent unexplained variability in the carbon budget imbalance limits our ability to verify reported emissions (Peters et al., 2017) and suggests we do not yet have a complete understanding of the underlying carbon cycle dynamics on annual to decadal timescales. Resolving most of this unexplained variability should be possible through different and complementary approaches. First, as intended with our annual updates, the imbalance as an error term should be reduced by improvements of individual components of the global carbon budget that follow from improving the underlying data and statistics and by improving the models through the resolution of some of the key uncertainties detailed in Table 10. Second, additional clues to the origin and processes responsible for the variability in the budget imbalance could be obtained through a closer scrutiny of carbon variability in light of other Earth system data (e.g., heat balance, water balance), and the use of a wider range of biogeochemical observations to better understand the land-ocean partitioning of the carbon imbalance such as the constraint from atmospheric oxygen included this year. Finally, additional information could also be obtained through better inclusion of process knowledge at the regional level, and through the introduction of inferred fluxes such as those based on satellite xCO₂ retrievals. The limit of the resolution of the carbon budget imbalance is yet unclear, but most certainly not yet reached given the possibilities for improvements that lie ahead.

Estimates of global fossil CO₂ emissions from different datasets are in relatively good agreement when the different system boundaries of these datasets are considered (Andrew, 2020a). But while estimates of E_FOS are derived from reported activity data requiring much fewer complex transformations than some other components of the budget, uncertainties remain, and one reason for the apparently low variation between datasets is precisely the reliance on the same underlying reported energy data. The budget excludes some sources of fossil CO₂ emissions, which available evidence suggests are relatively small (<1%). We have added emissions from lime production in China and the US, but these are still absent in most other non-Annex I countries, and before 1990 in other Annex I countries.

Estimates of E_LUC suffer from a range of intertwined issues, including the poor quality of historical land-cover and land-use change maps, the rudimentary representation of management processes in most models, and the confusion in methodologies and boundary conditions used across methods (e.g., Arneth et al., 2017; Pongratz et al., 2014, see also Supplement S.6.4 on the loss of sink capacity; Bastos et al., 2021). Uncertainties in current and historical carbon stocks in soils and vegetation also add uncertainty in the E_LUC estimates. Unless a major effort to resolve these issues is made, little progress is expected in the resolution of E_LUC. This is particularly concerning given the growing importance of E_LUC for climate mitigation strategies, and the large issues in the quantification of the cumulative emissions over the historical period that arise from large uncertainties in E_LUC.
By adding the DGVMs estimates of CO\textsubscript{2} fluxes due to environmental change from countries’ managed forest areas (part of S\textsubscript{LAND} in this budget) to the budget E\textsubscript{LUC} estimate, we successfully reconciled the large gap between our E\textsubscript{LUC} estimate and the land use flux from NGHGIs using the approach described in Grassi et al. (2021) for future scenarios and in Grassi et al. (2023) using data from the Global Carbon Budget 2021. The updated data presented here can be used as potential adjustment in the policy context, e.g., to help assess the collective countries’ progress towards the goal of the Paris Agreement and avoiding double-accounting for the sink in managed forests. In the absence of this adjustment, collective progress would hence appear better than it is (Grassi et al., 2021). The application of this adjustment is also recommended in the UNFCCC Synthesis report for the first Global Stocktake (UNFCCC, 2022) whenever a comparison between LULUCF fluxes reported by countries and the global emission estimates of the IPCC is conducted. However, this adjustment should be seen as a short-term and pragmatic fix based on existing data, rather than a definitive solution to bridge the differences between global models and national inventories. Additional steps are needed to understand and reconcile the remaining differences, some of which are relevant at the country level (Grassi et al., 2023, Schwingshackl, et al., 2022).

The comparison of GOBMs, /CO\textsubscript{2}-products, and inversions highlights substantial discrepancy in the temporal evolution of S\textsubscript{OCEAN} in the Southern Ocean and northern high-latitudes (Figure 13, Hauck et al., 2023) and in the mean S\textsubscript{OCEAN} in the tropics. A large part of the uncertainty in the mean fluxes stems from the regional distribution of the river flux adjustment term. The current distribution simulates the largest share of the outgassing to occur in the tropics (Lacroix et al., 2020) in contrast to the regional distribution previously used with the largest riverine outgassing flux south of 20°S (Aumont et al., 2001). The long-standing sparse data coverage of /CO\textsubscript{2} observations in the Southern compared to the Northern Hemisphere (e.g., Takahashi et al., 2009) continues to exist (Bakker et al., 2016, 2022, Figure S1) and to lead to substantially higher uncertainty in the S\textsubscript{OCEAN} estimate for the Southern Hemisphere (Watson et al., 2020, Gloege et al., 2021, Hauck et al., 2023). This discrepancy, which also hampers model improvement, points to the need for increased high-quality /CO\textsubscript{2} observations especially in the Southern Ocean. At the same time, model uncertainty is illustrated by the large spread of individual GOBM estimates (indicated by shading in Figure 13) and highlights the need for model improvement. The diverging trends in S\textsubscript{OCEAN} from different methods is a matter of concern. Recent and ongoing work suggests that the /CO\textsubscript{2}-products may overestimate the trend (Hauck et al., 2023), though many products remain to be tested, whereas evidence is accumulating that GOBMs likely underestimate the mean flux (Section 3.6.2, Terhaar et al., 2022, DeVries et al., 2023, Müller et al., 2023). The independent constraint from atmospheric oxygen measurements is consistent within errors with the relatively larger ocean sink in the /CO\textsubscript{2}-products. The assessment of the net land-atmosphere exchange from DGVMs and atmospheric inversions also shows substantial discrepancy, particularly for the estimate of the net land flux over the northern extra-tropic. This discrepancy highlights the difficulty to quantify complex processes (CO\textsubscript{2} fertilisation, nitrogen deposition and fertilisers, climate change and variability, land management, etc.) that collectively determine the net land CO\textsubscript{2} flux. Resolving the differences in the Northern Hemisphere land sink will require the consideration and inclusion of larger volumes of observations.
We provide metrics for the evaluation of the ocean and land models and the atmospheric inversions (Figures B2 to B4, Table S10). These metrics expand the use of observations in the global carbon budget, helping 1) to support improvements in the ocean and land carbon models that produce the sink estimates, and 2) to constrain the representation of key underlying processes in the models and to allocate the regional partitioning of the CO₂ fluxes. The introduction of process-based metrics targeted to evaluate the simulation of $S_{\text{OCEAN}}$ in the ocean biogeochemistry models is an important addition to the evaluation based on ocean carbon observations. This is an initial step towards the introduction of a broader range of observations and more stringent model evaluation that we hope will support continued improvements in the annual estimates of the global carbon budget.

We assessed before that a sustained decrease of $-1\%$ in global emissions could be detected at the 66% likelihood level after a decade only (Peters et al., 2017). Similarly, a change in behaviour of the land and/or ocean carbon sink would take as long to detect, and much longer if it emerges more slowly. To continue reducing the carbon imbalance on annual to decadal time scales, regionalising the carbon budget, and integrating multiple variables are powerful ways to shorten the detection limit and ensure the research community can rapidly identify issues of concern in the evolution of the global carbon cycle under the current rapid and unprecedented changing environmental conditions.

6 Conclusions

The estimation of global CO₂ emissions and sinks is a major effort by the carbon cycle research community that requires a careful compilation and synthesis of measurements, statistical estimates, and model results. The delivery of an annual carbon budget serves two purposes. First, there is a large demand for up-to-date information on the state of the anthropogenic perturbation of the climate system and its underpinning causes. A broad stakeholder community relies on the data sets associated with the annual carbon budget including scientists, policy makers, businesses, journalists, and non-governmental organisations engaged in adapting to and mitigating human-driven climate change. Second, over the last decades we have seen unprecedented changes in the human and biophysical environments (e.g., changes in the growth of fossil fuel emissions, impact of COVID-19 pandemic, Earth’s warming, and strength of the carbon sinks), which call for frequent assessments of the state of the planet, a better quantification of the causes of changes in the contemporary global carbon cycle, and an improved capacity to anticipate its evolution in the future. Building this scientific understanding to meet the extraordinary climate mitigation challenge requires frequent, robust, transparent, and traceable data sets and methods that can be scrutinised and replicated. This paper via ‘living data’ helps to keep track of new budget updates.

Data availability

The data presented here are made available in the belief that their wide dissemination will lead to greater understanding and new scientific insights of how the carbon cycle works, how humans are altering it, and how we can mitigate the resulting human-driven climate change. Full contact details and information on how to cite the data shown here are given at the top of each page in the accompanying database and summarised in Table 2.
The accompanying database includes three Excel files organised in the following spreadsheets:

File Global_Carbon_Budget_2023v1.0.xlsx includes the following:

1. Summary
2. The global carbon budget (1959-2022);
3. The historical global carbon budget (1750-2022);
4. Global CO₂ emissions from fossil fuels and cement production by fuel type, and the per-capita emissions (1850-2022);
5. CO₂ emissions from land-use change from the individual bookkeeping models (1959-2022);
6. Ocean CO₂ sink from the individual global ocean biogeochemistry models and CO₂-products (1959-2022);
7. Terrestrial CO₂ sink from the individual DGVMs (1959-2022);

File National_Fossil_Carbon_Emissions_2023v1.0.xlsx includes the following:

1. Summary
2. Territorial country CO₂ emissions from fossil fuels and cement production (1850-2022);
3. Consumption country CO₂ emissions from fossil fuels and cement production and emissions transfer from the international trade of goods and services (1990-2020) using CDIAC/UNFCCC data as reference;
4. Emissions transfers (Consumption minus territorial emissions; 1990-2020);
5. Country definitions.

File National_LandUseChange_Carbon_Emissions_2023v1.0.xlsx includes the following:

1. Summary
2. Territorial country CO₂ emissions from Land Use Change (1850-2022) from three bookkeeping models;

All three spreadsheets are published by the Integrated Carbon Observation System (ICOS) Carbon Portal and are available at https://doi.org/10.18160/GCP-2023 (Friedlingstein et al., 2023). National emissions data are also available on Zenodo (Andrew and Peters, 2022), from the Global Carbon Atlas (http://www.globalcarbonatlas.org/, last access: 9 November 2023) and from Our World in Data (https://ourworldindata.org/co2-emissions, last access: 9 November 2023).
**Author contributions**

PF, MO, MWJ, RMA, DCEB, JH, PL, CLQ, ITL, GPP, WP, JP, CSc, and SSi designed the study, conducted the analysis, and wrote the paper with input from JGC, PCl and RBJ. RMA, GPP and JIK produced the fossil CO2 emissions and their uncertainties and analysed the emissions data. MH and GMa provided fossil fuel emission data. JP, TGa, CSc and RAH provided the bookkeeping land-use change emissions with synthesis by JP and CSc. FJo provided peat drainage emission estimates. SSm and CMP provided the estimates of non-vegetation CDR fluxes. LBo, MCh, ÖG, NG, Ti, TJ, LR, JS, RS, and HiT provided an update of the global ocean biogeochemical models, TTTC, DF, LG, YI, AJ, GMc, ChR, and JZ provided an update of the ocean fCO2-data products, with synthesis on both streams by JH, PL and NMa. SRA, LBa, NRB, MB, MCr, KE, WE, RAF, TGk, AK, NL, DRM, SN, AO, AMO, TO, MEP, DP, KP, GR, AJS, CSw, ST, BT, EvO, RW, and CWR provided ocean fCO2 measurements for the year 2022, with synthesis by DCEB and KMO. PA, DB, SF, JG, HJ, AKJ, EK, DK, JK, GMe, LM, MO, BP, TLS, QS, HTi, WY, XYua, XYue, and SZ provided an update of the Dynamic Global Vegetation Models, with synthesis by SSi and MO. HL, RSA, MW, and PCa provided estimates of land and ocean sinks from Earth System Models, as well as a projection of the atmospheric growth rate for 2023. FC, ITL, NC, LF, ARJ, FJi, JL, ZJin, ZLi, YN, CR, DY, and BZ provided an updated atmospheric inversion, WP, FC, and ITL developed the protocol and produced the synthesis and evaluation of the atmospheric inversions. RMA provided projections of the 2023 fossil emissions and atmospheric CO2 growth rate. PL provided the predictions of the 2023 ocean and land sinks. IBMB, LPC, GCH, KKG, TMR, and GRvdW provided forcing data for land-use change. FT and GG provided data for the land-use change NGHGI harmonisation. RK provided key atmospheric CO2 data. EJM and RFK provided the atmospheric oxygen constraint on surface net carbon sinks. XL, PPT and MWJ provided the historical atmospheric CO2 concentration and growth rate. MO and NB produced the aerosol diffuse radiative forcing for the DGVMs. IH provided the climate forcing data for the DGVMs. ER provided the evaluation of the DGVMs. MWJ provided the emissions prior for use in the inversion systems. XD provided seasonal emissions data for most recent years for the emission prior. PF, MO and MWJ coordinated the effort, revised all figures, tables, text and numbers to ensure the update was clear from the 2022 edition and in line with the globalcarbonatlas.org.
Competing interests.

At least one of the (co-)authors is a member of the editorial board of Earth System Science Data

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Norjiri, Y., Olsen, A., Ono, T., Peng, S., Peters, W., Pfeil, B., Poulter, B., Raupach, M. R., Regnier, P., Rödenbeck, C., Saito,


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O’Brien, K., Olsen, A., Ono, T., Pérez, F. F., Pfeil, B., Pierrot, D., Poulter, B., Rehder, G., Rödenbeck, C., Saito, S.,


P., Ciais, P., Currie, K., Delire, C., Doney, S. C., Friedlingstein, P., Gkritzalis, T., Harris, I., Hauck, J., Haverd, V.,


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J., Séférian, R., Skjelvan, I., Stocker, B. D., Sutton, A. J., Takahashi, T., Tian, H., Tilbrook, B., van der Laan-Luijkx, I. T.,


Becker, M., Betts, R. A., Bopp, L., Chevallier, F., Chini, L. P., Ciais, P., Cosca, C. E., Cross, J., Currie, K., Gasser, T.,


Lombardozzi, D., Metzl, N., Millero, F., Monteiro, P. M. S., Munro, D. R., Nabel, J. E. M. S., Nakaoka, S., Norjiri, Y.,

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Skjelvan, I., Stocker, B. D., Tian, H., Tilbrook, B., Tubiolo, F. N., van der Laan-Luijkx, I. T., van der Werf, G. R., van


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Moore, D. J. P., Norby, R. J., Zaehle, S., Anderson-Teixeira, K. J., Battipaglia, G., Brienen, R. J. W., Cabugao, K. G.,
Cailleret, M., Campbell, E., Canadell, J. G., Ciais, P., Craig, M. E., Ellsworth, D. S., Farquhar, G. D., Fatichi, S., Fisher, J.
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Taylor, B., Terrer, C., Torn, M. S., Treseder, K. K., Trugman, A. T., Trumbore, S. E., van Mantgem, P. J., Voelker, S. L.,


<table>
<thead>
<tr>
<th>Unit 1</th>
<th>Unit 2</th>
<th>Conversion</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>GtC (gigatonnes of carbon)</td>
<td>ppm (parts per million) (a)</td>
<td>2.124 (b)</td>
<td>Ballantyne et al. (2012)</td>
</tr>
<tr>
<td>GtC (gigatonnes of carbon)</td>
<td>PgC (petagrams of carbon)</td>
<td>1</td>
<td>SI unit conversion</td>
</tr>
<tr>
<td>GtCO2 (gigatonnes of carbon dioxide)</td>
<td>GtC (gigatonnes of carbon)</td>
<td>3.664</td>
<td>44.01/12.011 in mass equivalent</td>
</tr>
<tr>
<td>GtC (gigatonnes of carbon)</td>
<td>MtC (megatonnes of carbon)</td>
<td>1000</td>
<td>SI unit conversion</td>
</tr>
</tbody>
</table>

(a) Measurements of atmospheric CO2 concentration have units of dry-air mole fraction. ‘ppm’ is an abbreviation for micromole/mol, dry air.

(b) The use of a factor of 2.124 assumes that all the atmosphere is well mixed within one year. In reality, only the troposphere is well mixed and the growth rate of CO2 concentration in the less well-mixed stratosphere is not measured by sites from the NOAA network. Using a factor of 2.124 makes the approximation that the growth rate of CO2 concentration in the stratosphere equals that of the troposphere on a yearly basis.

Table 1. Factors used to convert carbon in various units (by convention, Unit 1 = Unit 2 × conversion).
<table>
<thead>
<tr>
<th>Component</th>
<th>Primary reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global fossil CO2 emissions (EFOS), total and by fuel type</td>
<td>Updated from Andrew and Peters (2022)</td>
</tr>
<tr>
<td>National territorial fossil CO2 emissions (EFOS)</td>
<td>Gilfillan and Marland (2021), UNFCCC (2022)</td>
</tr>
<tr>
<td>National consumption-based fossil CO2 emissions (EFOS) by country (consumption)</td>
<td>Peters et al. (2011a) updated as described in this paper</td>
</tr>
<tr>
<td>Net land-use change flux (ELUC)</td>
<td>This paper (see Table 4 for individual model references).</td>
</tr>
<tr>
<td>Growth rate in atmospheric CO2 concentration (GATM)</td>
<td>Lan et al. (2023)</td>
</tr>
<tr>
<td>Ocean and land CO2 sinks (SOCEAN and SLAND)</td>
<td>This paper (see Table 4 for individual model and data products references).</td>
</tr>
</tbody>
</table>

**Table 2.** How to cite the individual components of the global carbon budget presented here.
<table>
<thead>
<tr>
<th>Publication year</th>
<th>Fossil fuel emissions</th>
<th>LUC emissions</th>
<th>Reservoirs</th>
<th>Other changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019</td>
<td>Global</td>
<td>Country</td>
<td>Atmosphere</td>
<td>Based on nine models</td>
</tr>
<tr>
<td>Friedlingstein et al. (2019) GCB2019</td>
<td>Global emissions calculated as sum of all countries plus bunkers, rather than taken directly from CDIAC.</td>
<td>Average of two bookkeeping models; use of 15 DGVMs</td>
<td>Use of three atmospheric inversions</td>
<td>Based on 16 models</td>
</tr>
<tr>
<td>2020</td>
<td>India’s emissions from Andrew (2020: India); Corrections to Netherland Antilles and Aruba and Soviet emissions before 1950 as per Andrew (2020: CO2); China’s coal emissions in 2019 derived from official statistics, emissions now shown for EU27 instead of EU28. Projection for 2020 based on assessment of four approaches.</td>
<td>Average of three bookkeeping models; use of 17 DGVMs. Estimate of gross land use sources and sinks provided</td>
<td>Use of six atmospheric inversions</td>
<td>Based on 17 models</td>
</tr>
<tr>
<td>Friedlingstein et al. (2020) GCB2020</td>
<td>Cement carbonation now included in the EFOS estimate, reducing EFOS by about 0.2GtC yr⁻¹ for the last decade</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2021</td>
<td>Official data included for a number of additional countries, new estimates for South Korea, added emissions from lime</td>
<td>ELUC estimate compared to the estimates adopted in national GHG inventories (NGHGI)</td>
<td>Average of means of eight models and means of seven data-products. Current year prediction of SOCEAN using a feed-forward neural network method</td>
<td>Current year prediction of SLAND using a feed-forward neural network method</td>
</tr>
<tr>
<td>Year</td>
<td>Production in China</td>
<td>Neural Network Method</td>
<td>Neural Network Method</td>
<td>Neural Network Method</td>
</tr>
<tr>
<td>------</td>
<td>-------------------</td>
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</tr>
<tr>
<td>2022</td>
<td>ELUC provided at country level. Revised components decomposition of ELUC fluxes. Revision of LUC maps for Brazil. New datasets for peat drainage.</td>
<td>Use of nine atmospheric inversions</td>
<td>Use of nine atmospheric inversions</td>
<td>Based on 16 models. Revision of LUC maps for Brazil.</td>
</tr>
</tbody>
</table>

**Table 3.** Main methodological changes in the global carbon budget since 2019. Methodological changes introduced in one year are kept for the following years unless noted. Empty cells mean there were no methodological changes introduced that year. Table S8 lists methodological changes from the first global carbon budget publication up to 2018.
<table>
<thead>
<tr>
<th>Model/data name</th>
<th>Reference</th>
<th>Change from Global Carbon Budget 2022 (Friedlingstein et al., 2022b)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bookkeeping models for land-use change emissions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLUE</td>
<td>Hansis et al. (2015)</td>
<td>No change to model, but simulations performed with LUH2-GCB2023 forcing. Update in added peat drainage emissions.</td>
</tr>
<tr>
<td><strong>Dynamic global vegetation models</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CABLE-POP</td>
<td>Haverd et al. (2018)</td>
<td>Improved representation of nitrogen retranslocation and plant uptake, minor bug fixes, parameter changes</td>
</tr>
<tr>
<td>CLASSIC</td>
<td>Melton et al. (2020), Asaadi et al. (2018)</td>
<td>Bug fixes, correct allocation of leaves after summer solstice for latitudes higher than 45°N, improved phenology for several PFTs</td>
</tr>
<tr>
<td>CLM5.0</td>
<td>Lawrence et al. (2019)</td>
<td>No change.</td>
</tr>
<tr>
<td>DLEM</td>
<td>Tian et al. (2011, 2015)</td>
<td>No change.</td>
</tr>
<tr>
<td>EDv3</td>
<td>Moorcroft et al. (2001), Ma et al. (2022)</td>
<td>New this year.</td>
</tr>
<tr>
<td>IBIS</td>
<td>Yuan et al. (2014)</td>
<td>Changes in parameterisation and new module of soil nitrogen dynamics (Ma et al., 2022)</td>
</tr>
<tr>
<td>ISAM</td>
<td>Jain et al. (2013), Meiyappan et al. (2015), Shu et al. (2020)</td>
<td>Vertically resolved soil biogeochemistry (carbon and nitrogen) module, following Shu et al. (2020),</td>
</tr>
<tr>
<td>ISBA-CTRIP</td>
<td>Delire et al. (2020)</td>
<td>No change.</td>
</tr>
<tr>
<td>JSBACH</td>
<td>Mauritsen et al. (2019), Reick et al. (2021)</td>
<td>No change.</td>
</tr>
<tr>
<td>JULES-ES</td>
<td>Wiltshire et al. (2021), Sellar et al. (2019), Burton et al. (2019)</td>
<td>Minor bug fixes. (Using JULES v6.3, suite u-co002)</td>
</tr>
<tr>
<td>LPJ-GUESS</td>
<td>Smith et al. (2014)</td>
<td>Minor bug fixes.</td>
</tr>
<tr>
<td>Model</td>
<td>Description</td>
<td>Change</td>
</tr>
<tr>
<td>-----------</td>
<td>------------------------------------------------------------------------------</td>
<td>-------------------------</td>
</tr>
<tr>
<td>LPJml</td>
<td>Schaphoff et al., 2018, von Bloh et al., 2018, Lutz et al., 2019 (tillage), Heinke et al., 2023 (livestock grazing)</td>
<td>New this year.</td>
</tr>
<tr>
<td>LPJwsl</td>
<td>Poulter et al. (2011) (d)</td>
<td>No change.</td>
</tr>
<tr>
<td>LPX-Bern</td>
<td>Lienert and Joos (2018)</td>
<td>No change.</td>
</tr>
<tr>
<td>OCN</td>
<td>Zaehle and Friend (2010), Zaehle et al. (2011)</td>
<td>Minor bug fixes</td>
</tr>
<tr>
<td>ORCHIDEEv3</td>
<td>Krinner et al. (2005), Zaehle and Friend (2010), Vuichard et al. (2019)</td>
<td>Small update for leaf senescence (ORCHIDEE - V3; revision 8119)</td>
</tr>
<tr>
<td>SDGVM</td>
<td>Woodward and Lomas (2004), Walker et al. (2017)</td>
<td>Implement gross land-use transitions, tracking of carbon from wood &amp; crop harvest, and tracking of primary &amp; secondary vegetation</td>
</tr>
<tr>
<td>VISIT</td>
<td>Ito and Inatomi (2012), Kato et al. (2013)</td>
<td>No change.</td>
</tr>
<tr>
<td>YIBs</td>
<td>Yue and Unger (2015)</td>
<td>Inclusion of process-based water cycle from Noah-MP (Niu et al., 2011)</td>
</tr>
</tbody>
</table>

**Intermediate complexity land carbon cycle model**

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>CARDAMOM</td>
<td>Bloom et al. (2016), Smallman et al. (2021)</td>
<td>New this year.</td>
</tr>
</tbody>
</table>

**Global ocean biogeochemistry models**

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEMO3.6-PISCESv2-gas (CNRM)</td>
<td>Berthet et al. (2019), Séférian et al. (2019)</td>
<td>No change.</td>
</tr>
<tr>
<td>FESOM-2.1-REcoM2</td>
<td>Gürses et al. (2023)</td>
<td>No change</td>
</tr>
<tr>
<td>MOM6-COBALT (Princeton)</td>
<td>Liao et al. (2020)</td>
<td>No change.</td>
</tr>
<tr>
<td>MRI-ESM2-2</td>
<td>Nakano et al. (2011)</td>
<td>The ocean model has been updated to MRI.COMv5 (Sakamoto et al. 2023). The distribution of background vertical diffusivity is changed to the one proposed by Kawasaki et al. (2021). Model was spup-up with a preindustrial xCO2 of 278 ppm.</td>
</tr>
<tr>
<td>MICOM-HAMOCC (NorESM-OCv1.2)</td>
<td>Schwinger et al. (2016)</td>
<td>No change.</td>
</tr>
<tr>
<td>NEMO-PlankTOM12</td>
<td>Wright et al. (2021)</td>
<td>Minor bug fixes, switch to ERA5 forcing, salinity restoring</td>
</tr>
<tr>
<td>Source</td>
<td>Reference</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>----------------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>CESM-ETHZ</td>
<td>Doney et al. (2009)</td>
<td>Model was spup-up with a preindustrial xCO2 of 278 ppm.</td>
</tr>
<tr>
<td>MPIOM-HAMOCC6</td>
<td>Lacroix et al. (2021)</td>
<td>No change.</td>
</tr>
</tbody>
</table>

**fCO2-products**

<table>
<thead>
<tr>
<th>Source</th>
<th>Reference</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMEMS-LSCE-FFNNv2</td>
<td>Chau et al. (2022)</td>
<td>Update to SOCATv2023 measurements and time period 1985-2022. The mapping approach by Chau et al (2022) has been upgraded by increasing spatial resolution from 1° to 0.25°.</td>
</tr>
<tr>
<td>JMA-MLR</td>
<td>Iida et al. (2021)</td>
<td>Updated to SOCATv2023</td>
</tr>
<tr>
<td>LDEO-HPD</td>
<td>Gloege et al. (2022), Bennington et al. (2022)</td>
<td>Updated with SOCATv2023. Updated with current GCB2023 models and extending back in time using Bennington et al. (2022) method.</td>
</tr>
<tr>
<td>MPI-SOMFFN</td>
<td>Landschützer et al. (2016)</td>
<td>Update to SOCATv2023. Since GCB2022, fluxes cover open ocean and coastal domains as well as the Arctic Ocean extension.</td>
</tr>
<tr>
<td>NIES-ML3</td>
<td>Zeng et al. (2022)</td>
<td>New this year</td>
</tr>
<tr>
<td>OS-ETHZ-GRaCER</td>
<td>Gregor et al. (2021)</td>
<td>Updated to SOCATv2023</td>
</tr>
<tr>
<td>Jena-MLS</td>
<td>Rödenbeck et al. (2014, 2022)</td>
<td>Update to SOCATv2023 measurements, time period extended to 1957-2022</td>
</tr>
</tbody>
</table>

**Atmospheric inversions**

<table>
<thead>
<tr>
<th>Source</th>
<th>Reference</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jena</td>
<td>Rödenbeck et al. (2003, 2018)</td>
<td>Extension to 2022, re-addition of a 2.5-year relaxation term.</td>
</tr>
<tr>
<td>CAMS</td>
<td>Chevallier et al. (2005), Remaud et al. (2018)</td>
<td>Increase of the 3D resolution (4.5 times more 3D cells than the previous submission); extension to year 2022; update of the prior fluxes.</td>
</tr>
<tr>
<td>NISMON-CO2</td>
<td>Niwa et al. (2020, 2022)</td>
<td>Prior terrestrial fluxes include minor fluxes (BVOC and CH4) in addition to GPP, RE and LUC.</td>
</tr>
<tr>
<td>CT-NOAA</td>
<td>Peters et al. (2005), Jacobson et al. (2023a, 2023b)</td>
<td>New this year.</td>
</tr>
<tr>
<td>CMS-Flux</td>
<td>Liu et al. (2021)</td>
<td>Update of OCO-2 observations and prior fluxes.</td>
</tr>
<tr>
<td>Model</td>
<td>References</td>
<td>Description</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>CAMS-Satellite</td>
<td>Chevallier et al. (2005), Remaud et al. (2018)</td>
<td>Increase of the 3D resolution, extension to year 2022 and the first months of 2023; removal of the pre-OCO-2 period (2010-2014 with GOSAT); update of the prior fluxes.</td>
</tr>
<tr>
<td>GONGGA</td>
<td>Jin et al. (2023)</td>
<td>Update of OCO-2 observations and prior fluxes.</td>
</tr>
<tr>
<td>THU</td>
<td>Kong et al. (2022)</td>
<td>Updates to the OCO-2 product and the fossil fuel data.</td>
</tr>
<tr>
<td>COLA</td>
<td>Liu et al. (2022)</td>
<td>New this year.</td>
</tr>
<tr>
<td>GCASv2</td>
<td>Jiang et al. (2021, 2022)</td>
<td>New this year.</td>
</tr>
<tr>
<td>UoE in-situ</td>
<td>Feng et al. (2009), Feng et al. (2016), Palmer et al. (2019)</td>
<td>Update of the inversion system by using new version of GEOS-Chem.</td>
</tr>
<tr>
<td>IAPCAS</td>
<td>Feng et al. (2016), Yang et al. (2021)</td>
<td>New this year.</td>
</tr>
<tr>
<td>MIROC4-ACTM</td>
<td>Chandra et al. (2022)</td>
<td>New this year.</td>
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</table>

**Earth System Models**

<table>
<thead>
<tr>
<th>Model</th>
<th>References</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>CanESM5</td>
<td>Swart et al. (2019), Sospedia-Alfonso et al. (2021)</td>
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<tr>
<td>IPSL-CM6a-CO2-LR</td>
<td>Boucher et al. (2020)</td>
<td>New this year.</td>
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<tr>
<td>MIROC-ES2L</td>
<td>Watanabe et al. (2020)</td>
<td>New this year.</td>
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<tr>
<td>MPI-ESM1-2-LR</td>
<td>Mauritsen et al. (2019), Li et al. (2023)</td>
<td>New this year.</td>
</tr>
</tbody>
</table>

**Table 4.** References for the process models, bookkeeping models, ocean data products, and atmospheric inversions. All models and products are updated with new data to the end of year 2022, and the atmospheric forcing for the DGVMs has been updated as described in Section C.2.2 and C.4.1.
*Estimates are adjusted for the pre-industrial influence of river fluxes, for the cement carbonation sink, and adjusted to common EFS (Sect. 2.7). The ranges given include varying numbers (in parentheses) of inversions in each decade (Table S4).

**Table 5.** Comparison of results from the bookkeeping method and budget residuals with results from the DGVMs, as well as additional estimates from atmospheric oxygen, atmospheric inversions and Earth System Models (ESMs) for different periods, the last decade, and the last year available. All values are in GtCyr⁻¹. See Figure 7 for explanation of the bookkeeping component fluxes. The DGVM uncertainties represent ±1σ of the decadal or annual (for 2022) estimates from the individual DGVMs: for the inverse systems the mean and range of available results is given. All values are rounded to the nearest 0.1 GtC and therefore columns do not necessarily add to zero.

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<tbody>
<tr>
<td>Bookkeeping (BK) Net flux (1a)</td>
<td>1.5±0.7</td>
<td>1.3±0.7</td>
<td>1.4±0.7</td>
<td>1.6±0.7</td>
<td>1.4±0.7</td>
<td>1.3±0.7</td>
<td>1.2±0.7</td>
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<tr>
<td>BK - deforestation (total)</td>
<td>[1.3, 2.1]</td>
<td>[1.5, 2.1]</td>
<td>[1.7]</td>
<td>[1.7]</td>
<td>[1.6, 2.2]</td>
<td>[1.6, 2.4]</td>
<td>[1.9, 2.4]</td>
</tr>
<tr>
<td>BK - forest regrowth (total)</td>
<td>[0.8, 1.0, 0.6]</td>
<td>[0.9, 1.0, 0.7]</td>
<td>[0.9, 1.1, 0.7]</td>
<td>[1.3, 2.2, 0.7]</td>
<td>[1.3, 3.0, 0.7]</td>
<td>[1.3, 3.0, 0.9]</td>
<td>[1.3, 4.1]</td>
</tr>
<tr>
<td>BK - peat drainage &amp; peat fires</td>
<td>[0.5, 0.3, 0.4]</td>
<td>[0.2, 0.3]</td>
<td>[0.2, 0.3]</td>
<td>[0.2, 0.3]</td>
<td>[0.1, 0.3]</td>
<td>[0.2, 0.3]</td>
<td>[0.2, 0.3]</td>
</tr>
<tr>
<td>BK - wood harvest &amp; forest management</td>
<td>0.2±0.2</td>
<td>0.2±0.2</td>
<td>0.2±0.2</td>
<td>0.2±0.2</td>
<td>0.2±0.2</td>
<td>0.2±0.2</td>
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<tr>
<td>DGVMs-net flux (1b)</td>
<td>1.5±0.5</td>
<td>1.5±0.5</td>
<td>1.5±0.5</td>
<td>1.5±0.5</td>
<td>1.5±0.5</td>
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<tbody>
<tr>
<td>Residual sink from global budget</td>
<td>-1.7±0.8</td>
<td>1.8±0.8</td>
<td>1.7±0.9</td>
<td>2.7±0.9</td>
<td>2.9±0.9</td>
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<td>DGVMs (2b)</td>
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<td>2±0.7</td>
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<tbody>
<tr>
<td>GCB2023 Budget (2b-1a)</td>
<td>-0.2±0.8</td>
<td>0.8±1</td>
<td>0.5±1</td>
<td>0.9±0.9</td>
<td>1.4±1</td>
<td>2.1±1</td>
<td>2.6±1</td>
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<tr>
<td>Atmospheric O₂</td>
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<td>-...</td>
<td>-...</td>
<td>1.2±1</td>
<td>1.1±1</td>
<td>1.1±1</td>
<td>-</td>
</tr>
<tr>
<td>DGVMs-net (2b-1b)</td>
<td>-0.2±0.4</td>
<td>0.7±0.7</td>
<td>0.3±0.6</td>
<td>0.7±0.5</td>
<td>1.1±0.4</td>
<td>1.7±0.6</td>
<td>2.1±0.6</td>
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<tr>
<td>ESMs</td>
<td>-...</td>
<td>-...</td>
<td>-[±1]</td>
<td>-[±1]</td>
<td>-[±1]</td>
<td>-[±1]</td>
<td>-[±1]</td>
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</tbody>
</table>
Table 6: Comparison of results for the ocean sink from the \( f\mathrm{CO}_2 \)-products, from global ocean biogeochemistry models (GOBMs), the best estimate for GCB2023 as calculated from \( f\mathrm{CO}_2 \)-products and GOBMs that is used in the budget Table 7, as well as additional estimates from atmospheric oxygen, atmospheric inversions and Earth System Models (ESMs) for different periods, the last decade, and the last year available. All values are in GtCyr\(^{-1}\). Uncertainties represent \( \pm 1\sigma \) of the estimates from the GOBMs (\( N>10 \)) and range of ensemble members is given for ensembles with \( N<10 \) (\( f\mathrm{CO}_2 \)-products, inversions, ESMs). The uncertainty of the GCB2023 budget estimate is based on expert judgement (Section 2 and Supplementary S1 to S4) and for oxygen it is the standard deviation of a Monte Carlo ensemble (Section 2.8).

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<tbody>
<tr>
<td>( f\mathrm{CO}_2 )-products</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>( 2.3 ) ([2.2,2.9])</td>
<td>( 2.4 ) ([2.2,2.7])</td>
<td>( 3.1 ) ([2.6,3.3])</td>
<td>( 3.1 ) ([2.5,3.3])</td>
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<tr>
<td>GOBMs</td>
<td>( 1\pm 0.3 )</td>
<td>( 1.2\pm 0.3 )</td>
<td>( 1.7\pm 0.3 )</td>
<td>( 2\pm 0.3 )</td>
<td>( 2.1\pm 0.4 )</td>
<td>( 2.6\pm 0.4 )</td>
<td>( 2.5\pm 0.4 )</td>
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<tr>
<td>GCB2023 Budget</td>
<td>( 1.1\pm 0.4 )</td>
<td>( 1.4\pm 0.4 )</td>
<td>( 1.9\pm 0.4 )</td>
<td>( 2.1\pm 0.4 )</td>
<td>( 2.3\pm 0.4 )</td>
<td>( 2.8\pm 0.4 )</td>
<td>( 2.8\pm 0.4 )</td>
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<tr>
<td>Atmospheric ( O_2 )</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>( 2\pm 0.7 )</td>
<td>( 2.6\pm 0.6 )</td>
<td>( 3.3\pm 0.6 )</td>
<td>-</td>
</tr>
<tr>
<td>Inversions</td>
<td>- [..]</td>
<td>- [..]</td>
<td>( 1.7 ) ([1.6,1.8])</td>
<td>( 2.2 ) ([1.9,2.5])</td>
<td>( 2.4 ) ([1.8,3.1])</td>
<td>( 3 ) ([2.4,4.1])</td>
<td>( 3 ) ([2.2,4.2])</td>
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<tr>
<td>ESMs</td>
<td>---</td>
<td>---</td>
<td>( 1.6 ) ([0.7,2.4])</td>
<td>( 1.8 ) ([1.1,2.5])</td>
<td>( 2.1 ) ([1.5,2.8])</td>
<td>( 2.6 ) ([2.2,3.4])</td>
<td>( 2.7 ) ([2.3-3.5])</td>
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Table 7: Decadal mean in the five components of the anthropogenic CO2 budget for different periods, and last year available. All values are in GtC yr⁻¹, and uncertainties are reported as ±1σ. Fossil CO₂ emissions include cement carbonation. The table also shows the budget imbalance (Bᵢₓᵢ), which provides a measure of the discrepancies among the nearly independent estimates. A positive imbalance means the emissions are overestimated and/or the sinks are too small. All values are rounded to the nearest 0.1 GtC and therefore columns do not necessarily add to zero.
Table 8. Cumulative CO₂ for different time periods in gigatonnes of carbon (GtC). Fossil CO₂ emissions include cement carbonation. The budget imbalance (BIM) provides a measure of the discrepancies among the nearly independent estimates. All values are rounded to the nearest 5 GtC and therefore columns do not necessarily add to zero. Uncertainties are reported as follows: EFOS is 5% of cumulative emissions; ELUC prior to 1959 is 1σ spread from the DGVMs, ELUC post-1959 is 0.7*number of years (where 0.7 GtC/yr is the uncertainty on the annual ELUC flux estimate); GATM uncertainty is held constant at 5 GtC for all time periods; SOCEAN uncertainty is 20% of the cumulative sink (20% relates to the annual uncertainty of 0.4 GtC/yr, which is ~20% of the current ocean sink); and SLAND is the 1σ spread from the DGVMs estimates.
Table 9: Translation of global carbon cycle models’ land flux definitions to the definition of the LULUCF net flux used in national Greenhouse Gas Inventories reported to UNFCCC. See Sec. C.2.3 and Table S9 for detail on methodology and comparison to other datasets. Units are GtC yr⁻¹.

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<td>ELUC from bookkeeping estimates (from Table 5)</td>
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<td>1.3</td>
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<td>SLAND on non-intact forest from DGVMs</td>
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<td>2.0</td>
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<td>ELUC subtract SLAND on non-intact forests</td>
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<td>National Greenhouse Gas Inventories</td>
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### Source of uncertainty

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<th>Location</th>
<th>Evidence</th>
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<td>Fossil CO2 emissions (EFOS; Section 2.1)</td>
<td></td>
<td>global, but mainly China &amp; major developing countries</td>
<td>(Korsbakken et al., 2016, Guan et al., 2012)</td>
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<td>energy statistics</td>
<td>annual to decadal</td>
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<tr>
<td>carbon content of coal</td>
<td>annual to decadal</td>
<td>global, but mainly China &amp; major developing countries</td>
<td>(Liu et al., 2015)</td>
</tr>
<tr>
<td>system boundary</td>
<td>annual to decadal</td>
<td>all countries</td>
<td>(Andrew, 2020a)</td>
</tr>
</tbody>
</table>

### Net land-use change flux (ELUC; section 2.2)

| land-cover and land-use change statistics | continuous | global; in particular tropics | (Houghton et al., 2012, Gasser et al., 2020, Ganzenmüller et al., 2022, Yu et al. 2022) |
| sub-grid-scale transitions | annual to decadal | global | (Wilkenskjeld et al., 2014) |
| vegetation biomass | annual to decadal | global; in particular tropics | (Houghton et al., 2012, Bastos et al., 2021) |
| forest degradation (fire, selective logging) | annual to decadal | tropics | (Aragão et al., 2018, Qin et al., 2021) |
| wood and crop harvest | annual to decadal | global; SE Asia | (Arneth et al., 2017, Erb et al., 2018) |
| peat burning | multi-decadal trend | global | (van der Werf et al., 2010, 2017) |
| loss of additional sink capacity | multi-decadal trend | global | (Pongratz et al, 2014, Gasser et al, 2020; Obermeier et al., 2021) |

**Atmospheric growth rate (GATM; section 2.4)** no demonstrated uncertainties larger than ±0.3 GtC yr⁻¹. The uncertainties in GATM have been estimated as ±0.2 GtC yr⁻¹, although the conversion of the growth rate into a global annual flux assuming instantaneous mixing throughout the atmosphere introduces additional errors that have not yet been quantified.

### Ocean sink (SOCEAN; section 2.5)

| sparsity in surface fCO2 observations | mean, decadal variability and trend | global, in particular southern hemisphere | (Gloege et al., 2021, Denvil-Sommer et al., 2021, Hauck et al., 2023) |
Table 10. Major known sources of uncertainties in each component of the Global Carbon Budget, defined as input data or processes that have a demonstrated effect of at least ±0.3 GtC yr⁻¹.
Figure 1. Surface average atmospheric CO$_2$ concentration (ppm). Since 1980, monthly data are from NOAA/GML (Lan et al., 2023) and are based on an average of direct atmospheric CO$_2$ measurements from multiple stations in the marine boundary layer (Masarie and Tans, 1995). The 1958-1979 monthly data are from the Scripps Institution of Oceanography, based on an average of direct atmospheric CO$_2$ measurements from the Mauna Loa and South Pole stations (Keeling et al., 1976). To account for the difference of mean CO$_2$ and seasonality between the NOAA/GML and the Scripps station networks used here, the Scripps surface average (from two stations) was de-seasonalised and adjusted to match the NOAA/GML surface average (from multiple stations) by adding the mean difference of 0.667 ppm, calculated here from overlapping data during 1980-2012.
Figure 2. Schematic representation of the overall perturbation of the global carbon cycle caused by anthropogenic activities, averaged globally for the decade 2013-2022. See legends for the corresponding arrows. Fluxes estimates and their 1 standard deviation uncertainty are as reported in Table 7. The uncertainty in the atmospheric CO$_2$ growth rate is very small (±0.02 GtC yr$^{-1}$) and is neglected for the figure. The anthropogenic perturbation occurs on top of an active carbon cycle, with fluxes and stocks represented in the background and taken from Canadell et al. (2021) for all numbers, except for the carbon stocks in coasts which is from a literature review of coastal marine sediments (Price and Warren, 2016). Fluxes are in GtC yr$^{-1}$ and reservoirs in GtC.
Figure 3. Combined components of the global carbon budget as a function of time, for fossil CO₂ emissions (Eₖₒₛ, including a small sink from cement carbonation; grey) and emissions from land-use change (Eₗᵤₖ; brown), as well as their partitioning among the atmosphere (Gₐₜₐₘ; cyan), ocean (Sₒₑₒₐₜₑₐₜ; blue), and land (Sₙₐⁿᵈ; green). Panel (a) shows annual estimates of each flux (in GtC yr⁻¹) and panel (b) the cumulative flux (the sum of all prior annual fluxes, in GtC) since the year 1850. The partitioning is based on nearly independent estimates from observations (for Gₐₜₐₘ) and from process model ensembles constrained by data (for Sₒₑₒₐₜₑₐₜ and Sₙₐⁿᵈ) and does not exactly add up to the sum of the emissions, resulting in a budget imbalance (Bₘ) which is represented by the difference between the bottom red line (mirroring total emissions) and the sum of carbon fluxes in the ocean, land, and atmosphere reservoirs. All data are in GtC yr⁻¹ (panel a) and GtC (panel b). The Eₖₒₛ estimate is based on a mosaic of different datasets and has an uncertainty of ±5% (±1σ). The Eₗᵤₖ estimate is from three bookkeeping models (Table 4) with uncertainty of ±0.7 GtC yr⁻¹. The Gₐₜₐₘ estimates prior to 1959 are from Joos and Spahni (2008) with uncertainties equivalent to about ±0.1-0.15 GtC yr⁻¹ and from Lan et al. (2023) since 1959 with uncertainties of about ±0.07 GtC yr⁻¹ during 1959-1979 and ±0.02 GtC yr⁻¹ since 1980. The Sₒₑₒₐₜₑₐₜ estimate is the average from Khatiwala et al. (2013) and DeVries (2014) with uncertainty of about ±30% prior to 1959, and the average of an ensemble of models and an ensemble of fCO₂-products (Table 4) with uncertainties of about ±0.4 GtC yr⁻¹ since 1959. The Sₙₐⁿᵈ estimate is the average of an ensemble of models (Table 4) with uncertainties of about ±1 GtC yr⁻¹. See the text for more details of each component and their uncertainties.
Figure 4. Components of the global carbon budget and their uncertainties as a function of time, presented individually for (a) fossil CO₂ and cement carbonation emissions (E\textsubscript{FOS}), (b) growth rate in atmospheric CO₂ concentration (G\textsubscript{ATM}), (c) emissions from land-use change (E\textsubscript{LUC}), (d) the land CO₂ sink (S\textsubscript{LAND}), (e) the ocean CO₂ sink (S\textsubscript{OCEAN}), (f) the budget imbalance that is not accounted for by the other terms. Positive values of S\textsubscript{LAND} and S\textsubscript{OCEAN} represent a flux from the atmosphere to land or the ocean. All data are in GtC yr\(^{-1}\) with the uncertainty bounds representing ±1 standard deviation in shaded colour. Data sources are as in Figure 3. The red dots indicate our projections for the year 2023 and the red error bars the uncertainty in the projections (see methods).
Figure 5. Fossil CO₂ emissions for (a) the globe, including an uncertainty of ± 5% (grey shading) and a projection through the year 2023 (red dot and uncertainty range), (b) territorial (solid lines) and consumption (dashed lines) emissions for the top three country emitters (USA, China, India) and for the European Union (EU27), (c) global emissions by fuel type, including coal, oil, gas, and cement, and cement minus cement carbonation (dashed), and (d) per-capita emissions the world and for the large emitters as in panel (b). Territorial emissions are primarily from a draft update of Gilfillan and Marland (2021) except for national data for Annex I countries for 1990-2021, which are reported to the UNFCCC as detailed in the text, as well as some improvements in individual countries, and extrapolated forward to 2022 using data from Energy Institute. Consumption-based emissions are updated from Peters et al. (2011a). See Section 2.1 and Supplement S.1 for details of the calculations and data sources.
Figure 6. The 2013–2022 decadal mean components of the global carbon budget, presented for (a) fossil CO$_2$ emissions ($E_{FOS}$), (b) land-use change emissions ($E_{LUC}$), (c) the ocean CO$_2$ sink ($S_{OCEAN}$), and (d) the land CO$_2$ sink ($S_{LAND}$). Positive values for $E_{FOS}$ and $E_{LUC}$ represent a flux to the atmosphere, whereas positive values of $S_{OCEAN}$ and $S_{LAND}$ represent a flux from the atmosphere to the ocean or the land (carbon sink). In all panels, yellow/red colours represent a source (flux from the land/ocean to the atmosphere), green/blue colours represent a sink (flux from the atmosphere into the land/ocean). All units are in kgC m$^{-2}$ yr$^{-1}$. Note the different scales in each panel. $E_{FOS}$ data shown is from GCP-GridFEDv2023.1 and does not include cement carbonation. The $E_{LUC}$ map shows the average $E_{LUC}$ from the three bookkeeping models plus emissions from peat drainage and peat fires. Gridded $E_{LUC}$ estimates for H&C2023 and OSCAR are derived by spatially distributing their national data based on the spatial patterns of BLUE gross fluxes in each country (see Schwingshackl et al., 2022, for more details about the methodology). $S_{OCEAN}$ data shown is the average of GOBMs and data-products means, using GOBMs simulation A, no adjustment for bias and drift applied to the gridded fields (see Section 2.5). $S_{LAND}$ data shown is the average of the DGVMs for simulation S2 (see Section 2.6).
Figure 7. Net CO₂ exchanges between the atmosphere and the terrestrial biosphere related to land use change.

(a) Net CO₂ emissions from land-use change (E\text{LUC}) with estimates from the three bookkeeping models (yellow lines) and the budget estimate (black with ±1σ uncertainty), which is the average of the three bookkeeping models. Estimates from individual DGVMs (narrow green lines) and the DGVM ensemble mean (thick green line) are also shown. (b) Net CO₂ emissions from land-use change from the four countries with largest cumulative emissions since 1959. Values shown are the average of the three bookkeeping models, with shaded regions as ±1σ uncertainty. (c) Sub-components of E\text{LUC}: (i) emissions from deforestation (including permanent deforestation and deforestation in shifting cultivation cycles), (ii) emissions from peat drainage & peat fires, (iii) removals from forest (re-)growth (including forest (re-)growth due to afforestation and reforestation and forest regrowth in shifting cultivation cycles), (iv) fluxes from wood harvest and other forest management (comprising slash and product decay following wood harvest, regrowth after wood harvest, and fire suppression), and (v) emissions and removals related to other land-use transitions. The sum of the five components is E\text{LUC} shown in panel (a). (d) Sub-components of ‘deforestation (total)’ and of ‘forest (re-)growth (total)’: (i) deforestation in shifting cultivation cycles, (ii) permanent deforestation, (iii) forest (re-)growth due to afforestation and/or reforestation, and (iv) forest regrowth in shifting cultivation cycles.
Figure 8. (a) The land CO$_2$ sink ($S_{\text{LAND}}$) estimated by individual DGVMs (green), as well as the budget estimate (black with ±1σ uncertainty), which is the average of all DGVMs. (b) Net atmosphere-land CO$_2$ fluxes ($S_{\text{LAND}} - E_{\text{LUC}}$). The budget estimate of the net land flux (black with ±1σ uncertainty) combines the DGVM estimate of $S_{\text{LAND}}$ from panel (a) with the bookkeeping estimate of $E_{\text{LUC}}$ from Figure 7a. Uncertainties are similarly propagated in quadrature. DGVMs also provide estimates of $E_{\text{LUC}}$ (see Figure 7a), which can be combined with their own estimates of the land sink. Hence panel (b) also includes an estimate for the net land flux for individual DGVMs (thin green lines) and their multi-model mean (thick green line).
Figure 9. The partitioning of total anthropogenic CO₂ emissions (Eₐvfs + EₐLuc) across (a) the atmosphere (airborne fraction), (b) land (land-borne fraction), and (c) ocean (ocean-borne fraction). Black lines represent the central estimate, and the coloured shading represents the uncertainty. The grey dashed lines represent the long-term average of the airborne (44%), land-borne (30%) and ocean-borne (25%) fractions during 1960-2022 (with a BIM of 1%).
Figure 10. Comparison of the anthropogenic atmosphere-ocean CO₂ flux showing the budget values of $S_{\text{OCEAN}}$ (black; with the uncertainty in grey shading), individual ocean models (royal blue), and the ocean $fCO_2$-products (cyan; with Watson et al. (2020) in dashed line as not used for ensemble mean). Only one $fCO_2$-product (Jena-MLS) extends back to 1959 (Rödenbeck et al., 2022). The $fCO_2$-products were adjusted for the pre-industrial ocean source of CO₂ from river input to the ocean, by subtracting a source of 0.65 GtC yr⁻¹ to make them comparable to $S_{\text{OCEAN}}$ (see Section 2.5). Bar-plot in the lower right illustrates the number of $fCO_2$ observations in the SOCAT v2023 database (Bakker et al., 2023). Grey bars indicate the number of data points in SOCAT v2022, and coloured bars the newly added observations in v2023.
Figure 11. Attribution of the atmosphere-ocean (SOCEAN) and atmosphere-land (SLAND) CO₂ fluxes to (a) increasing atmospheric CO₂ concentrations and (b) changes in climate, averaged over the previous decade 2013-2022. All data shown is from the processed-based GOBM and DGVMs. Note that the sum of ocean CO₂ and climate effects shown here will not equal the ocean sink shown in Figure 6 which includes the fCO₂-products. See Supplement S.3.2 and S.4.1 for attribution methodology. Units are in kgC m⁻² yr⁻¹ (note the non-linear colour scale).
Figure 12. The 2013-2022 decadal mean global net atmosphere-ocean and atmosphere-land fluxes derived from the ocean models and fCO₂ products (y-axis, right and left pointing blue triangles respectively), and from the DGVMs (x-axis, green symbols), and the same fluxes estimated from the atmospheric inversions (purple symbols). The shaded distributions show the densities of the ensembles of individual estimates. The grey central cross is the mean (±1σ) of SOCEAN and (SLAND – ELUC) as assessed in this budget. The grey diagonal line represents the constraint on the global land + ocean net flux, i.e. global fossil fuel emissions minus the atmospheric growth rate from this budget (EFOS – GATM). The orange cross represents the same global net atmosphere-ocean and atmosphere-land fluxes as estimated from the atmospheric O₂ constraint (±1σ for each of the fluxes although caution is needed to interpret these error bars, since solutions outside the grey band are unlikely, as outside of the 1σ uncertainty). Positive values are CO₂ sinks. Note that the inverse estimates have been scaled for a minor difference between EFOS and GridFEDv2023.1 (Jones et al., 2023).
**Figure 13.** CO$_2$ fluxes between the atmosphere and the Earth’s surface separated between land and oceans, globally and in three latitude bands. The ocean flux is S$_{OCEAN}$ and the land flux is the net atmosphere-land fluxes from the DGVMs. The latitude bands are (top row) global, (2nd row) north (>30°N), (3rd row) tropics (30°S-30°N), and (bottom row) south (<30°S), and over ocean (left column), land (middle column), and total (right column). Estimates are shown for: process-based models (DGVMs for land, GOBMs for oceans); inversion systems (land and ocean); and f/CO$_2$-products (ocean only). Positive values are CO$_2$ sinks. Mean estimates from the combination of the process models for the land and oceans are shown (black line) with ±1 σ of the model ensemble (grey shading). For the total uncertainty in the process-based estimate of the total sink, uncertainties are summed in quadrature. Mean estimates from the atmospheric inversions are shown (purple lines) with their full spread (purple shading). Mean estimates from the f/CO$_2$-products are shown for the ocean domain (light blue lines) with full model spread (light blue shading). The global S$_{OCEAN}$ (upper left) and the sum of S$_{OCEAN}$ in all three regions represents the anthropogenic atmosphere-to-ocean flux based on the assumption that the preindustrial ocean sink was 0 GtC yr$^{-1}$ when riverine fluxes are not considered. This assumption does not hold at the regional level, where preindustrial fluxes can be significantly different from zero. Hence, the regional panels for S$_{OCEAN}$ represent a combination of natural and anthropogenic fluxes. Bias-correction and area-weighting were only applied to global S$_{OCEAN}$; hence the sum of the regions is slightly different from the global estimate (<0.05 GtC yr$^{-1}$).
Figure 14. Decadal mean (a) land and (b) ocean fluxes for RECCAP-2 regions over 2013-2022. For land fluxes, $S_{\text{LAND}}$ is estimated by the DGVMs (green bars), with the error bar as ±1σ spread among models. A positive $S_{\text{LAND}}$ is a net transfer of carbon from the atmosphere to the land. $E_{\text{LUC}}$ fluxes are shown for both DGVMs (green) and bookkeeping models (orange), again with the uncertainty calculated as the ±1σ spread. Note, a positive $E_{\text{LUC}}$ flux indicates a loss of carbon from the land. The net land flux is shown for both DGVMs (green) and atmospheric inversions (purple), including the full model spread for inversions. The net ocean sink ($S_{\text{OCEAN}}$) is estimated by GOBMs (royal blue), $\delta$CO$_2$-products (cyan), and atmospheric inversions (purple). Uncertainty is estimated as the ±1σ spread for GOBMs, and the full model spread for the other two products. The dotted lines show the $\delta$CO$_2$-products and inversion results without river flux adjustment. Positive values are CO$_2$ sinks.
Figure 15. Cumulative changes over the 1850-2022 period (left) and average fluxes over the 2013-2022 period (right) for the anthropogenic perturbation of the global carbon cycle. See the caption of Figure 3 for key information and the methods in text for full details.
Figure 16. Kaya decomposition of the main drivers of fossil CO\textsubscript{2} emissions, considering population, GDP per person, Energy per GDP, and CO\textsubscript{2} emissions per energy, for China (top left), USA (top right), EU27 (middle left), India (middle right), Rest of the World (bottom left), and World (bottom right). Black dots are the annual fossil CO\textsubscript{2} emissions growth rate, coloured bars are the contributions from the different drivers to this growth rate. A general trend is that population and GDP growth put upward pressure on emissions (positive values), while energy per GDP and, more recently, CO\textsubscript{2} emissions per energy put downward pressure on emissions (negative values). Both the COVID-19 induced drop during 2020 and the recovery in 2021 led to a stark contrast to previous years, with different drivers in each region. The EU27 had strong Energy/GDP improvements in 2022.