Global Carbon Budget 2018

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3	Corinne Le Quéré ¹ , Robbie M. Andrew ² , Pierre Friedlingstein ³ , Stephen Sitch ⁴ , Judith Hauck ⁵ , Julia
4	Pongratz ^{6,7} , Penelope Pickers ⁸ , Jan Ivar Korsbakken ² , Glen P. Peters ² , Josep G. Canadell ⁹ , Almut
5	Arneth ¹⁰ , Vivek K. Arora ¹¹ , Leticia Barbero ^{12,13} , Ana Bastos ⁶ , Laurent Bopp ¹⁴ , Frédéric Chevallier ¹⁵ ,
6	Louise P. Chini ¹⁶ , Philippe Ciais ¹⁵ , Scott C. Doney ¹⁷ , Thanos Gkritzalis ¹⁸ , Daniel S. Goll ¹⁵ , Ian Harris ¹⁹ ,
7	Vanessa Haverd ²⁰ , Forrest M. Hoffman ²¹ , Mario Hoppema ⁵ , Richard A. Houghton ²² , Tatiana Ilvina ⁷ ,
8	Atul K. Jain ²³ , Truls Johannessen ²⁴ , Chris D. Jones ²⁵ , Etsushi Kato ²⁶ , Ralph F. Keeling ²⁷ , Kees Klein
9	Goldewijk ^{28,29} , Peter Landschützer ⁷ , Nathalie Lefèvre ³⁰ , Sebastian Lienert ³¹ , Danica Lombardozzi ³² ,
10	Nicolas Metzl ³⁰ , David R. Munro ³³ , Julia E. M. S. Nabel ⁷ , Shin-ichiro Nakaoka ³⁴ , Craig Neill ^{35,36} , Are
11	Olsen ³⁷ , Tsueno Ono ³⁸ , Prabir Patra ³⁹ , Anna Peregon ¹⁵ , Wouter Peters ^{40,41} , Philippe Peylin ¹⁵ ,
12	Benjamin Pfeil ^{24,37} , Denis Pierrot ^{12,13} , Benjamin Poulter ⁴² , Gregor Rehder ⁴³ , Laure Resplandy ⁴⁴ ,
13	Eddy Robertson ²⁵ , Matthias Rocher ⁴⁵ , Christian Rödenbeck ⁴⁶ , Ute Schuster ⁴ , Jörg Schwinger ³⁷ ,
14	Roland Séférian ⁴⁵ , Ingunn Skjelvan ³⁷ , Tobias Steinhoff ⁴⁷ , Adrienne Sutton ⁴⁸ , Pieter P. Tans ⁴⁹ ,
15	Hangin Tian ⁵⁰ , Bronte Tilbrook ^{35,36} , Francesco N Tubiello ⁵¹ , Ingrid T. van der Laan-Luijkx ⁴⁰ , Guido R.
16	van der Werf ⁵² , Nicolas Viovy ¹⁵ , Anthony P. Walker ⁵³ , Andrew J. Wiltshire ²⁵ , Rebecca Wright ⁸ ,
17	Sönke Zaehle ⁴⁵
18	¹ Tyndall Centre for Climate Change Research, University of East Anglia, Norwich Research Park,
19	Norwich NR4 7TJ, UK
20	² CICERO Center for International Climate Research, Oslo 0349, Norway
21	³ College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter EX4 4QF, UK
22	⁴ College of Life and Environmental Sciences, University of Exeter, Exeter EX4 4RJ, UK
23	⁵ Alfred Wegener Institute Helmholtz Centre for Polar and Marine Research, Postfach 120161, 27515
24	Bremerhaven, Germany
25	⁶ Ludwig-Maximilans-Universität Munich, Luisenstr. 37, 80333 München, Germany
26	⁷ Max Planck Institute for Meteorology, Hamburg, Germany
27	⁸ Centre for Ocean and Atmospheric Sciences, School of Environmental Sciences, University of East
28	Anglia, Norwich Research Park, Norwich NR4 7TJ, UK
29	⁹ Global Carbon Project, CSIRO Oceans and Atmosphere, GPO Box 1700, Canberra, ACT 2601, Australia
30	¹⁰ Karlsruhe Institute of Technology (KIT, IMK-IFU)
31	¹¹ Canadian Centre for Climate Modelling and Analysis, Climate Research Division, Environment and
32	Climate Change Canada, Victoria, BC, Canada
33	¹² Cooperative Institute for Marine and Atmospheric Studies, Rosenstiel School for Marine and
34	Atmospheric Science, University of Milami, Milami, FL 33149, USA
35	National Oceanic & Atmospheric Administration/Atlantic Oceanographic & Meteorological Laboratory
30 27	(NUAA/AUML), MIAMI, FL 33149, USA
37 20	Laboratoire de Meteorologie Dynamique, institut Pierre-Simon Lapiace, CNRS-ENS-OPMC-X,
30 20	¹⁵ aboratoire des Sciences du Climat et de l'Environnement Institut Dierre Simon Laplace. CEA CNPS
40 29	Laboratorie des Sciences du Climat et de l'Environmement, institut Pierre-Simon Lapiace, CEA-CINKS-
40 //1	¹⁶ Department of Geographical Sciences, University of Manyland, College Park, Manyland 20742, USA
→⊥ //2	1^{7} University of Virginia Charlottesville VA 22004 USA
43 43	¹⁸ Flanders Marine Institute (VII7) Wanelaarkaai 7 8400 Ostend Belgium
44	¹⁹ NCAS-Climate, Climatic Research Unit, School of Environmental Sciences, University of Fast Anglia
45	Norwich Research Park. Norwich. NR4 7TJ. UK

1	²⁰ CSIRO Oceans and Atmosphere, GPO Box 1700, Canberra, ACT 2601, Australia
2	²¹ Computational Earth Sciences Group, Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA
3	²² Woods Hole Research Centre (WHRC), Falmouth, MA 02540, USA
4	²³ Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61821, USA
5	²⁴ Geophysical Institute, University of Bergen and Bjerknes Centre for Climate Research, Allégaten 70,
6	5007 Bergen, Norway
7	²⁵ Met Office Hadley Centre, FitzRoy Road, Exeter EX1 3PB, UK
8	²⁶ Institute of Applied Energy (IAE), Minato-ku, Tokyo 105-0003, Japan
9	²⁷ University of California, San Diego, Scripps Institution of Oceanography, La Jolla, CA 92093-0244, USA
10	²⁸ PBL Netherlands Environmental Assessment Agency, Bezuidenhoutseweg 30, P.O. Box 30314, 2500
11	GH, The Hague, the Netherlands
12	²⁹ Faculty of Geosciences, Department IMEW, Copernicus Institute of Sustainable Development,
13	Heidelberglaan 2, P.O. Box 80115, 3508 TC, Utrecht, the Netherlands
14	³⁰ Sorbonne Universités (UPMC, Univ Paris 06), CNRS, IRD, MNHN, LOCEAN/IPSL Laboratory, 75252
15	Paris, France
16	³¹ Climate and Environmental Physics, Physics Institute and Oeschger Centre for Climate Change
17	Research, University of Bern, Bern, Switzerland
18	³² National Center for Atmospheric Research, Climate and Global Dynamics, Terrestrial Sciences Section,
19	Boulder, CO 80305, USA
20	³³ Department of Atmospheric and Oceanic Sciences and Institute of Arctic and Alpine Research,
21	University of Colorado, Campus Box 450, Boulder, CO 80309-0450, USA
22	³⁴ Center for Global Environmental Research, National Institute for Environmental Studies (NIES), 16-2
23	Onogawa, Tsukuba, Ibaraki 305-8506, Japan
24	³⁵ CSIRO Oceans and Atmosphere, PO Box 1538, Hobart, Tasmania, 7001, Australia
25	³⁶ Antarctic Climate and Ecosystem Cooperative Research Centre, University of Tasmania, Hobart,
26	Australia
27	³⁷ NORCE Norwegian Research Centre and Bjerknes Centre for Climate Research, Jahnebakken 5, 5007
28	Bergen, Norway
29	³⁸ National Research Institute for Far Sea Fisheries, Japan Fisheries Research and Education Agency, 2-
30	12-4 Fukuura, Kanazawa-Ku, Yokohama 236-8648, Japan
31	³⁹ Department of Environmental Geochemical Cycle Research, JAMSTEC, Yokohama, Japan
32	⁴⁰ Department of Meteorology and Air Quality, Wageningen University & Research, PO Box 47, 6700AA
33	Wageningen, The Netherlands
34	⁴¹ Centre for Isotope Research, University of Groningen, Nijenborgh 6, 9747 AG Groningen, the
35	Netherlands
36	⁴² NASA Goddard Space Flight Center, Biospheric Science Laboratory, Greenbelt, Maryland 20771, USA
37	⁴³ Leibniz Institute for Baltic Sea Research Warnemünde, 18119 Rostock, Germany
38	⁴⁴ Princeton University Department of Geosciences and Princeton Environmental Institute Princeton,
39	New Jersey, USA
40	⁴⁵ Centre National de Recherche Météorologique, Unite mixte de recherche 3589 Météo-France/CNRS,
41	42 Avenue Gaspard Coriolis, 31100 Toulouse, France
42	⁴⁶ Max Planck Institute for Biogeochemistry, P.O. Box 600164, Hans-Knöll-Str. 10, 07745 Jena, Germany
43	⁴⁷ GEOMAR Helmholtz Centre for Ocean Research Kiel, Düsternbrooker Weg 20, 24105, Kiel, Germany
44	⁴⁸ National Oceanic & Atmospheric Administration/Pacific Marine Environmental Laboratory
45	(NOAA/PMEL), 7600 Sand Point Way NE, Seattle, WA 98115, USA
46	⁴⁹ National Oceanic & Atmospheric Administration, Earth System Research Laboratory (NOAA/ESRL),
47	Boulder, CO 80305, USA
48	⁵⁰ School of Forestry and Wildlife Sciences, Auburn University, 602 Ducan Drive, Auburn, AL 36849, USA

1	⁵¹ Statistics Division, Food and Agriculture Organization of the United Nations, Via Terme di Caracalla,
2	Rome 00153, Italy
3	⁵² Faculty of Science, Vrije Universiteit, Amsterdam, The Netherlands
4	⁵³ Environmental Sciences Division & Climate Change Science Institute, Oak Ridge National Laboratory,
5	Oak Ridge, Tennessee, USA
6	
7	
8	
9	

1 Abstract

2 Accurate assessment of anthropogenic carbon dioxide (CO₂) emissions and their redistribution 3 among the atmosphere, ocean, and terrestrial biosphere – the 'global carbon budget' – is 4 important to better understand the global carbon cycle, support the development of climate 5 policies, and project future climate change. Here we describe data sets and methodology to 6 quantify the five major components of the global carbon budget and their uncertainties. Fossil CO₂ emissions (E_{FF}) are based on energy statistics and cement production data, while emissions 7 8 from land-use change (E_{LUC}), mainly deforestation, are based on land-use and land-use change data and bookkeeping models. Atmospheric CO₂ concentration is measured directly and its 9 10 growth rate (G_{ATM}) is computed from the annual changes in concentration. The ocean CO₂ sink 11 (S_{OCEAN}) and terrestrial CO₂ sink (S_{LAND}) are estimated with global process models constrained by 12 observations. 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 13 14 a measure of imperfect data and understanding of the contemporary carbon cycle. All 15 uncertainties are reported as $\pm 1\sigma$. For the last decade available (2008-2017), E_{FF} was 9.4 \pm 0.5 GtC yr⁻¹, E_{LUC} 1.5 ± 0.7 GtC yr⁻¹, G_{ATM} 4.7 ± 0.02 GtC yr⁻¹, S_{OCEAN} 2.4 ± 0.5 GtC yr⁻¹, and S_{LAND} 3.2 ± 0.8 GtC 16 17 yr⁻¹, with a budget imbalance B_{IM} of 0.5 GtC yr⁻¹ indicating overestimated emissions and/or underestimated sinks. For year 2017 alone, the growth in E_{FF} was about 1.6% and emissions 18 19 increased to 9.9 ± 0.5 GtC yr⁻¹. Also for 2017, E_{LUC} was 1.4 ± 0.7 GtC yr⁻¹, G_{ATM} was 4.6 ± 0.2 GtC yr⁻¹ 20 ¹, S_{OCEAN} was 2.5 \pm 0.5 GtC yr⁻¹ and S_{LAND} was 3.8 \pm 0.8 GtC yr⁻¹, with a small B_{IM} of 0.3 GtC. The global atmospheric CO₂ concentration reached 405.0 ± 0.1 ppm averaged over 2017. For 2018, 21 preliminary data for the first 6-9 months indicate a renewed growth in E_{FF} of +2.7% (range of 1.8% 22 to 3.7%) based on national emissions projections for China, USA, the EU and India, and projections 23 24 of Gross Domestic Product corrected for recent changes in the carbon intensity of the economy for the rest of the world. The analysis presented here shows that the mean and trend in the five 25 components of the global carbon budget are consistently estimated over the period 1959-2017, 26 but discrepancies of up to 1 GtC yr⁻¹ persist for the representation of semi-decadal variability in 27 CO₂ fluxes. A detailed comparison among individual estimates and the introduction of a broad 28 range of observations shows: (1) no consensus in the mean and trend in land-use change 29 30 emissions, (2) a persistent low agreement between the different methods on the magnitude of 31 the land CO₂ flux in the northern extra-tropics, and (3) an apparent underestimation of the CO₂ variability by ocean models, originating outside the tropics. This living data update documents 32

changes in the methods and data sets used in this new global carbon budget and the progress in
 understanding of the global carbon cycle compared with previous publications of this data set (Le
 Quéré et al., 2018, 2016; 2015b; 2015a; 2014; 2013). All results presented here can be
 downloaded from https://doi.org/10.18160/GCP-2018.

5 1 Introduction

6 The concentration of carbon dioxide (CO_2) in the atmosphere has increased from approximately 7 277 parts per million (ppm) in 1750 (Joos and Spahni, 2008), the beginning of the Industrial Era, to 8 405.0 ± 0.1 ppm in 2017 (Dlugokencky and Tans, 2018; Fig. 1). The atmospheric CO₂ increase above preindustrial levels was, initially, primarily caused by the release of carbon to the 9 10 atmosphere from deforestation and other land-use change activities (Ciais et al., 2013). While emissions from fossil fuels started before the Industrial Era, they only became the dominant 11 12 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 13 14 carbon cycle that circulates carbon between the reservoirs of the atmosphere, ocean, and 15 terrestrial biosphere on time scales from sub-daily to millennia, while exchanges with geologic 16 reservoirs occur at longer timescales (Archer et al., 2009).

17 The global carbon budget presented here refers to the mean, variations, and trends in the perturbation of CO₂ in the environment, referenced to the beginning of the Industrial Era. It 18 19 quantifies the input of CO_2 to the atmosphere by emissions from human activities, the growth rate 20 of atmospheric CO₂ concentration, and the resulting changes in the storage of carbon in the land and ocean reservoirs in response to increasing atmospheric CO₂ levels, climate change and 21 variability, and other anthropogenic and natural changes (Fig. 2). An understanding of this 22 23 perturbation budget over time and the underlying variability and trends of the natural carbon cycle are necessary to understand the response of natural sinks to changes in climate, CO₂ and 24 25 land-use change drivers, and the permissible emissions for a given climate stabilization target. 26 The components of the CO₂ budget that are reported annually in this paper include separate estimates for the CO₂ emissions from (1) fossil fuel combustion and oxidation from all energy and 27 industrial processes and cement production (E_{FF}; GtC yr⁻¹) and (2) the emissions resulting from 28 29 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 CO₂ concentration (G_{ATM}; GtC yr⁻ 30

¹), and the uptake of CO₂ (the 'CO₂ sinks') in (4) the ocean (S_{OCEAN}; GtC yr⁻¹) and (5) on land (S_{LAND}; 1 2 GtC yr⁻¹). The CO₂ sinks as defined here conceptually include the response of the land (including 3 inland waters and estuaries) and ocean (including coasts and territorial sea) to elevated CO₂ and 4 changes in climate, rivers, and other environmental conditions, although in practice not all 5 processes are accounted for (see Section 2.7). The global emissions and their partitioning among 6 the atmosphere, ocean and land are in reality in balance, however due to imperfect spatial and/or 7 temporal data coverage, errors in each estimate, and smaller terms not included in our budget 8 estimate (discussed in Section 2.7), their sum does not necessarily add up to zero. We estimate a 9 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, with the full global carbon budget 10 11 as follows:

$$E_{FF} + E_{LUC} = G_{ATM} + S_{OCEAN} + S_{LAND} + B_{IM}.$$
 (1)

12 G_{ATM} is usually reported in ppm yr⁻¹, which we convert to units of carbon mass per year, GtC yr⁻¹, 13 using 1 ppm = 2.124 GtC (Table 1). We also include a quantification of E_{FF} by country, computed 14 with both territorial and consumption based accounting (see Sect. 2), and discuss missing terms 15 from sources other than the combustion of fossil fuels (see Sect. 2.7).

The CO₂ budget has been assessed by the Intergovernmental Panel on Climate Change (IPCC) in all 16 17 assessment reports (Ciais et al., 2013; Denman et al., 2007; Prentice et al., 2001; Schimel et al., 18 1995; Watson et al., 1990), and by others (e.g. Ballantyne et al., 2012). The IPCC methodology has been adapted and used by the Global Carbon Project (GCP, www.globalcarbonproject.org), which 19 has coordinated a cooperative community effort for the annual publication of global carbon 20 budgets up to year 2005 (Raupach et al., 2007; including fossil emissions only), year 2006 21 22 (Canadell et al., 2007), year 2007 (published online; GCP, 2007), year 2008 (Le Quéré et al., 2009), year 2009 (Friedlingstein et al., 2010), year 2010 (Peters et al., 2012b), year 2012 (Le Quéré et al., 23 24 2013; Peters et al., 2013), year 2013 (Le Quéré et al., 2014), year 2014 (Friedlingstein et al., 25 2014;Le Quéré et al., 2015b), year 2015 (Jackson et al., 2016;Le Quéré et al., 2015a), year 2016 (Le Quéré et al., 2016), and most recently year 2017 (Le Quéré et al., 2018; Peters et al., 2017). Each of 26 these papers updated previous estimates with the latest available information for the entire time 27 28 series.

29 We adopt a range of ± 1 standard deviation (σ) to report the uncertainties in our estimates,

30 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 1 2 characterising the uncertainty in the CO₂ fluxes between the atmosphere and the ocean and land 3 reservoirs individually, particularly on an annual basis, as well as the difficulty of updating the CO₂ 4 emissions from land-use change. A likelihood of 68% provides an indication of our current 5 capability to quantify each term and its uncertainty given the available information. For 6 comparison, the Fifth Assessment Report of the IPCC (AR5) generally reported a likelihood of 90% 7 for large data sets whose uncertainty is well characterised, or for long time intervals less affected 8 by year-to-year variability. Our 68% uncertainty value is near the 66% which the IPCC 9 characterises as 'likely' for values falling into the ±1o interval. The uncertainties reported here combine statistical analysis of the underlying data and expert judgement of the likelihood of 10 11 results lying outside this range. The limitations of current information are discussed in the paper 12 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 13 each term based on the type, amount, quality and consistency of the evidence as defined by the 14 IPCC (Stocker et al., 2013). 15

All quantities are presented in units of gigatonnes of carbon (GtC, 10¹⁵ gC), which is the same as petagrams of carbon (PgC; Table 1). Units of gigatonnes of CO₂ (or billion tonnes of CO₂) used in policy are equal to 3.664 multiplied by the value in units of GtC.

This paper provides a detailed description of the data sets and methodology used to compute the 19 20 global carbon budget estimates for the period preindustrial (1750) to 2017 and in more detail for 21 the period since 1959. It also provides decadal averages starting in 1960 including the last decade 22 (2008-2017), results for the year 2017, and a projection for year 2018. Finally it provides cumulative emissions from fossil fuels and land-use change since year 1750, the preindustrial 23 24 period, and since year 1870, the reference year for the cumulative carbon estimate used by the 25 IPCC (AR5) based on the availability of global temperature data (Stocker et al., 2013). This paper is updated every year using the format of 'living data' to keep a record of budget versions and the 26 27 changes in new data, revision of data, and changes in methodology that lead to changes in 28 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 29 30 (http://www.globalcarbonproject.org/carbonbudget), with fossil fuel emissions also available

31 through the Global Carbon Atlas (http://www.globalcarbonatlas.org). With this approach, we aim

to provide the highest transparency and traceability in the reporting of CO₂, the key driver of
climate change.

3 2 Methods

Multiple organizations 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).
Descriptions of the measurements, models, and methodologies follow below and in depth
descriptions of each component are described elsewhere.

11 This is the 13th version of the global carbon budget and the seventh revised version in the format 12 of a living data update. It builds on the latest published global carbon budget of Le Quéré et 13 al. (2018). The main changes are: (1) the inclusion of data to year 2017 (inclusive) and a projection 14 for the global carbon budget for year 2018; (2) the introduction of metrics that evaluate components of the individual models used to estimate SOCEAN and SLAND using observations, as an 15 effort to document, encourage and support model improvements through time; (3) the revisions 16 17 of the CO_2 emissions associated with cement production based on revised clinker ratios; (4) a projection for fossil fuel emissions for European Union 28 member states based on compiled 18 19 energy statistics; and (5) the addition of sub-section 2.7.2 on additional emissions from calcination 20 not included in the budget. The main methodological differences between annual carbon budgets 21 are summarised in Table 3.

22 2.1 Fossil CO₂ emissions (E_{FF})

23 2.1.1 Emissions estimates

The estimates of global and national fossil CO₂ emissions (E_{FF}) include the combustion of fossil fuels through a wide range of activities (e.g. transport, heating and cooling, industry, fossil industry own use & gas flaring), the production of cement, and other process emissions (e.g. the production of chemicals & fertilizers). The estimates of E_{FF} rely primarily on energy consumption data, specifically data on hydrocarbon fuels, collated and archived by several organisations (Andres et al., 2012). We use four main data sets for historical emissions (1751-2017):

1 1. Global and national emission estimates for coal, oil, and gas from CDIAC for the time period 2 1751-2014 (Boden et al., 2017), as it is the only data set that extends back to 1751 by country. 3 2. Official UNFCCC national inventory reports for 1990-2016 for the 42 Annex I countries in the 4 UNFCCC (UNFCCC, 2018). We assess these to be the most accurate estimates because they are 5 compiled by experts within countries that have access to detailed energy data, and they are 6 periodically reviewed. 7 3. The BP Statistical Review of World Energy (BP, 2018), as these are the most up-to-date 8 estimates of national energy statistics.

9 4. Global and national cement emissions updated from Andrew (2018), which include revised
10 emissions factors.

In the following section we provide more details for each data set and describe the additional
 modifications that are required to make the data set consistent and usable.

13 CDIAC: The CDIAC estimates have been updated annually to the year 2014, derived primarily from

14 energy statistics published by the United Nations (UN, 2017b). Fuel masses and volumes are

15 converted to fuel energy content using country-level coefficients provided by the UN, and then

16 converted to CO₂ emissions using conversion factors that take into account the relationship

17 between carbon content and energy (heat) content of the different fuel types (coal, oil, gas, gas

18 flaring) and the combustion efficiency (Marland and Rotty, 1984).

19 UNFCCC: Estimates from the UNFCCC national inventory reports follow the IPCC guidelines (IPCC,

20 2006), but have a slightly larger system boundary than CDIAC by including emissions coming from

carbonates other than in cement manufacture. We reallocate the detailed UNFCCC estimates to

22 the CDIAC definitions of coal, oil, gas, cement, and other to allow consistent comparisons over

23 time and between countries.

24 BP: For the most recent period when the UNFCCC (2018) and CDIAC (2015-2017) estimates are not

available, we generate preliminary estimates using the BP Statistical Review of World Energy

26 (Andres et al., 2014; Myhre et al., 2009; BP, 2018). We apply the BP growth rates by fuel type (coal,

oil, gas) to estimate 2017 emissions based on 2016 estimates (UNFCCC), and to estimate 2015-

28 2017 emissions based on 2014 estimates (CDIAC). BP's data set explicitly covers about 70

countries (96% of global emissions), and for the remaining countries we use growth rates from the

30 sub-region the country belongs to. For the most recent years, flaring is assumed constant from the

most recent available year of data (2016 for countries that report to the UNFCCC, 2014 for the
remainder).

3 *Cement*: Estimates of emissions from cement production are taken directly from Andrew (2018).

4 Additional calcination and carbonation processes are not included explicitly here, except in

5 national inventories provided UNFCCC, but are discussed in Section 2.7.2.

6 Country mappings: The published CDIAC data set includes 256 countries and regions. This list 7 includes countries that no longer exist, such as the USSR and Yugoslavia. We reduce the list to 213 8 countries by reallocating emissions to the currently defined territories, using mass-preserving 9 aggregation or disaggregation. Examples of aggregation include merging East and West Germany 10 to the currently defined Germany. Examples of disaggregation include reallocating the emissions 11 from former USSR to the resulting independent countries. For disaggregation, we use the emission 12 shares when the current territories first appeared, and thus historical estimates of disaggregated 13 countries should be treated with extreme care. In addition, we aggregate some overseas 14 territories (e.g. Réunion, Guadeloupe) into their governing nations (e.g. France) to align with 15 UNFCCC reporting.

Global total: Our global estimate is based on CDIAC for fossil fuel combustion plus Andrew (2018) 16 for cement emissions. This is greater than the sum of emissions from all countries. This is largely 17 18 attributable to emissions that occur in international territory, in particular, the combustion of 19 fuels used in international shipping and aviation (bunker fuels). The emissions from international bunker fuels are calculated based on where the fuels were loaded, but we do not include them in 20 21 the national emissions estimates. Other differences occur 1) because the sum of imports in all countries is not equal to the sum of exports, and 2) because of inconsistent national reporting, 22 23 differing treatment of oxidation of non-fuel uses of hydrocarbons (e.g. as solvents, lubricants, feedstocks, etc.), and 3) changes in fuel stored (Andres et al., 2012). 24

25 2.1.2 Uncertainty assessment for EFF

We estimate the uncertainty of the global fossil CO₂ emissions at ±5% (scaled down from the published ±10 % at ±2σ to the use of ±1σ bounds reported here; Andres et al., 2012). This is consistent with a more detailed recent analysis of uncertainty of ±8.4% at ±2σ (Andres et al., 2014) and at the high-end of the range of ±5-10% at ±2σ reported by Ballantyne et al. (2015). This includes an assessment of uncertainties in the amounts of fuel consumed, the carbon and heat

1 contents of fuels, and the combustion efficiency. While we consider a fixed uncertainty of ±5% for 2 all years, the uncertainty as a percentage of the emissions is growing with time because of the 3 larger share of global emissions from emerging economies and developing countries (Marland et 4 al., 2009). Generally, emissions from mature economies with good statistical processes have an 5 uncertainty of only a few per cent (Marland, 2008), while emissions from developing countries 6 such as China have uncertainties of around ±10% (for ±1 σ ; Gregg et al., 2008). Uncertainties of 7 emissions are likely to be mainly systematic errors related to underlying biases of energy statistics 8 and to the accounting method used by each country.

9 We assign a medium confidence to the results presented here because they are based on indirect 10 estimates of emissions using energy data (Durant et al., 2011). There is only limited and indirect 11 evidence for emissions, although there is high agreement among the available estimates within 12 the given uncertainty (Andres et al., 2012;Andres et al., 2014), and emission estimates are 13 consistent with a range of other observations (Ciais et al., 2013), even though their regional and 14 national partitioning is more uncertain (Francey et al., 2013).

15 **2.1.3 Emissions embodied in goods and services**

16 CDIAC, UNFCCC, and BP national emission statistics 'include greenhouse gas emissions and 17 removals taking place within national territory and offshore areas over which the country has jurisdiction' (Rypdal et al., 2006), and are called territorial emission inventories. Consumption-18 19 based emission inventories allocate emissions to products that are consumed within a country, 20 and are conceptually calculated as the territorial emissions minus the 'embodied' territorial emissions to produce exported products plus the emissions in other countries to produce 21 imported products (Consumption = Territorial – Exports + Imports). Consumption-based emission 22 23 attribution results (e.g. Davis and Caldeira, 2010) provide additional information to territorialbased emissions that can be used to understand emission drivers (Hertwich and Peters, 2009) and 24 quantify emission transfers by the trade of products between countries (Peters et al., 2011b). The 25 26 consumption-based emissions have the same global total, but reflect the trade-driven movement 27 of emissions across the Earth's surface in response to human activities.

We estimate consumption-based emissions from 1990-2016 by enumerating the global supply chain using a global model of the economic relationships between economic sectors within and between every country (Andrew and Peters, 2013;Peters et al., 2011a). Our analysis is based on

1 the economic and trade data from the Global Trade and Analysis Project (GTAP; Narayanan et al., 2 2015), and we make detailed estimates for the years 1997 (GTAP version 5), 2001 (GTAP6), and 3 2004, 2007, and 2011 (GTAP9.2), covering 57 sectors and 141 countries and regions. The detailed 4 results are then extended into an annual time-series from 1990 to the latest year of the Gross 5 Domestic Product (GDP) data (2016 in this budget), using GDP data by expenditure in current 6 exchange rate of US dollars (USD; from the UN National Accounts main Aggregrates database; UN, 7 2017a) and time series of trade data from GTAP (based on the methodology in Peters et al., 2011b 8). We estimate the sector-level CO₂ emissions using the GTAP data and methodology, include 9 flaring and cement emissions from CDIAC, and then scale the national totals (excluding bunker fuels) to match the emission estimates from the carbon budget. We do not provide a separate 10 11 uncertainty estimate for the consumption-based emissions, but based on model comparisons and 12 sensitivity analysis, they are unlikely to be significantly different than for the territorial emission 13 estimates (Peters et al., 2012a).

14 2.1.4 Growth rate in emissions

We report the annual growth rate in emissions for adjacent years (in percent per year) by calculating the difference between the two years and then normalising to the emissions in the first year: $(E_{FF}(t_{0+1})-E_{FF}(t_0))/E_{FF}(t_0) \times 100\%$. We apply a leap-year adjustment where relevant to ensure valid interpretations of annual growth rates. This affects the growth rate by about 0.3% yr⁻¹ 1 (1/365) and causes growth rates to go up approximately 0.3% if the first year is a leap year and down 0.3% if the second year is a leap year.

The relative growth rate of E_{FF} over time periods of greater than one year can be re-written using its logarithm equivalent as follows:

$$\frac{1}{E_{FF}}\frac{dE_{FF}}{dt} = \frac{d(lnE_{FF})}{dt}$$
(2)

Here we calculate relative growth rates in emissions for multi-year periods (e.g. a decade) by fitting a linear trend to $ln(E_{FF})$ in Eq. (2), reported in percent per year.

25 2.1.5 Emissions projections

To gain insight on emission trends for the current year (2018), we provide an assessment of global fossil CO_2 emissions, E_{FF} , by combining individual assessments of emissions for China, USA, the EU, and India (the four countries/regions with the largest emissions), and the rest of the world.

Our 2018 estimate for China uses: (1) the sum of domestic production (NBS, 2018b) and net 1 imports (General Administration of Customs of the People's Republic of China, 2018) for coal, oil 2 3 and natural gas and production of cement (NBS, 2018b) from preliminary statistics for January 4 through September of 2018; and (2) historical relationships between January-September 5 production and import statistics and full-year consumption figures from final official statistics for 6 2000-2016 (NBS, 2015, 2017) and preliminary full-year data for 2017 (NBS, 2018a). See Jackson et 7 al. (2018b) for details. The uncertainty is based on the variance of the difference between the 8 January-September and full-year data from historical data, as well as typical variance in the 9 preliminary full-year data used for 2017 and typical changes in the energy content of coal for the period 2013-2016 (NBS, 2017, 2015). We note that developments for the final three months this 10 11 year may be atypical due to the ongoing trade disputes between China and the U.S., and this 12 additional uncertainty has not been quantified. Results and uncertainties are discussed further in Sect. 3.4.1. 13

For the USA, we use the forecast of the U.S. Energy Information Administration (EIA) for emissions 14 from fossil fuels (EIA, 2018). This is based on an energy forecasting model which is updated 15 16 monthly (last update to October), and takes into account heating-degree days, household 17 expenditures by fuel type, energy markets, policies, and other effects. We combine this with our estimate of emissions from cement production using the monthly U.S. cement data from USGS for 18 19 January-August, assuming changes in cement production over the first part of the year apply throughout the year. While the EIA's forecasts for current full-year emissions have on average 20 been revised downwards, only ten such forecasts are available, so we conservatively use the full 21 22 range of adjustments following revision, and additionally assume symmetrical uncertainty to give 23 ±2.5% around the central forecast.

24 For India, we use (1) monthly coal production and sales data from the Ministry of Mines (2018), 25 Coal India Limited (CIL, 2018) and Singareni Collieries Company Limited (SCCL, 2018), combined with import data from the Ministry of Commerce and Industry (MCI, 2018) and power station 26 27 stocks data from the Central Electricity Authority (CEA, 2018); (2) monthly oil production and 28 consumption data from the Ministry of Petroleum and Natural Gas (PPAC, 2018a); (3) monthly natural gas production and import data from the Ministry of Petroleum and Natural Gas (PPAC, 29 30 2018b); and (4) monthly cement production data from the Office of the Economic Advisor (OEA, 2018). All data were available for January to September or October. We use Holt-Winters 31

exponential smoothing with multiplicative seasonality (Chatfield, 1978) on each of these four
emissions series to project to the end of the current year. This iterative method produces
estimates of both trend and seasonality at the end of the observation period that are a function of
all prior observations, weighted most strongly to more recent data, while maintaining some
smoothing effect. The main source of uncertainty in the projection of India's emissions is the
assumption of continued trends and typical seasonality.

7 For the EU, we use (1) monthly coal supply data from Eurostat for the first 6-9 months of the year 8 (Eurostat, 2018) cross-checked with more recent data on coal-generated electricity from ENTSO-E 9 for January through October (ENTSO-E, 2018); (2) monthly oil and gas demand data for January 10 through August from the Joint Organisations Data Initiative (JODI, 2018); and (3) cement production is assumed stable. For oil and gas emissions we apply the Holt-Winters method 11 separately to each country and energy carrier to project to the end of the current year, while for 12 13 coal — which is much less strongly seasonal because of strong weather variations – we assume the remaining months of the year are the same as the previous year in each country. 14 For the rest of the world, we use the close relationship between the growth in GDP and the 15

16 growth in emissions (Raupach et al., 2007) to project emissions for the current year. This is based
 17 on a simplified Kaya Identity, whereby E_{FF} (GtC yr⁻¹) is decomposed by the product of GDP (USD yr⁻¹)

¹) and the fossil fuel carbon intensity of the economy (I_{FF}; GtC USD⁻¹) as follows:

$$E_{FF} = GDP \times I_{FF} \tag{3}$$

19 Taking a time derivative of Equation (3) and rearranging gives:

$$\frac{1}{E_{FF}}\frac{dE_{FF}}{dt} = \frac{1}{GDP}\frac{dGDP}{dt} + \frac{1}{I_{FF}}\frac{dI_{FF}}{dt}$$
(4)

where the left-hand term is the relative growth rate of E_{FF}, and the right-hand terms are the
 relative growth rates of GDP and I_{FF}, respectively, which can simply be added linearly to give the
 overall growth rate.

The growth rates are reported in percent by multiplying each term by 100. As preliminary
 estimates of annual change in GDP are made well before the end of a calendar year, making
 assumptions on the growth rate of I_{FF} allows us to make projections of the annual change in CO₂

26 emissions well before the end of a calendar year. The I_{FF} is based on GDP in constant PPP

27 (purchasing power parity) from the International Energy Agency (IEA) up to 2016 (IEA/OECD,

2017) and extended using the International Monetary Fund (IMF) growth rates for 2016 and 2017
 (IMF, 2018). Interannual variability in I_{FF} is the largest source of uncertainty in the GDP-based
 emissions projections. We thus use the standard deviation of the annual I_{FF} for the period 2007 2017 as a measure of uncertainty, reflecting a ±1σ as in the rest of the carbon budget. This is

5 ±1.0% yr⁻¹ for the rest of the world (global emissions minus China, USA, EU and India).

The 2018 projection for the world is made of the sum of the projections for China, USA, EU, India,
and the rest of the world. The uncertainty is added in quadrature among the five regions. The
uncertainty here reflects the best of our expert opinion.

9 2.2 CO₂ emissions from land use, land-use change and forestry (E_{LUC})

10 The net CO₂ flux from land use, land-use change and forestry (E_{LUC}, called land-use change emissions in the rest of the text) include CO₂ fluxes from deforestation, afforestation, logging and 11 12 forest degradation (including harvest activity), shifting cultivation (cycle of cutting forest for agriculture, then abandoning), and regrowth of forests following wood harvest or abandonment 13 14 of agriculture. Only some land management activities are included in our land-use change emissions estimates (Table A1). Some of these activities lead to emissions of CO₂ to the 15 atmosphere, while others lead to CO₂ sinks. E_{LUC} is the net sum of emissions and removals due to 16 17 all anthropogenic activities considered. Our annual estimate for 1959-2017 is provided as the 18 average of results from two bookkeeping models (Sect. 2.2.1): the estimate published by 19 Houghton and Nassikas (2017; hereafter H&N2017) extended here to 2017, and an estimate using 20 the BLUE model (Bookkeeping of Land Use Emissions; Hansis et al., 2015). In addition, we use results from Dynamic Global Vegetation Models (DGVMs; see Sect. 2.2.3 and Table 4), to help 21 22 quantify the uncertainty in ELUC, and thus better characterise our understanding. The three methods are described below, and differences are discussed in Sect. 3.2. 23

24 2.2.1 Bookkeeping models

Land-use change CO₂ emissions and uptake fluxes are calculated by two bookkeeping models.
Both are based on the original bookkeeping approach of Houghton (2003) that keeps track of the
carbon stored in vegetation and soils before and after a land-use change (transitions between
various natural vegetation types, croplands and pastures). Literature-based response curves
describe decay of vegetation and soil carbon, including transfer to product pools of different
lifetimes, as well as carbon uptake due to regrowth. In addition, the bookkeeping models

represent long-term degradation of primary forest as lowered standing vegetation and soil carbon
stocks in secondary forests, and also include forest management practices such as wood harvests.
The bookkeeping models do not include land ecosystems' transient response to changes in
climate, atmospheric CO₂ and other environmental factors, and the carbon densities are based on
contemporary data reflecting stable environmental conditions at that time. Since carbon densities
remain fixed over time in bookkeeping models, the additional sink capacity that ecosystems
provide in response to CO₂-fertilization and some other environmental changes is not captured by

8 these models (Pongratz et al., 2014; see Section 2.7.3).

9 The H&N2017 and BLUE models differ in (1) computational units (country-level vs spatially explicit 10 treatment of land-use change), (2) processes represented (see Table A1), and (3) carbon densities assigned to vegetation and soil of each vegetation type. A notable change of H&N2017 over the 11 12 original approach by Houghton et al. (2003) used in earlier budget estimates is that no shifting 13 cultivation or other back- and forth-transitions at a level below country are included. Only a 14 decline in forest area in a country as indicated by the Forest Resource Assessment of the FAO that exceeds the expansion of agricultural area as indicated by FAO is assumed to represent a 15 concurrent expansion and abandonment of cropland. In contrast, the BLUE model includes sub-16 17 grid-scale transitions at the grid level between all vegetation types as indicated by the harmonized 18 land-use change data (LUH2) data set (Hurtt et al., in prep.). Furthermore, H&N2017 assume 19 conversion of natural grasslands to pasture, while BLUE allocates pasture proportionally on all 20 natural vegetation that exist in a gridcell. This is one reason for generally higher emissions in 21 BLUE. H&N2017 add carbon emissions from peat burning based on the Global Fire Emission 22 Database (GFED4s; van der Werf et al. (2017)), and peat drainage, based on estimates by Hooijer et al. (2010) to the output of their bookkeeping model for the countries of Indonesia and 23 24 Malaysia. Peat burning and emissions from the organic layers of drained peat soils, which are not 25 captured by bookkeeping methods directly, need to be included to represent the substantially 26 larger emissions and interannual variability due to synergies of land-use and climate variability in 27 Southeast Asia, in particular during El-Niño events. Similarly to H&N2017, peat burning and 28 drainage-related emissions are also added to the BLUE estimate.

The two bookkeeping estimates used in this study also differ with respect to the land use change
data used to drive the models. H&N2017 base their estimates directly on the Forest Resource
Assessment of the FAO which provides statistics on forest-area change and management at

1 intervals of five years currently updated until 2015 (FAO, 2015). The data is based on country 2 reporting to FAO, and may include remote-sensing information in more recent assessments. 3 Changes in land use other than forests are based on annual, national changes in cropland and 4 pasture areas reported by FAO (FAOSTAT, 2015). BLUE uses the harmonized land-use change data 5 LUH2 (Hurtt et al., in prep.), which describes land use change, also based on the FAO data, but 6 downscaled at a quarter-degree spatial resolution, considering sub-grid-scale transitions between 7 primary forest, secondary forest, cropland, pasture and rangeland. The LUH2 data provides a new 8 distinction between rangelands and pasture. To constrain the models' interpretation on whether 9 rangeland implies the original natural vegetation to be transformed to grassland or not (e.g., 10 browsing on shrubland), a new forest mask was provided with LUH2; forest is assumed to be 11 transformed, while all other natural vegetation remains. This is implemented in BLUE. The estimate of H&N2017 was extended here by two years (to 2017) by adding the anomaly of 12

total tropical emissions (peat drainage from Hooijer et al. (2010), peat burning as well as tropical
 deforestation and degradation fires from GFED4s) over the previous decade (2006-2015) to the
 decadal average of the bookkeeping result.

16 2.2.2 Dynamic Global Vegetation Models (DGVMs)

17 Land-use change CO₂ emissions have also been estimated using an ensemble of 16 DGVM simulations. The DGVMs account for deforestation and regrowth, the most important 18 19 components of ELUC, but they do not represent all processes resulting directly from human 20 activities on land (Table A1). All DGVMs represent processes of vegetation growth and mortality, 21 as well as decomposition of dead organic matter associated with natural cycles, and include the vegetation and soil carbon response to increasing atmospheric CO₂ levels and to climate variability 22 23 and change. Some models explicitly simulate the coupling of carbon and nitrogen cycles and account for atmospheric N deposition (Table A1). The DGVMs are independent from the other 24 25 budget terms except for their use of atmospheric CO₂ concentration to calculate the fertilization 26 effect of CO₂ on plant photosynthesis.

The DGVMs used the HYDE land-use change data set (Klein Goldewijk et al., 2017a;Klein Goldewijk et al., 2017b), which provides annual, half-degree, fractional data on cropland and pasture. These data are based on annual FAO statistics of change in agricultural land area available to 2012. The FAOSTAT land use database is updated annually, currently covering the period 1961-2016 (but

1 used here to 2015 because of the timing of data availability). HYDE applied annual changes in FAO 2 data to the year 2012 data from the previous release to derive new 2013-2015 data. After the 3 year 2015 HYDE extrapolates cropland, pasture, and urban land use data until the year 2018. 4 Some models also use an update of the more comprehensive harmonised land-use data set (Hurtt 5 et al., 2011), that further includes fractional data on primary and secondary forest vegetation, as 6 well as all underlying transitions between land-use states (Hurtt et al., in prep.; Table A1). This 7 new data set is of quarter degree fractional areas of land use states and all transitions between 8 those states, including a new wood harvest reconstruction, new representation of shifting 9 cultivation, crop rotations, management information including irrigation and fertilizer application. The land-use states now include five different crop types in addition to the pasture-rangeland split 10 11 discussed before. Wood harvest patterns are constrained with Landsat tree cover loss data.

DGVMs implement land-use change differently (e.g. an increased cropland fraction in a grid cell can either be at the expense of grassland or shrubs, or forest, the latter resulting in deforestation; land cover fractions of the non-agricultural land differ between models). Similarly, model-specific assumptions are applied to convert deforested biomass or deforested area, and other forest product pools into carbon, and different choices are made regarding the allocation of rangelands as natural vegetation or pastures.

18 The DGVM model runs were forced by either the merged monthly CRU and 6 hourly JRA-55 19 dataset or by the monthly CRU dataset, both providing observation based temperature, 20 precipitation, and incoming surface radiation on a 0.5°x0.5° grid and updated to 2017 (Harris et 21 al., 2014). The combination of CRU monthly data with 6 hourly forcing is updated this year from 22 NCEP to JRA-55 (Kobayashi et al., 2015), adapting the methodology used in previous years (Viovy, 2016) to the specifics of the JRA-55 data. The forcing data also include global atmospheric CO₂, 23 24 which changes over time (Dlugokencky and Tans, 2018), and gridded, time dependent N 25 deposition (as used in some models; Table A1).

Two sets of simulations were performed with the DGVMs. Both applied historical changes in climate, atmospheric CO₂ concentration, and N deposition. The two sets of simulations differ, however, with respect to land use: one set applies historical changes in land use, the other a timeinvariant preindustrial land cover distribution and preindustrial wood harvest rates. By difference of the two simulations, the dynamic evolution of vegetation biomass and soil carbon pools in response to land use change can be quantified in each model (E_{LUC}). We only retain model outputs

with positive E_{LUC}, i.e. a positive flux to the atmosphere, during the 1990s (Table A1). Using the
difference between these two DGVM simulations to diagnose E_{LUC} means the DGVMs account for
the loss of additional sink capacity (around 0.3 GtC yr⁻¹; see Section 2.7.3), while the bookkeeping
models do not.

5 2.2.3 Uncertainty assessment for ELUC

Differences between the bookkeeping models and DGVM models originate from three main
sources: the different methodologies; the underlying land use/land cover data set, and the
different processes represented (Table A1). We examine the results from the DGVM models and
of the bookkeeping method, and use the resulting variations as a way to characterise the
uncertainty in E_{LUC}.

11 The E_{LUC} estimate from the DGVMs multi-model mean is consistent with the average of the 12 emissions from the bookkeeping models (Table 5). However there are large differences among individual DGVMs (standard deviation at around 0.6-0.7 GtC yr⁻¹; Table 5), between the two 13 bookkeeping models (average of 0.7 GtC yr⁻¹), and between the current estimate of H&N2017 and 14 its previous model version (Houghton et al., 2012). The uncertainty in ELUC of ±0.7 GtC yr⁻¹ reflects 15 our best value judgment that there is at least 68% chance $(\pm 1\sigma)$ that the true land-use change 16 17 emission lies within the given range, for the range of processes considered here. Prior to the year 1959, the uncertainty in ELUC was taken from the standard deviation of the DGVMs. We assign low 18 19 confidence to the annual estimates of E_{LUC} because of the inconsistencies among estimates and of 20 the difficulties to quantify some of the processes in DGVMs.

21 2.2.4 Emissions projections

We project emissions for both H&N2017 and BLUE for 2018 using the same approach as for the extrapolation of H&N2017 for 2016-2017. Peat burning as well as tropical deforestation and degradation are estimated using active fire data (MCD14ML; Giglio et al. (2016)), which scales almost linearly with GFED (van der Werf et al., 2017), and thus allows for tracking fire emissions in deforestation and tropical peat zones in near-real time. During most years, emissions during January-October cover most of the fire season in the Amazon and Southeast Asia, where a large part of the global deforestation takes place.

1 2.3 Growth rate in atmospheric CO₂ concentration (G_{ATM})

2 2.3.1 Global growth rate in atmospheric CO₂ concentration

3 The rate of growth of the atmospheric CO₂ concentration is provided by the US National Oceanic 4 and Atmospheric Administration Earth System Research Laboratory (NOAA/ESRL; Dlugokencky 5 and Tans, 2018), which is updated from Ballantyne et al. (2012). For the 1959-1979 period, the global growth rate is based on measurements of atmospheric CO₂ concentration averaged from 6 7 the Mauna Loa and South Pole stations, as observed by the CO₂ Program at Scripps Institution of 8 Oceanography (Keeling et al., 1976). For the 1980-2017 time period, the global growth rate is 9 based on the average of multiple stations selected from the marine boundary layer sites with wellmixed background air (Ballantyne et al., 2012), after fitting each station with a smoothed curve as 10 a function of time, and averaging by latitude band (Masarie and Tans, 1995). The annual growth 11 rate is estimated by Dlugokencky and Tans (2018) from atmospheric CO₂ concentration by taking 12 13 the average of the most recent December-January months corrected for the average seasonal 14 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 (Ballantyne et al., 15 16 2012).

17 The uncertainty around the atmospheric growth rate is due to three main factors. First, the longterm reproducibility of reference gas standards (around 0.03 ppm for 1o from the 1980s). Second, 18 19 small unexplained systematic analytical errors that may have a duration of several months to two 20 years come and go. They have been simulated by randomizing both the duration and the 21 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 22 time series at each site, etc (Dlugokencky and Tans, 2018). The latter uncertainty was estimated 23 by NOAA/ESRL with a Monte Carlo method by constructing 100 "alternative" networks 24 (NOAA/ESRL 2017; Masarie, and Tans, 1995). The second and third uncertainties, summed in 25 26 quadrature, add up to 0.085 ppm on average (Dlugokencky and Tans, 2018). Fourth, the 27 uncertainty associated with using the average CO₂ concentration from a surface network to 28 approximate the true atmospheric average CO_2 concentration (mass-weighted, in 3 dimensions) as needed to assess the total atmospheric CO₂ burden. In reality, CO₂ variations measured at the 29 stations will not exactly track changes in total atmospheric burden, with offsets in magnitude and 30 31 phasing due to vertical and horizontal mixing. This effect must be very small on decadal and

1 longer time scales, when the atmosphere can be considered well mixed. Preliminary estimates suggest this effect would increase the annual uncertainty, but a full analysis is not yet available. 2 We therefore maintain an uncertainty around the annual growth rate based on the multiple 3 4 stations data set ranges between 0.11 and 0.72 GtC yr⁻¹, with a mean of 0.61 GtC yr⁻¹ for 1959-5 1979 and 0.18 GtC yr⁻¹ for 1980-2017, when a larger set of stations were available as provided by 6 Dlugokencky and Tans (2018), but recognise further exploration of this uncertainty is required. At 7 this time, 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 8 9 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 (0.61/0.18*0.02 GtC 10 11 yr⁻¹).

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

In order to estimate the total carbon accumulated in the atmosphere since 1750 or 1870, we use an atmospheric CO₂ concentration of 277 ± 3 ppm or 288 ± 3 ppm, respectively, based on a cubic spline fit to ice core data (Joos and Spahni, 2008). The uncertainty of ±3 ppm (converted to ±1 σ) is taken directly from the IPCC's assessment (Ciais et al., 2013). Typical uncertainties in the growth rate in atmospheric CO₂ 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 1870 to 1960 (Bruno and Joos, 1997).

22 2.3.2 Atmospheric growth rate projection

We provide an assessment of G_{ATM} for 2018 based on the observed increase in atmospheric CO₂ 23 24 concentration at the Mauna Loa station for January to October, and a mean growth rate over the past 5 years for the months November to December. Growth at Mauna Loa is closely correlated 25 with the global growth (r=0.95) and is used here as a proxy for global growth, but the regression is 26 not 1-to-1. We also adjust the projected global growth rate to take this into account. The 27 assessment method used this year differs from the forecast method used in Le Quéré et al. (2018) 28 29 based on the relationship between annual CO₂ growth rate and sea surface temperatures (SSTs) in 30 the Niño3.4 region of Betts et al. (2016). A change was introduced because although the observed

1 growth rate for 2017 of 2.2 ppm was within the projection range of 2.5 ± 0.5 ppm of last year (Le 2 Quéré et al. 2018), the forecast values for 2018 for January to October are too high by 3 approximately 0.4 ppm above observed values on average. The reasons for the difference are 4 being investigated. The use of observed growth at MLO for the first half of the year is thought to 5 be more robust because of its high correlation with the global growth rate. Furthermore, 6 additional analysis suggests that the first half of the year shows more interannual variability than 7 the second half of the year, so that the exact projection method applied to November-December 8 has only a small impact (<0.1 ppm) on the projection of the full year. Uncertainty is estimated 9 from past variability using the standard deviation of the last 5 years' monthly growth rates.

10 **2.4 Ocean CO₂ sink**

Estimates of the global ocean CO₂ sink S_{OCEAN} are from an ensemble of global ocean
biogeochemistry models (GOBMs) that meet observational constraints over the 1990s (see
below). We use observation-based estimates of S_{OCEAN} to provide a qualitative assessment of
confidence in the reported results, and to estimate the cumulative accumulation of S_{OCEAN} over
the preindustrial period.

16 2.4.1 Observation-based estimates

We use the observational constraints assessed by IPCC of a mean ocean CO_2 sink of 2.2 ± 0.4 GtC 17 18 yr⁻¹ for the 1990s (Denman et al., 2007) to verify that the GOBMs provide a realistic assessment of 19 S_{OCEAN}. This is based on indirect observations with seven different methodologies and their 20 uncertainties, using the methods that are deemed most reliable for the assessment of this quantity (Denman et al., 2007). The IPCC confirmed this assessment in 2013 (Ciais et al., 2013). 21 22 The observational-based estimates use the ocean/land CO₂ sink partitioning from observed atmospheric O_2/N_2 concentration trends (Manning and Keeling, 2006; updated in Keeling and 23 Manning 2014), an oceanic inversion method constrained by ocean biogeochemistry data 24 25 (Mikaloff Fletcher et al., 2006), and a method based on penetration time scale for CFCs (McNeil et al., 2003). The IPCC estimate of 2.2 GtC yr⁻¹ for the 1990s is consistent with a range of methods 26 27 (Wanninkhof et al., 2013).

28 We also use two estimates of the ocean CO₂ sink and its variability based on interpolations of

29 measurements of surface ocean fugacity of CO₂ (pCO₂ corrected for the non-ideal behaviour of

30 the gas; Pfeil et al., 2013). We refer to these as pCO₂-based flux estimates. The measurements are

1 from the Surface Ocean CO_2 Atlas version 6, which is an update of version 3 (Bakker et al., 2016) and contains quality-controlled data to 2017 (see data attribution Table A4). The SOCAT v6 data 2 3 were mapped using a data-driven diagnostic method (Rödenbeck et al., 2013) and a combined 4 self-organising map and feed-forward neural network (Landschützer et al., 2014). The global pCO₂-5 based flux estimates were adjusted to remove the preindustrial ocean source of CO₂ to the 6 atmosphere of 0.78 GtC yr⁻¹ from river input to the ocean (Resplandy et al., 2018), per our 7 definition of S_{OCEAN}. Several other ocean sink products based on observations are also available 8 but they continue to show large unresolved discrepancies with observed variability. Here we used 9 the two pCO₂-based flux products that had the best fit to observations for their representation of tropical and global variability (Rödenbeck et al., 2015). 10

We further use results from two diagnostic ocean models of Khatiwala et al. (2013) and DeVries (2014) to estimate the anthropogenic carbon accumulated in the ocean prior to 1959. The two approaches assume constant ocean circulation and biological fluxes, with S_{OCEAN} estimated as a response in the change in atmospheric CO₂ concentration calibrated to observations. The uncertainty in cumulative uptake of ±20 GtC (converted to ±1 σ) is taken directly from the IPCC's review of the literature (Rhein et al., 2013), or about ±30% for the annual values (Khatiwala et al., 2009).

18 2.4.2 Global Ocean Biogeochemistry Models (GOBMs)

19 The ocean CO₂ sink for 1959-2017 is estimated using seven GOBMs (Table A2). The GOBMs represent the physical, chemical and biological processes that influence the surface ocean 20 21 concentration of CO₂ and thus the air-sea CO₂ flux. The GOBMs are forced by meteorological reanalysis and atmospheric CO₂ concentration data available for the entire time period. They 22 23 mostly differ in the source of the atmospheric forcing data (meteorological reanalysis), spin up strategies, and in their horizontal and vertical resolutions (Table A2). GOBMs do not include the 24 effects of anthropogenic changes in nutrient supply, which could lead to an increase of the ocean 25 sink of up to about 0.3 GtC yr⁻¹ over the industrial period (Duce et al., 2008). They also do not 26 include the perturbation associated with changes in riverine organic carbon (see Sect. 2.7.3). 27

1 2.4.3 GOBM evaluation and uncertainty assessment for Socean

The mean ocean CO₂ sink for all GOBMs fall within 90% confidence of the observed range, or 1.6 2 3 to 2.8 GtC yr⁻¹ for the 1990s. Here we have adjusted the confidence interval to the IPCC confidence interval of 90% to avoid rejecting models that may be outliers but are still plausible. 4 5 The GOBMs and flux products have been further evaluated using fCO₂ from the SOCAT v6 6 database. We focused this initial evaluation on the interannual mismatch metric proposed by 7 Rödenbeck et al. (2015) for the comparison of flux products. The metric provides a measure of the 8 mismatch between observations and models or flux products on the x-axis as well as a measure of 9 the amplitude of the interannual variability on the y-axis. A smaller number on the x-axis indicates 10 a better fit with observations. The amplitude of the interannual variability of S_{OCEAN} (y-axis) is 11 calculated as the temporal standard deviation of the CO₂ flux time-series.

The calculation for the x-axis is done as follows: 1) the mismatch between the observed and the 12 modelled fCO₂ is calculated for the period 1985 to 2017 (except for IPSL model which uses 1985 to 13 2015 due to data availability), but only for grid points where actual observations exist. 2) The 14 interannual variability of this mismatch is calculated as the temporal standard deviation of the 15 16 mismatch. 3) To put numbers into perspective, the interannual variability of the mismatch is reported relative to the interannual variability of the mismatch between a benchmark fCO₂ field 17 and the observations. The benchmark fCO₂ field is designed to have no interannual variability, i.e. 18 19 it is calculated as the mean seasonal cycle at each grid point over the full period plus the deseasonalized atmospheric fCO₂ increase over time. By definition, the interannual variability of 20 21 the misfit between benchmark and observations is large as the benchmark field does not contain 22 any interannual variability from the ocean. A smaller relative interannual variability mismatch 23 indicates a better fit between observed and modelled fCO2. This metric is chosen because it is the 24 most direct measure of the year-to-year variability of S_{OCEAN} in ocean biogeochemistry models. We apply the metric globally and by latitude bands (Fig. B1). Results are shown in Fig. B1 and 25 26 discussed in Section 3.1.3.

The uncertainty around the mean ocean sink of anthropogenic CO₂ was quantified by Denman et al. (2007) for the 1990s (see Sect. 2.4.1). To quantify the uncertainty around annual values, we examine the standard deviation of the GOBM ensemble, which averages between 0.2 and 0.3 GtC yr⁻¹ during 1959-2017. We estimate that the uncertainty in the annual ocean CO₂ sink is about \pm 0.5 GtC yr⁻¹ from the combined uncertainty of the mean flux based on observations of \pm 0.4 GtC

- 1 yr⁻¹ and the standard deviation across GOBMs of up to \pm 0.3 GtC yr⁻¹, reflecting both the
- 2 uncertainty in the mean sink from observations during the 1990's (Denman et al., 2007; Section

3 2.4.1) and in the interannual variability as assessed by GOBMs.

4 We examine the consistency between the variability of the model-based and the pCO₂-based flux 5 products to assess confidence in S_{OCEAN}. The interannual variability of the ocean fluxes (quantified 6 as the standard deviation) of the two pCO₂-based flux products for 1985-2017 (where they overlap) is \pm 0.36 GtC yr⁻¹ (Rödenbeck et al., 2014) and \pm 0.38 GtC yr⁻¹ (Landschützer et al., 2015), 7 compared to ± 0.29 GtC yr⁻¹ for the GOBM ensemble. The standard deviation includes a 8 9 component of trend and decadal variability in addition to interannual variability, and their relative influence differs across estimates. Individual estimates (both GOBM and flux products) generally 10 11 produce a higher ocean CO₂ sink during strong El Niño events. The annual pCO₂-based flux 12 products correlate with the ocean CO_2 sink estimated here with a correlation of r = 0.75 (0.59 to 0.79 for individual GOBMs), and r = 0.80 (0.71 to 0.81) for the pCO₂-based flux products of 13 Rödenbeck et al. (2014) and Landschützer et al. (2015), respectively (simple linear regression), 14 with their mutual correlation at 0.73. The agreement between models and the flux products 15 reflects some consistency in their representation of underlying variability since there is little 16 17 overlap in their methodology or use of observations. The use of annual data for the correlation may reduce the strength of the relationship because the dominant source of variability associated 18 19 with El Niño events is less than one year. We assess a medium confidence level to the annual 20 ocean CO_2 sink and its uncertainty because it is based on multiple lines of evidence, and the 21 results are consistent in that the interannual variability in the GOBMs and data-based estimates are all generally small compared to the variability in the growth rate of atmospheric CO₂ 22 23 concentration.

24 2.5 Terrestrial CO₂ sink

25 2.5.1 DGVM simulations

The terrestrial land sink (S_{LAND}) is thought to be due to the combined effects of fertilisation by rising atmospheric CO₂ and N deposition 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 CO₂ fluxes on land between S_{LAND} and E_{LUC} (Erb et al., 2013).

S_{LAND} is estimated from the multi-model mean of the DGVMs (Table 4). As described in section
 2.2.3, DGVM simulations include all climate variability and CO₂ effects over land, with some
 DGVMs also including the effect of N deposition. The DGVMs do not include the perturbation
 associated with changes in river organic carbon, which is discussed section 2.7.

5 2.5.2 DGVM evaluation and uncertainty assessment for SLAND

We apply three criteria for minimum DGVM realism by including only those DGVMs with (1)
steady state after spin up, (2) net land fluxes (S_{LAND} – E_{LUC}) that is an atmosphere-to-land carbon
flux over the 1990s ranging between -0.3 and 2.3GtC yr⁻¹, within 90% confidence of constraints by
global atmospheric and oceanic observations (Keeling and Manning, 2014; Wanninkhof et al.,
2013), and (3) global E_{LUC} that is a carbon source to the atmosphere over the 1990s. All 16 DGVMs
meet the three criteria.

12 In addition, the DGVM results are now also evaluated using the International Land Model

13 Benchmarking system (ILAMB; Collier et al., 2018). This evaluation is provided here to document,

14 encourage and support model improvements through time. ILAMB variables cover key processes

15 that are relevant for the quantification of S_{LAND} and resulting aggregated outcomes. The selected

16 variables are vegetation biomass, gross primary productivity, leaf area index, net ecosystem

17 exchange, ecosystem respiration, evapotranspiration, and runoff (see Fig. B2 for the results and

18 for the list of observed databases). Results are shown in Fig. B2 and discussed in Section 3.1.3.

19 For the uncertainty, we use the standard deviation of the annual CO₂ sink across the DGVMs,

which averages to \pm 0.8 GtC yr⁻¹ for the period 1959 to 2017. We attach a medium confidence

21 level to the annual land CO₂ sink and its uncertainty because the estimates from the residual

22 budget and averaged DGVMs match well within their respective uncertainties (Table 5).

23 **2.6 The atmospheric perspective**

The world-wide network of atmospheric measurements can be used with atmospheric inversion
 methods to constrain the location of the combined total surface CO₂ fluxes from all sources,

26 including fossil and land-use change emissions and land and ocean CO₂ fluxes. The inversions

27 assume E_{FF} to be well known, and they solve for the spatial and temporal distribution of land and

ocean fluxes from the residual gradients of CO₂ between stations that are not explained by fossil

29 fuel emissions.

1 Four atmospheric inversions (Table A3) used atmospheric CO₂ data to the end of 2017 (including 2 preliminary values in some cases) to infer the spatio-temporal distribution of the CO₂ flux 3 exchanged between the atmosphere and the land or oceans. We focus here on the largest and 4 most consistent sources of information, namely the total land and ocean CO₂ flux and their 5 partitioning among the mid-high latitude region of the Northern Hemisphere (30°N-90°N), the 6 tropics (30°S-30°N) and the mid-high latitude region of the Southern Hemisphere (30°S-90°S). We 7 also break down those estimates for the land and ocean regions separately, to further scrutinise 8 the constraints from atmospheric observations. We use these estimates to comment on the 9 consistency across various data streams and process-based estimates.

10 Atmospheric inversions

The four inversion systems used in this release are the CarbonTracker Europe (CTE; van der Laan-11 Luijkx et al., 2017), the Jena CarboScope (Rödenbeck, 2005), the Copernicus Atmosphere 12 Monitoring Service (CAMS; Chevallier et al., 2005), and MIROC (Patra et al., 2018). See Table A3 13 for version numbers. The inversions are based on the same Bayesian inversion principles that 14 15 interpret the same, for the most part, observed time series (or subsets thereof), but use different 16 methodologies (Table A3). These differences mainly concern the selection of atmospheric CO₂ data, the used prior fluxes, spatial breakdown (i.e. grid size), assumed correlation structures, and 17 mathematical approach. The details of these approaches are documented extensively in the 18 19 references provided above. Each system uses a different transport model, which was demonstrated to be a driving factor behind differences in atmospheric-based flux estimates, and 20 21 specifically their distribution across latitudinal bands (e.g., Gaubert et al., 2018).

The inversions use atmospheric CO₂ observations from various flask and in situ networks, as 22 detailed in Table A3. They prescribe global E_{FF}, which is scaled to the present study for CAMS and 23 CTE, while slightly lower E_{FF} values based on alternative emissions compilations were used in 24 25 CarboScope and MIROC. Since this is known to result directly in lower total CO₂ uptake in atmospheric inversions (Gaubert et al., 2018; Peylin et al., 2013) we adjusted the land sink of each 26 inversion estimate (where most of the emissions occur) by its fossil fuel difference to the CAMS 27 28 model. These differences amount to as much as 0.7 GtC for certain years (CarboScope inversion region NH) and are thus an important consideration in an inverse flux comparison. 29

1 The land/ocean CO₂ fluxes from atmospheric inversions contain anthropogenic perturbation and 2 natural pre-industrial CO₂ fluxes. Natural pre-industrial fluxes are land CO₂ sinks corresponding to 3 carbon transported to ocean by rivers. These land CO₂ sinks are compensated over the globe by 4 ocean CO₂ sources corresponding to the outgassing of riverine carbon inputs to the ocean. We 5 apply the distribution of land CO₂ fluxes in three latitude bands using estimates from Resplandy et 6 al. (2018), which are constrained by ocean heat transport to a total sink of 0.78 GtC y⁻¹. The 7 latitude distribution of river-induced ocean CO₂ sources are derived from a simulation of the IPSL 8 GOBM using as an input the river flux constrained by heat transport of Resplandy et al. (2018). We 9 adjusted the land/ocean fluxes per latitude band based on these results.

The atmospheric inversions are now evaluated using vertical profiles of atmospheric CO₂ concentrations (Fig. B3). More than 50 aircraft programs over the globe, either regular or occasional, have been used in order to draw a robust picture of the model performance but the space-time data coverage is irregular, denser around 2009 or in the 0-45°N latitude band. The four models are compared to independent CO₂ measurements made onboard aircraft over many places of the world between 1 and 7 km above sea level, between 2008 and 2016. Results are shown in Fig. B3 and discussed in Section 3.1.3.

17 **2.7** Processes not included in the global carbon budget

The contribution of anthropogenic CO and CH₄ to the global carbon budget has been partly 18 neglected in Eq. 1 and is described in Sect. 2.7.1. The contributions of other carbonates to CO₂ 19 20 emissions is described in Sect. 2.7.2. The contribution of anthropogenic changes in river fluxes is 21 conceptually included in Eq. 1 in S_{OCEAN} and in S_{LAND}, but it is not represented in the process models used to quantify these fluxes. This effect is discussed in Sect. 2.7.3. Similarly, the loss of 22 additional sink capacity from reduced forest cover is missing in the combination of approaches 23 24 used here to estimate both land fluxes (E_{LUC} and S_{LAND}) and its potential effect is discussed and quantified in Sect. 2.7.4. 25

26 2.7.1 Contribution of anthropogenic CO and CH₄ to the global carbon budget

Equation (1) includes only partly the net input of CO₂ to the atmosphere from the chemical
oxidation of reactive carbon-containing gases from sources other than the combustion of fossil

- 29 fuels, such as: (1) cement process emissions, since these do not come from combustion of fossil
- 30 fuels, (2) the oxidation of fossil fuels, (3) the assumption of immediate oxidation of vented

methane in oil production. It omits however any other anthropogenic carbon-containing gases
that are eventually oxidised in the atmosphere, such as anthropogenic emissions of CO and CH₄.
An attempt is made in this section to estimate their magnitude, and identify the sources of
uncertainty. Anthropogenic CO emissions are from incomplete fossil fuel and biofuel burning and
deforestation fires. The main anthropogenic emissions of fossil CH₄ that matter for the global
carbon budget are the fugitive emissions of coal, oil and gas upstream sectors (see below). These
emissions of CO and CH₄ contribute a net addition of fossil carbon to the atmosphere.

- 8 In our estimate of E_{FF} we assumed (Sect. 2.1.1) that all the fuel burned is emitted as CO₂, thus CO
- 9 anthropogenic emissions associated with incomplete combustion and their atmospheric oxidation
- 10 into CO₂ within a few months are already counted implicitly in E_{FF} and should not be counted
- 11 twice (same for E_{LUC} and anthropogenic CO emissions by deforestation fires). Anthropogenic
- 12 emissions of fossil CH₄ are not included in E_{FF}, because these fugitive emissions are not included in
- 13 the fuel inventories. Yet they contribute to the annual CO₂ growth rate after CH₄ gets oxidized into
- 14 CO₂. Anthropogenic emissions of fossil CH₄ represent 15% of total CH₄ emissions (Kirschke et al.,
- 15 2013) that is 0.061 GtC yr⁻¹ for the past decade. Assuming steady state, these emissions are all
- 16 converted to CO₂ by OH oxidation, and thus explain 0.06 GtC yr⁻¹ of the global CO₂ growth rate in
- the past decade, or 0.07-0.1 GtC yr⁻¹ using the higher CH₄ emissions reported recently (Schwietzke
 et al., 2016).
- 19 Other anthropogenic changes in the sources of CO and CH₄ from wildfires, vegetation biomass,
- 20 wetlands, ruminants or permafrost changes are similarly assumed to have a small effect on the
- 21 CO₂ growth rate. The CH₄ emissions and sinks are published and analysed separately in the Global
- 22 Methane Budget publication that follows a similar approach as presented here (Saunois et al.,
- 23 2016).

24 2.7.2 Contribution of other carbonates to CO₂ emissions

The contribution of fossil carbonates other than cement production is not systematically included in estimates of E_{FF}, except at the national level where they are accounted in the UNFCCC national inventories. The missing processes include CO₂ emissions associated with the calcination of lime and limestone outside cement production, and the reabsorption of CO₂ by the rocks and concrete from carbonation through their life time (Xi et al., 2016). Carbonates are used in various industries, including in iron and steel manufacture and in agriculture. They are found naturally in

some coals. Carbonation from cement life-cycle, including demolition and crushing, was estimated
 by one study to be around 0.25 GtC yr⁻¹ for year 2013 (Xi et al., 2016). Carbonation emissions
 from cement life-cycle would offset calcination emissions from lime and limestone production.

4 The balance of these two processes is not clear.

5 2.7.3 Anthropogenic carbon fluxes in the land to ocean aquatic continuum

6 The approach used to determine the global carbon budget refers to the mean, variations, and 7 trends in the perturbation of CO_2 in the atmosphere, referenced to the preindustrial era. Carbon is 8 continuously displaced from the land to the ocean through the land-ocean aquatic continuum 9 (LOAC) comprising freshwaters, estuaries and coastal areas (Bauer et al., 2013; Regnier et al., 2013). A significant fraction of this lateral carbon flux is entirely 'natural' and is thus a steady state 10 component of the preindustrial carbon cycle. We account for this preindustrial flux where 11 12 appropriate in our study. However, changes in environmental conditions and land use change have caused an increase in the lateral transport of carbon into the LOAC – a perturbation that is 13 relevant for the global carbon budget presented here. 14

The results of the analysis of Regnier et al. (2013) can be summarized in two points of relevance
for the anthropogenic CO₂ budget. First, the anthropogenic perturbation has increased the

17 organic carbon export from terrestrial ecosystems to the hydrosphere at a rate of 1.0 ± 0.5 GtC yr⁻

¹, mainly owing to enhanced carbon export from soils. Second, this exported anthropogenic

carbon is partly respired through the LOAC, partly sequestered in sediments along the LOAC and

20 to a lesser extent, transferred to the open ocean where it may accumulate. The increase in

21 storage of land-derived organic carbon in the LOAC and open ocean combined is estimated by

Regnier et al. (2013) at 0.65 \pm 0.35GtC yr⁻¹. We do not attempt to incorporate the changes in LOAC

in our study.

The inclusion of freshwater fluxes of anthropogenic CO₂ affects the estimates of, and partitioning between, S_{LAND} and S_{OCEAN} in Eq. (1), but does not affect the other terms. This effect is not included in the GOBMs and DGVMs used in our global carbon budget analysis presented here.

27 2.7.4 Loss of additional sink capacity

Historical land-cover change was dominated by transitions from vegetation types that can provide
a large sink per area unit (typically, forests) to others less efficient in removing CO₂ from the
atmosphere (typically, croplands). The resultant decrease in land sink, called the 'loss of sink

capacity', is calculated as the difference between the actual land sink under changing land-cover 1 2 and the counter-factual land sink under preindustrial land-cover. An efficient protocol has yet to 3 be designed to estimate the magnitude of the loss of additional sink capacity in DGVMs. Here, we 4 provide a quantitative estimate of this term to be used in the discussion. Our estimate uses the 5 compact Earth system model OSCAR whose land carbon cycle component is designed to emulate 6 the behaviour of DGMVs (Gasser et al., 2017). We use OSCAR v2.2.1 (an update of v2.2 with minor 7 changes) in a probabilistic setup identical to the one of Arneth et al. (2017) but with a Monte Carlo 8 ensemble of 2000 simulations. For each, we calculate separately SLAND and the loss of additional 9 sink capacity. We then constrain the ensemble by weighting each member to obtain a distribution of cumulative SLAND over 1850-2005 close to the DGVMs used here. From this ensemble, we 10 11 estimate a loss of additional sink capacity of 0.4 ± 0.3 GtC yr⁻¹ on average over 2005-2014, and 20 12 ± 15 GtC accumulated between 1870 and 2017 (using a linear extrapolation of the trend to estimate the last few years). 13

14 3 Results

15 **3.1** Global carbon budget mean and variability for 1959 – 2017

The global carbon budget averaged over the last half-century is shown in Fig. 3. For this time period, 82% of the total emissions ($E_{FF} + E_{LUC}$) were caused by fossil CO₂ emissions, and 18% by land-use change. The total emissions were partitioned among the atmosphere (45%), ocean (24%) and land (30%). All components except land-use change emissions have grown since 1959, with important interannual variability in the growth rate in atmospheric CO₂ concentration and in the land CO₂ sink (Fig. 4), and some decadal variability in all terms (Table 6). Differences with previous budget releases is documented in Fig. B4.

23 3.1.1 CO₂ emissions

Global fossil CO₂ emissions have increased every decade from an average of 3.1 ± 0.2 GtC yr⁻¹ in the 1960s to an average of 9.4 ± 0.5 GtC yr⁻¹ during 2008-2017 (Table 6, Fig. 2 and Fig. 5). The growth rate in these emissions decreased between the 1960s and the 1990s, from 4.5% yr⁻¹ in the 1960s (1960-1969), 2.8% yr⁻¹ in the 1970s (1970-1979), 1.9% yr⁻¹ in the 1980s (1980-1989), and 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 3.2% yr⁻¹, decreasing to 1.5% yr⁻¹ for the last decade (2008-

30 2017), with a 3-year period of no or low growth during 2014-2016 (Fig. 5).

1 In contrast, CO₂ emissions from land use, land-use change and forestry have remained relatively

2 constant, at around 1.3 ± 0.7 GtC yr⁻¹ over the past half-century but with large spread across

3 estimates (Fig. 6). These emissions are also relatively constant in the DGVM ensemble of models,

4 except during the last decade when they increase to 1.9 ± 0.7 GtC yr⁻¹. However, there is no

5 agreement on this recent increase between the two bookkeeping models, each suggesting an

6 opposite trend (Fig. 6).

7 3.1.2 Partitioning among the atmosphere, ocean and land

8 The growth rate in atmospheric CO₂ level increased from 1.7 ± 0.07 GtC yr⁻¹ in the 1960s to $4.7 \pm$

9 0.02 GtC yr⁻¹ during 2008-2017 with important decadal variations (Table 6 and Fig. 2). Both ocean

and land CO₂ sinks increased roughly in line with the atmospheric increase, but with significant

11 decadal variability on land (Table 6), and possibly in the ocean (Fig. 7).

- 12 The ocean CO₂ sink increased from 1.0 ± 0.5 GtC yr⁻¹ in the 1960s to 2.4 ± 0.5 GtC yr⁻¹ during 2008-
- 13 2017, with interannual variations of the order of a few tenths of GtC yr⁻¹ generally showing an
- 14 increased ocean sink during large El Niño events (i.e. 1997-1998) (Fig. 7; Rödenbeck et al., 2014).
- 15 Although there is some coherence among the GOBMs and pCO₂-based flux products regarding the
- 16 mean, there is poor agreement for interannual variability and the ocean models underestimate

17 decadal variability (Sect. 2.4.3 and Fig. 7; DeVries et al. (2017)).

- 18 The terrestrial CO₂ sink increased from 1.2 ± 0.5 GtC yr⁻¹ in the 1960s to 3.2 ± 0.7 GtC yr⁻¹ during
- 19 2008-2017, with important interannual variations of up to 2 GtC yr⁻¹ generally showing a
- 20 decreased land sink during El Niño events (Fig. 6), responsible for the corresponding enhanced
- 21 growth rate in atmospheric CO₂ concentration. The larger land CO₂ sink during 2008-2017

22 compared to the 1960s is reproduced by all the DGVMs in response to the combined atmospheric

CO₂ increase and changes in climate, and consistent with constraints from the other budget terms
(Table 5).

- 25 Estimates of total atmosphere-to-land fluxes (S_{LAND} E_{LUC}) from the DGVMs are consistent with
- the budget constraints (Table 5), except during 2008-2017, where the DGVM ensemble estimates
- a total atmosphere-to-land flux of 1.3 ± 0.5 GtC yr⁻¹, likely below the budget constraints of $2.1 \pm$
- 28 0.7 GtC yr⁻¹ and outside the range of the inversions (Table 5). This comparison suggests that the
- 29 DGVMs could overestimate E_{LUC} emissions and/or underestimate the terrestrial sink S_{LAND} during
- 30 the last decade.

1 3.1.3 Model evaluation

2 The evaluation of ocean estimates (Fig. B1) shows a relative interannual mismatch of 15% and 3 17% for the two pCO₂-based flux products over the globe, relative to the pCO₂ observations from the SOCAT v6 database for the period 1985-2017. A 0% mismatch would indicate a perfect model, 4 and a field with no interannual variability would result in a 100% mismatch. A larger than 100% 5 6 mismatch is possible when the method produces a larger mismatch than the benchmark field with 7 no interannual variability (see section 2.4.3). This mismatch by the pCO₂-based flux products is 8 improved compared with earlier published versions of these two flux products of around 20-25% for the 1992-2009 time period (Rödenbeck et al. 2015), likely because of the larger data 9 10 availability after 2009. The GOBMs show a global relative interannual mismatch between 50% and 60%, with one model at 94% and one at 193%. The GOBM mismatch is of the same order as the 11 mismatch calculated in an ensemble of 14 flux products, but larger than the two flux products 12 13 used in this report (Fig. 5 in Rödenbeck et al. 2015). The mismatch is generally larger at high 14 latitudes compared to the tropics, for both the flux products and the GOBMs. The two flux 15 products have similar mismatch of around 10-15% in the tropics, around 25% in the north, and 30-55% in the south. The GOBM mismatch is more spread across regions, ranging from 29% to 178% 16 in the tropics, 70% to 192% in the North, and 108% to 304% in the South. The higher mismatch 17 occurs in regions with stronger climate variability, such as the northern and southern high-18 latitudes (poleward of the subtropical gyres) and the equatorial Pacific. The latter is also apparent 19 20 in the model mismatch, but is hidden in Figure B1 due to the averaging over 30°S to 30°N (see also 21 section 4).

The evaluation of the DGVMs (Fig. B2) shows generally high skill scores across models for runoff, and to a lesser extent for vegetation biomass, GPP, and ecosystem respiration (Fig. B2, left panel). Skill score was lowest for leaf area index and net ecosystem exchange, with a widest disparity among models for soil carbon. Further analysis of the results will be provided separately, focusing the strengths and weaknesses in the DGVM ensemble and its validity for use in the global carbon budget.

The evaluation of the atmospheric inversions (Fig. B3) shows long-term mean biases in the free troposphere better than 0.8 ppm in absolute values for each product. CAMS and CTE biases show some dependency on latitude (a trend of -0.0018 ± 0.0005 and 0.0043 ± 0.0004 ppm per degree for CAMS and CTE, respectively). These latitude-dependent biases may reveal biases in the surface

fluxes (e.g., Houweling et al., 2015) but the link is not straight-forward and will be analysed
separately. The biases for MIROC and CarboScope behave similarly together in relative values, but
they are less regular than the two other products, which hampers the interpretation. Lesser
model performance for specific aircraft programs, like for the four-year Discover-AQ campaign in
continental US (https://discover-aq.larc.nasa.gov/), contributes to this variability.

6 3.1.4 Budget imbalance

7 The carbon budget imbalance (B_{IM} ; Eq. 1) quantifies the mismatch between the estimated total 8 emissions and the estimated changes in the atmosphere, land and ocean reservoirs. The mean budget imbalance from 1959 to 2017 is small (0.14 GtC yr⁻¹) and shows no trend over the full time 9 series. The process models (GOBMs and DGVMs) have been selected to match observational 10 constraints in the 1990s but no further constraints have been applied to their representation of 11 12 trend and variability. Therefore, the near-zero mean and trend in the budget imbalance is an indirect evidence of a coherent community understanding of the emissions and their partitioning 13 on those time scales (Fig. 4). However, the budget imbalance shows substantial variability of the 14 15 order of ± 1 GtC yr⁻¹, particularly over semi-decadal time scales, although most of the variability is 16 within the uncertainty of the estimates. The positive carbon imbalance during the 1960s, early 1990s, and in the last decade, suggest that either the emissions were overestimated or the sinks 17 were underestimated during these periods. The reverse is true for the 1970s and around 1995-18 19 2000 (Fig. 4).

We cannot attribute the cause of the variability in the budget imbalance with our analysis, only to 20 note that the budget imbalance is unlikely to be explained by errors or biases in the emissions 21 22 alone because of its large semi-decadal variability component, a variability that is untypical of 23 emissions and has not changed in the past 50 years in spite of a nearly tripling in emissions (Fig. 4). Errors in SLAND and SOCEAN are more likely to be the main cause for the budget imbalance. For 24 example, underestimation of the SLAND by DGVMs has been reported following the eruption of 25 26 Mount Pinatubo in 1991 possibly due to missing responses to changes in diffuse radiation (Mercado et al., 2009) or other yet unknown factor, and DGVMs are suspected to overestimate 27 28 the land sink in response to the wet decade of the 1970s (Sitch et al., 2008). Decadal and semidecadal variability in the ocean sink has been also reported recently (DeVries et al., 29 30 2017;Landschützer et al., 2015), with the pCO_2 -based ocean flux products suggesting a smaller 31 than expected ocean CO_2 sink in the 1990s and a larger than expected sink in the 2000s (Fig. 7),

1 possibly caused by changes in ocean circulation (DeVries et al., 2017) not captured in coarse 2 resolution GOBMs used here (Dufour et al., 2013). The absence of internal variability could also be 3 at fault. Internal variability is not captured by single realizations of coarse resolution model 4 simulations (Li and Ilyina, 2017), and is thought to be largest in regions with strong seasonal and 5 interannual climate variability, i.e. the high latitude ocean regions (poleward of the subtropical 6 gyres) and the equatorial Pacific (McKinley et al., 2016). Some of these errors could be driven by 7 errors in the climatic forcing data, particularly precipitation (for SLAND) and wind (for SOCEAN) rather 8 than in the models.

9 **3.2** Global carbon budget for the last decade (2008 – 2017)

The global carbon budget averaged over the last decade (2008-2017) is shown in Fig. 2 and Fig. 9. For this time period, 87% of the total emissions ($E_{FF} + E_{LUC}$) were from fossil CO₂ emissions (E_{FF}), and 13% from land-use change (E_{LUC}). The total emissions were partitioned among the atmosphere (44%), ocean (22%) and land (29%), with a remaining unattributed budget imbalance (5%).

15 **3.2.1 CO₂ emissions**

Global fossil CO₂ emissions grew at a rate of 1.5% yr⁻¹ for the last decade (2008-2017). China's 16 emissions increased by +3.0% yr⁻¹ on average (increasing by +0.64 GtC yr⁻¹ during the 10-year 17 period) dominating the global trends, followed by India's emissions increase by +5.2% yr⁻¹ 18 (increasing by +0.25 GtC yr⁻¹), while emissions decreased in EU28 by -1.8% yr⁻¹ (decreasing by -19 0.17 GtC yr⁻¹), and in the USA by 0.9% yr⁻¹ (decreasing by –0.18 GtC yr⁻¹). In the past decade, fossil 20 CO₂ emissions decreased significantly (at the 95% level) in 25 countries: Aruba, Barbados, Croatia, 21 22 Czech Republic, North Korea, Denmark, France, Greece, Greenland, Iceland, Ireland, Malta, 23 Netherlands, Romania, Slovakia, Slovenia, Sweden, Switzerland, Syria, Trinidad and Tobago, Ukraine, United Kingdom, USA, Uzbekistan and Venezuela. Notable was Germany, whose 24 25 emissions did not decrease significantly.

In contrast, there is no apparent trend in CO₂ emissions from land-use change (Fig. 6), though the data are very uncertain, with the two bookkeeping estimates showing opposite trends over the last decade. Larger emissions are expected increasingly over time for DGVM-based estimates as they include the loss of additional sink capacity, while the bookkeeping estimates don't. The LUH2

dataset also features large dynamics in land use in particular in the tropics in recent years, causing
higher emissions in DGVMs and BLUE than in H&N.

3 3.2.2 Partitioning among the atmosphere, ocean and land

The growth rate in atmospheric CO₂ concentration increased during 2008-2017, in contrast to
more constant levels the previous decade and reflecting a similar decrease in the land sink
compared to an increase in the previous decade, albeit with large interannual variability (Fig. 4).
During the same period, the ocean CO₂ sink appears to have intensified, an effect which is
particularly apparent in the pCO₂-based flux products (Fig. 7) and is thought to originate at least in
part in the Southern Ocean (Landschützer et al., 2015).

10 The budget imbalance (Table 6) and the residual sink from global budget (Table 5) include an error 11 term due to the inconsistency that arises from using ELUC from bookkeeping models, but SLAND 12 from DGVMs. This error term includes the fundamental differences between bookkeeping models 13 and DGVMs, most notably the loss of additional sink capacity. Other differences include: an 14 incomplete accounting of LUC practices and processes in DGVMs, while they are all accounted for in bookkeeping models by using observed carbon densities, and bookkeeping error of keeping 15 16 present-day carbon densities fixed in the past. That the budget imbalance shows no clear trend 17 towards larger values over time is an indication that the loss of additional sink capacity plays a 18 minor role compared to other errors in SLAND or SOCEAN (discussed in 3.1.4).

19 3.2.3 Regional distribution

Fig. 8 shows the partitioning of the total atmosphere-to-surface fluxes excluding fossil CO₂ 20 emissions (SLAND + SOCEAN - ELUC) according to the multi-model average of the process models in the 21 ocean and on land (GOBMs and DGVMs), and to the atmospheric inversions. Fig. 8 provides 22 23 information on the regional distribution of those fluxes by latitude bands. The global mean total 24 atmosphere-to-surface CO₂ fluxes from process models for 2008-2017 is 3.7 ± 1.2 GtC yr⁻¹. This is below but still within the uncertainty range of a global mean atmosphere-to-surface flux of 4.6 ± 25 0.5 GtC yr⁻¹ inferred from the carbon budget ($E_{FF} - G_{ATM}$ in Equation 1; Table 6). The total 26 atmosphere-to-surface CO₂ fluxes from the four inversions are very similar, ranging from 4.7 to 27 28 5.0 GtC yr⁻¹, consistent with the carbon budget as expected from the constraints on the inversions and the adjustments to the same E_{FF} distribution (See Section 2.6). 29
1 In the south (south of 30°S), the atmospheric inversions suggest an atmosphere-to-surface flux for 2008-2017 around 1.6-1.7 GtC yr⁻¹, close to the process models' estimate of 1.4 ± 0.7 GtC yr⁻¹ (Fig. 2 3 8). The interannual variability in the south is low because of the dominance of ocean area with 4 low variability compared to land areas. The split between land (SLAND-ELUC) and ocean (SOCEAN) 5 shows a small contribution to variability in the south coming from the land, with no consistency 6 between the DGVMs and the inversions or among inversions. This is expected due to the difficulty 7 of separating exactly the land and oceanic fluxes when viewed from atmospheric observations 8 alone. The oceanic variability in the south is estimated to be significant in the two flux products 9 and in at least one of the inversions, with decadal variability of around 0.5 GtC yr⁻¹. The GOBMs do not reproduce this variability. 10

In the tropics (30°S-30°N), both the atmospheric inversions and process models suggest the total 11 12 carbon balance in this region is close to neutral on average over the past decade, with 13 atmosphere-to-surface fluxes for the 2008-2017 average ranging between –0.4 and +0.4 GtC yr⁻¹. The agreement between inversions and models is significantly better for the last decade than for 14 15 any previous decade, although the reasons for this better agreement are still unclear. Both the process models and the inversions consistently allocate more year-to-year variability of CO₂ fluxes 16 17 to the tropics compared to the north (north of 30°N; Fig. 8). The split between the land and ocean indicates the land is the origin of most of the tropical variability, consistently among models (both 18 for the land and for the ocean) and inversions. The oceanic variability in the tropics is similar 19 20 among models and with the two ocean flux products, reflected in their lower observational mismatch (Section 3.1.3). While the inversions indicate that atmosphere-to-land CO₂ fluxes are 21 more variable than atmosphere-to-ocean CO₂ fluxes in the tropics, the correspondence between 22 the inversions and the ocean flux products or GOBMs is much poorer. 23

24 In the north (north of 30°N), the inversions and process models show less agreement on the 25 magnitude of the atmosphere-to-land flux, with the ensemble mean of the process models 26 suggesting a total Northern Hemisphere sink for 2008-2017 of 2.2 ± 0.6 GtC yr⁻¹, likely below the estimates from the inversions ranging from 2.6 to 3.6 GtC yr⁻¹ (Fig. 8). The discrepancy in the 27 28 north-tropics distribution of CO₂ fluxes between the inversions and models arises from the 29 differences in mean fluxes over the northern land. This discrepancy is also evidenced over the previous decade and highlights not only persistent issues with the quantification of the drivers of 30 the net land CO₂ flux (Arneth et al., 2017;Huntzinger et al., 2017) but also the distribution of 31

atmosphere-to-land fluxes between the tropics and higher latitudes that is particularly marked in
 previous decades, as highlighted previously (Stephens et al., 2007;Baccini et al., 2017;Schimel et
 al., 2015).

4 Differences between inversions may be related for example to differences in their 5 interhemispheric transport, and other inversion settings (Table A3). Separate analysis has shown 6 that the influence of the chosen prior land and ocean fluxes is minor compared to other aspects of each inversion. In comparison to the previous global carbon budget publication, the fossil fuel 7 8 inputs were adjusted to match that of E_{FF} used in this analysis (see Section 2.6), therefore 9 removing differences due to fossil emissions prior. Differences between inversions and the 10 ensemble of process models in the north cannot be simply explained. They could either reflect a bias in the inversions or missing processes or biases in the process models, such as the lack of 11 12 adequate parameterizations for forest management in the north and for forest degradation 13 emissions in the tropics for the DGVMs. The estimated contribution of the north and its uncertainty from process models is sensitive both to the ensemble of process models used and to 14 15 the specifics of each inversion.

16 Resolving the differences in the Northern Hemisphere land sink will require the consideration and 17 inclusion of larger volumes of semi-continuous observations from tall towers close to the surface 18 CO₂ exchange. Some of this data is becoming available, but not used in the current inverse models 19 sometimes due to the short records, and sometimes because the coarse transport models cannot 20 adequately represent these time series. Improvements in model resolution and atmospheric 21 transport realism together with expansion of the observational record (also in the data sparse 22 Boreal Eurasian area) will help anchor the mid-latitude fluxes per continent. In addition, new 23 metrics could potentially differentiate between the more- and less realistic realisations of the 24 Northern Hemisphere land sink shown in Fig. 8.

25 3.2.4 Budget imbalance

The budget imbalance was +0.5 GtC yr⁻¹ on average over 2008-2017. Although the uncertainties are large in each term, the sustained imbalance over this last decade suggests an overestimation of the emissions and/or an underestimation of the sinks. An origin in the land and/or ocean sink may be more likely, given the large variability of the land sink and the suspected underestimation of decadal variability in the ocean sink. An underestimate of S_{LAND} would also reconcile model

results with inversions estimates for fluxes in the total land during the past decade (Fig. 8; Table
5). However, we cannot exclude that the budget imbalance over the last decade could partly be
due to an overestimation of CO₂ emissions from land-use change, given their large uncertainty, as
has been suggested elsewhere (Piao et al., 2018). 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; Section 4).

7 3.3 Global carbon budget for year 2017

8 3.3.1 CO₂ emissions

Preliminary estimates of global fossil CO₂ emissions based on BP energy statistics are for emissions
growing by 1.6% between 2016 and 2017 to 9.9 ± 0.5 GtC in 2017 (Fig. 5), distributed among coal
(40%), oil (35%), gas (20%), cement (4%) and gas flaring (0.7%). Compared to the previous year,
emissions from coal increased by 1.6%, while emissions from oil, gas, and cement increased by
1.7%, 3.0%, and 1.2%, respectively. All growth rates presented are adjusted for the leap year,
unless stated otherwise.

The growth in emissions of 1.6% in 2017 is within the range of the projected growth of 2.0% (range of 0.8 to 3.0%) published in Le Quéré et al. (2018) based on national emissions projections for China, the USA, and India and projections of gross domestic product corrected for I_{FF} trends for the rest of the world. The growth in emissions in 2017 for China, UEA, and the rest of the world is also within their previously projected range, while the growth in India was slightly above the projection (Table 7).

In 2017, the largest absolute contributions to global CO₂ emissions were from China (27%), the

USA (15%), the EU (28-member states; 10%), India (7%), while the rest of the world contributed

42%. The percentages are the fraction of the global emissions including bunker fuels (3.1%). These

four regions account for 59% of global CO₂ emissions. Growth rates for these countries from 2016

25 to 2017 were +1.5% (China), -0.5% (USA), +1.2% (EU28), and +3.9% (India), with +1.9% for the rest

of the world. The per-capita CO₂ emissions in 2017 were 1.1 tC person⁻¹ yr⁻¹ for the globe, and

were 4.4 (USA), 2.0 (China), 1.9 (EU28) and 0.5 (India) tC person⁻¹ yr⁻¹ for the four highest emitting

countries (Fig. 5).

29 In 2016 (the last year available), the largest absolute contributions to global CO₂ emissions from a

30 consumption perspective were China (25%), USA (16%), the EU (12%), and India (6%). The

- 1 difference between territorial and consumption emissions (the net emission transfer via
- 2 international trade) has generally increased from 1990 to around 2005 and remained relatively
- 3 stable afterwards until the last year available (2016; Fig. 5).
- 4 The global CO₂ emissions from land-use change are estimated as 1.4 ± 0.7 GtC in 2017, close to
- 5 the previous decade but with low confidence in the annual change.

6 3.3.2 Partitioning among the atmosphere, ocean and land

- 7 The growth rate in atmospheric CO₂ concentration was 4.6 ± 0.2 GtC in 2017 (2.16 ± 0.09 ppm; Fig.
- 4; Dlugokencky and Tans, 2018). This is near the 2008-2017 average of 4.7 \pm 0.1 GtC yr⁻¹ and
- 9 reflects the return to normal conditions after the El Niño of 2015-2016.
- 10 The estimated ocean CO₂ sink was 2.5 ± 0.5 GtC in 2017. All models and data products estimate a
- small reduction or no change in the sink (average of 0.1, ranging from +0.02 to -0.4 GtC),
- 12 consistent with the return to normal conditions after the El Niño which caused an enhanced sink
- 13 in previous years (Fig. 7).
- 14 The terrestrial CO₂ sink from the model ensemble was 3.8 ± 0.8 GtC in 2017, above the decadal
- average (Fig. 4) and consistent with constraints from the rest of the budget (Table 5).
- 16 The budget imbalance was +0.3 GtC in 2017, indicating, as for the last decade, a small
- 17 overestimation of the emissions and/or underestimation of the sinks for that year. This imbalance
- 18 is indicative only, given the large uncertainties in the estimation of the B_{IM} .

19 **3.4** Global carbon budget projection for year 2018

20 3.4.1 CO₂ emissions

- 21 Based on available data as of 7 November 2018 (see Sect. 2.1.5), fossil CO₂ emissions (E_{FF}) for 2018
- are projected to increase by +2.7% (range of 1.8% to +3.7%; Table 7). Our method contains several
- assumptions that could influence the estimate beyond the given range, and as such, it has an
- indicative value only. Within the given assumptions, global emissions would be 10.1 ± 0.5 GtC
- 25 (37.1 ± 1.8 GtCO₂) in 2018. The interpretation of the 2018 emissions projection is provided
- 26 elsewhere (Figueres et al., 2018; Jackson et al., 2018a).
- 27 For China, the expected change is for an increase in emissions of +4.7% (range of +2.0% to +7.4%)
- in 2018 compared to 2017. This is based on estimated growth in coal (+4.5%; the main fuel source

1 in China), oil (+3.6%), natural gas (+17.7%) consumption, and cement production (+1.0%). The

2 uncertainty range considers the variations in the difference between preliminary January-

3 September data and final full-year data, the uncertainty in the preliminary data used for the 2017

4 base, and uncertainty in the evolution of energy density and carbon content of coal.

For the USA, the EIA emissions projection for 2018 combined with cement data from USGS gives
an increase of 2.5 % (range of +0.5 to +4.5 %) compared to 2017.

7 For the European Union, our projection for 2018 is for a decrease of -0.7% (range of -2.6% to

+1.3%) over 2017. This is based on estimates for coal of -1.2%, oil of +1.2%, gas of -2.9%, and
stable cement emissions.

10 For India, our projection for 2018 is for an increase of +6.3% (range of 4.3% to +8.3%) over 2017.

11 This is based on separate projections for coal (+7.1%), oil (+2.9%), gas (+6.0%) and cement

12 (+13.4%).

13 For the rest of the world, the expected growth for 2018 is +1.8% (range of +0.5% to +3.0%). This is

14 computed using the GDP projection for the world excluding China, USA, EU, and India, of 2.8%

made by the IMF (IMF, 2018) and a decrease in I_{FF} of -1.0% yr⁻¹ which is the average from 2008-

16 2017. The uncertainty range is based on the standard deviation of the interannual variability in IFF

during 2008-2017 of $\pm 0.7\%$ yr⁻¹ and our estimate of uncertainty in the IMF's GDP forecast of $\pm 0.5\%$.

19 Preliminary estimate of fire emissions in deforestation zones indicate that emissions from land-

20 use change (E_{LUC}) for 2018 were below average until October, and are expected to range between

21 0.1 and 0.2 lower than the 2008-2017 average. We therefore expect E_{LUC} emissions of around 1.2

22 GtC in 2018.

23 **3.4.2** Partitioning among the atmosphere, ocean and land

The 2018 growth in atmospheric CO₂ concentration (G_{ATM}) is projected to be 4.9 ± 0.7 GtC (2.3 ±

25 0.3 ppm) based on MLO observations until the end of August 2018. Combining projected E_{FF}, E_{LUC}

26 and G_{ATM} suggests a combined land and ocean sink (S_{LAND} + S_{OCEAN}) of about 6.5 GtC for 2018.

27 Although each term has large uncertainty, the oceanic sink S_{OCEAN} has generally low interannual

variability and is likely to remain close to its 2017 value of around 2.5 GtC, leaving a rough

29 estimated land sink S_{LAND} of around 4.0 GtC. If realised, it would be among the largest S_{LAND} over

the historical period. However, the possible onset of an El Niño at the end of 2018 could reduce
 S_{LAND}, with G_{ATM} returning to high growth rate towards the end of the year.

3 3.5 Cumulative sources and sinks

4 Cumulative historical sources and sinks are estimated as in Eq. (1) with semi-independent 5 estimates for each term and a global carbon budget imbalance. Cumulative fossil CO₂ emissions 6 for 1870-2017 were 425 \pm 20 GtC for E_{FF} and 190 \pm 75 GtC for E_{LUC} (Table 8; Fig. 9), for a total of 7 615 ± 80 GtC. The cumulative emissions from E_{LUC} are particularly uncertain, with large spread 8 among individual estimates of 135 GtC (Houghton) and 240 GtC (BLUE) for the two bookkeeping models and a similar wide estimate of 180± 75 GtC for the DGVMs. These estimates are consistent 9 with indirect constraints from vegetation biomass observations (Li et al., 2017), but given the large 10 spread a best estimate is difficult to ascertain. 11

Emissions were partitioned among the atmosphere (250 \pm 5 GtC), ocean (150 \pm 20 GtC), and the 12 13 land (190 ± 50 GtC). The use of nearly independent estimates for the individual terms shows a 14 cumulative budget imbalance of 25 GtC during 1870-2017 (Fig. 2), which, if correct, suggests emissions are too high by the same proportion or the land or ocean sinks are underestimated. The 15 bulk of the imbalance is likely to originate largely from the large estimation of ELUC between the 16 17 mid 1920s and the mid 1960s which is unmatched by a growth in atmospheric CO₂ concentration as recorded in ice cores (Fig. 3). The known loss of additional sink capacity of about 20 GtC due to 18 19 reduced forest cover has not been accounted in our method and would further exacerbate the budget imbalance (Section 2.7.4). 20

21 Cumulative emissions through to year 2018 increase to 625 ± 80 GtC (2290 ± 290 GtCO₂), with

22 about 70% contribution from E_{FF} and about 30% contribution from E_{LUC}. Cumulative emissions and

their partitioning for different periods are provided in Table 8.

Given the large and persistent uncertainties in cumulative emissions, we suggest extreme caution is needed if using cumulative emission estimate to determine the "remaining carbon budget" to stay below given temperature limit (Rogelj et al., 2016). We suggest estimating the remaining carbon budget by integrating scenario data from the current time to some time in the future (Millar et al., 2017).

1 4 Discussion

2 Each year when the global carbon budget is published, each flux component is updated for all 3 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 improve with improvements 4 5 in data quality and timeliness (e.g. to eliminate need for extrapolation of forcing data such as land 6 use). Of the various terms in the global budget, only the fossil CO_2 emissions and the growth rate 7 in atmospheric CO₂ concentration are based primarily on empirical inputs supporting annual 8 estimates in this carbon budget. Although it is an imperfect measure, the carbon budget 9 imbalance provides a strong indication of the limitations in observations, in understanding or full representation of processes in models, and/or in the integration of the carbon budget 10 11 components.

The persistent unexplained variability in the carbon budget imbalance limits our ability to verify 12 reported emissions (Peters et al., 2017) and suggests we do not yet have a complete 13 14 understanding of the underlying carbon cycle processes. Resolving most of this unexplained variability should be possible through different and complementary approaches. First, as intended 15 16 with our annual updates, the imbalance as an error term is reduced by improvements of individual 17 components of the global carbon budget that follow from improving the underlying data and 18 statistics and by improving the models through the resolution of some of the key uncertainties 19 detailed in Table 9. Second, additional clues to the origin and processes responsible for the 20 current 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 21 biogeochemical observations to better understand the land/over partitioning of the carbon 22 23 imbalance (e.g. oxygen, carbon isotopes). Finally, additional information could also be obtained 24 through higher resolution and process knowledge at the regional level, and through the 25 introduction of inferred fluxes such as those based on satellite CO₂ retrievals. The limit of the resolution of the carbon budget imbalance is yet unclear, but most certainly not yet reached given 26 27 the possibilities for improvements that lie ahead.

28 The assessment of the GOBMs used for S_{OCEAN} with flux products based on observations highlights

substantial discrepancy at mid and high latitudes. Given the good data coverage of pCO₂

30 observations in the Northern Hemisphere (Bakker et al., 2016), this discrepancy points at an

31 underestimation of variability in the GOBMs globally and consequently, the variability in SOCEAN

appears to be underestimated. The size of this underestimate (order of 0.5 GtC yr⁻¹) could account
for some of the budget imbalance, but not all. Increasing model resolution or incorporating
internal variability (Li and Ilyina, 2017) have been suggested as ways to increase model variability
(Section 3.1.4).

5 The assessment of the net land-atmosphere exchange derived from land sink and net land use 6 change flux with atmospheric inversions also shows substantial discrepancy, particularly for the 7 estimate of the total land flux over the northern extra-tropics in the past decade. This discrepancy 8 highlights the difficulty to quantify complex processes (CO₂ fertilisation, nitrogen deposition, 9 climate change and variability, land management, etc.) that collectively determine the net land 10 CO₂ flux. Resolving the differences in the Northern Hemisphere land sink will require the 11 consideration and inclusion of larger volumes of observations (Section 3.2.3).

12 Estimates of E_{LUC} suffer from a range of intertwined issues, including the poor quality of historical 13 land-cover and land-use change maps, the rudimentary representation of management processes 14 in most models, and the confusion in methodologies and boundary conditions used across methods (e.g. Pongratz et al., 2014, Arneth et al. 2017, and Section 2.7.4 on the loss of sink 15 capacity). Uncertainties in current and historical carbon stocks in soils and vegetation also add 16 17 uncertainty in the LUC flux estimates. Unless a major effort to resolve these issues is made, little 18 progress is expected in the resolution of E_{LUC}. This is particularly concerning given the growing 19 important of ELUC 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} . 20

21 To move towards the resolution of the carbon budget imbalance, this year we have introduced 22 metrics for the evaluation of the ocean and land models and atmospheric inversions. These 23 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 24 25 constrain the representation of key underlying processes in the models and to allocate the 26 regional partitioning of the CO₂ fluxes. This is an initial step towards the introduction of a broader range of observations that we hope will support continued improvements in the annual estimates 27 of the global carbon budget. 28

We assessed elsewhere (Peters et al. 2017) that a sustained decrease of -1% in global emissions could be detected at the 66% likelihood level after a decade only. 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

1 more slowly. Reducing the carbon imbalance, regionalising the carbon budget, and integrating

2 multiple variables are powerful ways to shorten the detection limit and ensure the research

3 community can rapidly identify growing issues of concern in the evolution of the global carbon

4 cycle under the current rapid and unprecedented changing environmental conditions.

5

6 **5 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. The free
availability of these data does not constitute permission for publication of the data. For research

projects, if the data are essential to the work, or if an important result or conclusion depends on

12 the data, co-authorship may need to be considered. Full contact details and information on how

13 to cite the data included in the GCP (2018) release are given at the top of each page in the

- 14 accompanying database and summarised in Table 2.
- 15 The accompanying database includes two Excel files organised in the following spreadsheets
- 16 (accessible with the free viewer https://support.microsoft.com/en-gb/help/273711/how-to-
- 17 obtain-the-latest-excel-viewer):
- 18 File Global_Carbon_Budget_2018v1.0.xlsx includes the following:
- 19 1. Summary
- 20 2. The global carbon budget (1959-2017);
- Global CO₂ emissions from fossil fuels and cement production by fuel type, and the per-capita
 emissions (1959-2017);
- 23 4. CO₂ emissions from land-use change from the individual methods and models (1959-2017);
- 24 5. Ocean CO_2 sink from the individual ocean models and p CO_2 -based products (1959-2017);
- 25 6. Terrestrial CO₂ sink from the DGVMs (1959-2017);
- 26 7. Additional information on the carbon balance prior to 1959 (1750-2017).
- 27 File National_Carbon_Emissions_2018v1.0.xlsx includes the following:
- 28 1. Summary
- 29 2. Territorial country CO₂ emissions from fossil CO₂ emissions (1959-2017) from CDIAC,
- 30 extended to 2016 using BP data;

- 1 3. Territorial country CO₂ emissions from fossil CO₂ emissions (1959-2017) from CDIAC with
- 2 UNFCCC data overwritten where available, extended to 2017 using BP data;
- 3 4. Consumption country CO₂ emissions from fossil CO₂ emissions and emissions transfer from
- 4 the international trade of goods and services (1990-2016) using CDIAC/UNFCCC data
- 5 (worksheet 3 above) as reference;

6 5. Emissions transfers (Consumption minus territorial emissions; 1990-2016);

- 7 6. Country definitions;
- 8 7. Details of disaggregated countries;
- 9 8. Details of aggregated countries.

10 National emissions data are also available from the Global Carbon Atlas (globalcarbonatlas.org).

11 6 Conclusions

12 The estimation of global CO₂ emissions and sinks is a major effort by the carbon cycle research 13 community that requires a careful compilation and synthesis of measurements, statistical 14 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 15 of the climate system and its underpinning causes. A broad stakeholder community relies on the 16 17 data sets associated with the annual carbon budget including scientists, policy makers, businesses, 18 journalists, and non-governmental organizations engaged in adapting to and mitigating human-19 driven climate change. Second, over the last decade we have seen unprecedented changes in the 20 human and biophysical environments (e.g. changes in the growth of fossil fuel emissions, Earth's temperatures, and strength of the carbon sinks), which call for frequent assessments of the state 21 of the planet, a growing understanding, and an improved capacity to anticipate the evolution of 22 23 the carbon cycle in the future. Building this scientific understanding to meet the extraordinary climate mitigation challenge requires frequent, robust, and transparent data sets and methods 24 25 that can be scrutinized and replicated. This paper via 'living data' helps to keep track of new 26 budget updates.

27

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29

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26

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1 Tables

2 **Table 1.** Factors used to convert carbon in various units (by convention, Unit 1 = Unit 2

3 conversion).

Unit 1	Unit 2	Conversion	Source
GtC (gigatonnes of carbon)	ppm (parts per million) ^a	2.124 ^b	Ballantyne et al. (2012)
GtC (gigatonnes of carbon)	PgC (petagrams of carbon)	1	SI unit conversion
GtCO ₂ (gigatonnes of carbon dioxide)	GtC (gigatonnes of carbon)	3.664	44.01/12.011 in mass equivalent
GtC (gigatonnes of carbon)	MtC (megatonnes of carbon)	1000	SI unit conversion

^a Measurements of atmospheric CO₂ concentration have units of dry-air mole fraction. 'ppm' is an

5 abbreviation for micromole/mol, dry air.

⁶ ^bThe use of a factor of 2.124 assumes that all the atmosphere is well mixed within one year. In

7 reality, only the troposphere is well mixed and the growth rate of CO_2 concentration in the less

8 well-mixed stratosphere is not measured by sites from the NOAA network. Using a factor of 2.124

9 makes the approximation that the growth rate of CO₂ concentration in the stratosphere equals

10 that of the troposphere on a yearly basis.

Primary reference Component Global fossil CO₂ emissions (E_{FF}), total and by fuel type Boden et al., (2017) National territorial fossil CO₂ emissions (E_{FF}) CDIAC source: Boden et al., (2017) UNFCCC (2018) National consumption-based fossil CO₂ emissions (E_{FF}) Peters et al. (2011b) updated as described in this paper by country (consumption) Land-use change emissions (E_{LUC}) Average from Houghton and Nassikas (2017) and Hansis et al., (2015), both updated as described in this paper Growth rate in atmospheric CO₂ concentration (G_{ATM}) Dlugokencky and Tans (2018) Ocean and land CO₂ sinks (S_{OCEAN} and S_{LAND}) This paper for $S_{\mbox{\scriptsize OCEAN}}$ and $S_{\mbox{\scriptsize LAND}}$ and references in Table 4 for individual models.

1 **Table 2.** How to cite the individual components of the global carbon budget presented here.

Table 3. Main methodological changes in the global carbon budget since first publication. Methodological changes introduced in one year are

2 kept for the following years unless noted. Empty cells mean there were no methodological changes introduced that year.

Dublication was		Fossil fuel emiss	ions		Reservoirs		Uncertainty & other	
Publication year*	Global	Country (territorial)	Country (consumption)	LUC emissions	Atmosphere	Ocean	Land	changes
2006		Split in regions						
Raupach et al. (2007)								
2007				E _{LUC} based on FAO-FRA	1959-1979 data	Based on one ocean		±1σ provided for all
Canadell et al. (2007)				2005; constant E _{LUC} for 2006	from Mauna Loa;	model tuned to		components
					data after 1980 from	reproduced observed		
					global average	1990s sink		
2008 (online)				Constant E _{LUC} for 2007				
2009		Split between Annex	Results from an	Fire-based emission		Based on four ocean	First use of five DGVMs to	
Le Quéré et al. (2009)		B and non-Annex B	independent study	anomalies used for 2006-		models normalised to	compare with budget	
			discussed	2008		observations with	residual	
2010 5 1 11: 1 1						constant delta		
2010 Friedlingstein et	Projection	Emissions for top		E _{LUC} updated with FAO-FRA				
al. (2010)	for current	emitters		2010				
	year based							
2011	OILGDP		Split between Appey B					
Peters et al. (2012h)			and non-Annex B					
2012		129 countries from	129 countries and regions	Fue for 1997-2011 includes	All years from global	Based on 5 ocean models	Ten DGVMs available for	
Le Ouéré et al. (2013)		1959	from 1990-2010 based on	interannual anomalies from	average	normalised to	SLAND: First use of four	
Peters et al. (2013)			GTAP8.0	fire-based emissions		observations with ratio	models to compare with	
· · ·							E _{LUC}	
2013		250 countries ^b	134 countries and regions	E _{LUC} for 2012 estimated		Based on six models	Coordinated DGVM	Confidence levels;
Le Quéré et al. (2014)			1990-2011 based on	from 2001-2010 average		compared with two data-	experiments for SLAND and	cumulative emissions;
			GTAP8.1, with detailed			products to year 2011	ELUC	budget from 1750
			estimates for years 1997,					
			2001, 2004, and 2007					
2014	Three years	Three years of BP	Extended to 2012 with	E _{LUC} for 1997-2013 includes		Based on seven models	Based on ten models	Inclusion of breakdown of
Le Quéré et al. (2015b)	of BP data	data	updated GDP data	interannual anomalies from				the sinks in three latitude
				fire-based emissions				bands and comparison with
								three atmospheric
								Inversions
2015	Projection	National emissions	Detailed estimates			Based on eight models	Based on ten models with	The decadal uncertainty for
Le Quere et al. (2015a)	for current	from UNFCCC	introduced for 2011				assessment of minimum	the DGVM ensemble mean
Jackson et al. (2016)	year based	extended to 2014	based on GTAP9				realism	now uses ±10 of the decadal
2016	Jan-Aug data	also provided		Proliminany E using ERA		Pacad on soven models	Pasad on fourtoon	Spread across models
2010 La Quárá at al. (2016)	RD data	Added three small		2015 shown for comparison:		Based on seven models	Based off fourteen	full budget for current year
Le Quere et al. (2010)	DF Udid	emissions from 1990		2013 Shown for comparison,			models	full budget for current year
		from BP data (this		use of five Dovivis				
		release only)						
2017	Projection	,)		Average of two		Based on eight models	Based on fifteen models	Land multi-model average
Le Quéré et al. (2018)	includes			bookkeeping models; use of		that match the observed	that meet observation-	now used in main carbon
	India-specific			twelve DGVMs		sink for the 1990s; no	based criteria (see Sect.	budget, with the carbon
	data					longer normalised	2.5)	imbalance presented
								separately; new table of key
								uncertainties
2018 (this study)	Revision in	Aggregation of		Use of sixteen DGVMs ^c	Use of four	Based on seven models	Based on sixteen models;	Introduction of metrics for
	cement	overseas territories			atmospheric		revised atmospheric	evaluation of individual

emissions;	into governing	inversions fo	orcing from CRUNCEP to	models using observations
Projection	nations for total of		CRU-JRA-55	
includes EU-	213 countries ^b			
specific data				

^aThe naming convention of the budgets has changed. Up to and including 2010, the budget year (Carbon Budget 2010) represented the latest year of the data. From 2012,

2 the budget year (Carbon Budget 2012) refers to the initial publication year.

3 ^bThe CDIAC database has about 250 countries, but we show data for 213 countries since we aggregate and disaggregate some countries to be consistent with current

4 country definitions (see Sect. 2.1.1 for more details)

5 ^cE_{LUC} is still estimated based on bookkeeping models as in 2017, but the number of DGVMs used to characterise the uncertainty has changed.

- 1 **Table 4.** References for the process models, pCO₂-based ocean flux products, and atmospheric
- 2 inversions included in Figs. 6-8. All models and products are updated with new data to end of year
- 3 2017, and the atmospheric forcing for the DGVMs has been updated as described in Section 2.2.2.

Model/data name Reference			Change from Le Quéré et al. (2018)						
	Bookkeeping models for land-use change emissions								
	BLUE Hansis et al. (2015)		LUH2 rangelands were treated differently, using the static LUH2 information on forest/non-forest grid-cells to determine clearing for rangelands. Additionally effects on degradation of primary to secondary lands due to rangelands on natural (uncleared) vegetation were added to BLUE.						
	H&N2017	Houghton and Nassikas (2017)	No change.						
	Dynamic global veg	getation models ^a							
	CABLE-POP	Haverd et al. (2018)	Simple crop harvest and grazing implemented. Small adjustments to photosynthesis parameters to compensate for effect of new climate forcing on GPP.						
	CLASS-CTEM	Melton and Arora (2016)	20 soil layers used. Soil depth is prescribed following Pelletier et al. (2016).						
	CLM5.0	Oleson et al. (2013)	No change.						
	DLEM	Tian et al. (2015)	Using observed irrigation data instead of a potential irrigation map.						
	ISAM	Meiyappan et al. (2015)	Crop harvest and N fertilizer application as described in Song et al (2016).						
Mauritsen et al. (In JSBACH review)		Mauritsen et al. (In review)	New version of JSBACH (JSBACH 3.2), as used for CMIP6 simulations. Changes include a new fire algorithm, as well as new processes (land nitrogen cycle, carbon storage of wood products). Furthermore, LUH2 rangelands were treated differently, using the static LUH2 information on forest/non- forest grid-cells to determine clearing for rangelands.						
	JULES	Clarke et al. (2011)	No Change.						
	LPJ-GUESS	Smith et al. (2014) ^b	No Change.						
	LPJ	Poulter et al. (2011) ^c	Uses monthly litter update (previously annual), 3 product pools for deforestation flux, shifting cultivation, wood harvest, and inclusion of boreal needleleaf deciduous PFT.						
	LPX-Bern	Lienert and Joos (2018)	Minor refinement of parameterization. Changed from 1x1 degree to 0.5x0.5 degree resolution. Nitrogen deposition and fertilization from NMIP.						
	OCN	Zaehle and Friend (2010)	No change (uses r294).						
	ORCHIDEE-Trunk	Krinner et al. (2005) ^d	Updated soil water stress and albedo scheme; overall C-cycle optimisation (gross fluxes).						
	ORCHIDEE-CNP	Goll et al. (2017)	First time contribution (ORCHIDEE with nitrogen and phosphorus dynamics).						
	SDGVM	Walker et al. (2017)	No change.						

SURFEXv8	Joetzjer et al. (2015)	Not applicable (not used in 2017).				
VISIT	Kato et al. (2013)	Updated spinup protocol.				
Global ocean biog	eochemistry models					
CCSM-BEC	Doney et al. (2009)	No change.				
MICOM-HAMOCC (NorESM-OC)	Schwinger et al. (2016)	No drift correction.				
MITgcm-REcoM2	Hauck et al. (2016)	No change.				
MPIOM-HAMOCC	Mauritsen et al. (In review)	Change of atmospheric forcing; cmip6 model version includine modifications and bug-fixes in HAMOCC and MPIOM.				
NEMO-PISCES (CNRM)	Berthet et al. (Submitted)	New model version with update to NEMOv3.6 and improved exchange.				
NEMO-PISCES (IPSL)	Aumont and Bopp (2006)	No change.				
NEMO-PlankTOM5	Buitenhuis et al. (2010) ^e	No change.				
pCO2-based flux o	cean products					
Landschützer	Landschützer et al. (2016)	No change.				
Jena CarboScope	Rödenbeck et al. (2014)	No change.				
Atmospheric inver	sions					
CAMS	Chevallier et al. (2005)	No change.				
CarbonTracker Europe (CTE)	van der Laan-Luijkx et al. (2017)	Minor changes in the inversion set up.				
Jena CarboScope	Rödenbeck et al. (2003)	No change.				

3 SWRAD from CRU-JRA-55, the photosythesis scaling parameter α_a was modified (-15%) to yield similar results.

4 ^c Compared to published version, decreased LPJ wood harvest efficiency so that 50% of biomass was removed off-site

5 compared to 85% used in the 2012 budget. Residue management of managed grasslands increased so that 100% of 6 harvested grass enters the litter pool.

7 ^d Compared to published version, new hydrology and snow scheme; revised parameter values for photosynthetic

8 capacity for all ecosystem (following assimilation of FLUXNET data), updated parameters values for stem allocation,

9 maintenance respiration and biomass export for tropical forests (based on literature) and, CO₂ down-regulation

10 process added to photosynthesis. Version used for CMIP6.

11 ^e With no nutrient restoring below the mixed layer depth.

12

Table 5. Comparison of results from the bookkeeping method and budget residuals with results from the DGVMs and inverse estimates for

2 different periods, last decade, and last year available. All values are in GtC yr⁻¹. The DGVM uncertainties represent ±1 σ of the decadal or annual

3 (for 2017 only) estimates from the individual DGVMs: for the inverse models all three results are given where available.

4

Mean (GtC yr ⁻¹)										
	1960-1969	1970-1979	1980-1989	1990-1999	2000-2009	2008-2017	2017			
Land-use change emissions (E _L	υς)									
Bookkeeping methods	1.5 ± 0.7	1.2 ± 0.7	1.2 ± 0.7	1.4 ± 0.7	1.3 ± 0.7	1.5 ± 0.7	1.4 ± 0.7			
DGVMs	1.5 ± 0.7	1.4 ± 0.7	1.5 ± 0.7	1.3 ± 0.6	1.4 ± 0.6	1.9 ± 0.6	2.0 ± 0.7			
Terrestrial sink (S _{LAND})										
Residual sink from global budget (E _{FF} +E _{LUC} -G _{ATM} -S _{OCEAN})	1.8 ± 0.9	1.8 ± 0.9	1.5 ± 0.9	2.6 ± 0.9	2.9 ± 0.9	3.5 ± 1.0	4.1 ± 1.0			
DGVMs	1.2 ± 0.5	2.1 ± 0.4	1.8 ± 0.6	2.4 ± 0.5	2.7 ± 0.7	3.2 ± 0.7	3.8 ± 0.8			
Total land fluxes (S _{LAND} – E _{LUC})										
Budget constraint (E _{FF} -G _{ATM} - S _{OCEAN})	0.3 ± 0.5	0.6 ± 0.6	0.4 ± 0.6	1.2 ± 0.6	1.6 ± 0.6	2.1 ± 0.7	2.7 ± 0.7			
DGVMs	-0.3 ± 0.6	0.7 ± 0.5	0.3 ± 0.6	1.1 ± 0.5	1.3 ± 0.5	1.3 ± 0.5	1.8 ± 0.5			
Inversions*	_/_/_	_/_/_	-0.2–0.1	0.5–1.1	0.8–1.5	1.4–2.4	1.2-3.1			

5 *Estimates are corrected for the pre-industrial influence of river fluxes and adjusted to common E_{FF} (Sect. 2.7.2). Two inversions are available for the 1980s and 1990s. Two

6 additional inversions are available from 2001 and used from the decade of the 2000 (Tables A3).

- 1 **Table 6.** Decadal mean in the five components of the anthropogenic CO₂ budget for different periods, and last year available. All values are in
- 2 GtC yr⁻¹, and uncertainties are reported as ±1 σ . The table also shows the budget imbalance (B_{IM}), which provides a measure of the
- 3 discrepancies among the nearly independent estimates and has an uncertainty exceeding ± 1 GtC yr⁻¹. A positive imbalance means the
- 4 emissions are overestimated and/or the sinks are too small.

	Mean (GtC yr ⁻¹)								
	1960-1969	1970-1979	1980-1989	1990-1999	2000-2009	2008-2017	2017		
Total emissions (E _{FF} +E _{LUC})									
Fossil CO ₂ emissions (E _{FF})	3.1 ± 0.2	4.7 ± 0.2	5.4 ± 0.3	6.3 ± 0.3	7.8 ± 0.4	9.4 ± 0.5	9.9 ± 0.5		
Land-use change emissions	1.5 ± 0.7	1.2 ± 0.7	1.2 ± 0.7	1.4 ± 0.7	1.3 ± 0.7	1.5 ± 0.7	1.4 ± 0.7		
(E _{LUC})									
Partitioning									
Growth rate in atmospheric CO_2 concentration (G_{ATM})	1.7 ± 0.07	2.8 ± 0.07	3.4 ± 0.02	3.1 ± 0.02	4.0 ± 0.02	4.7 ± 0.02	4.6 ± 0.2		
Ocean sink (S _{OCEAN})	1.0 ± 0.5	1.3 ± 0.5	1.7 ± 0.5	2.0 ± 0.5	2.1 ± 0.5	2.4 ± 0.5	2.5 ± 0.5		
Terrestrial sink (S _{LAND})	1.2 ± 0.5	2.1 ± 0.4	1.8 ± 0.6	2.4 ± 0.5	2.7 ± 0.7	3.2 ± 0.7	3.8 ± 0.8		
Budget imbalance									
B _{IM} = E _{FF} +E _{LUC} -	(0.6)	(0.3)	(0.3)	(0.2)	(0.2)	(0.5)	(0.3)		
(G _{ATM} +S _{OCEAN} +S _{LAND})									

- 1 Table 7. Comparison of the projection with realised fossil CO₂ emissions (E_{FF}). The 'Actual' values are first estimate available using actual data,
- 2 and the 'Projected' values refers to estimate made before the end of the year for each publication. Projections based on a different method
- from that described here during 2008-2014 are available in Le Quéré et al., (2016). All values are adjusted for leap years.
- 4

	World China USA		EU28		India		Rest of World					
	Projected	Actual										
2015ª	-0.6% (-1.6 to 0.5)	0.06%	-3.9% (-4.6 to -1.1)	-0.7%	-1.5% (-5.5 to 0.3)	-2.5%	_	_	_	-	1.2% (-0.2 to 2.6)	+1.2%
2016 ^b	-0.2% (-1.0 to +1.8)	0.2%	-0.5% (-3.8 to +1.3)	-0.3%	-1.7% (-4.0 to +0.6)	-2.1%	-	_	-	-	+1.0% (–0.4 to +2.5)	+1.3%
2017 ^c	+2.0% (+0.8 to +3.0)	+1.6%	+3.5 (+0.7 to +5.4)	+1.5%	-0.4% (-2.7 to +1.0)	-0.5%	-	_	+2.0% (+0.2 to +3.8)	+3.9%	+1.6% (0.0 to +3.2)	+1.9%
2018 ^d	+2.7% (+1.8 to +3.7)	_	+4.7 (+2.0 to +7.4)	-	+2.5% (+0.5 to +4.5)	_	-0.7% (-2.6 to +1.3)	_	+6.3% (+4.3 to +8.3)	-	+1.8% (+0.5 to +3.0)	-

⁵ ^aJackson et al. (2016) and Le Quéré et al. (2015a). ^bLe Quéré et al. (2016). ^cLe Quéré et al. (2018). ^dThis study.

1 **Table 8.** Cumulative CO₂ for different time periods in gigatonnes of carbon (GtC). All uncertainties are

2 reported as $\pm 1\sigma$. E_{LUC} and S_{OCEAN} have been revised to incorporate multiple estimates (Section 3.5), and the

3 terrestrial sink (S_{LAND}) is now estimated independently, from the mean of the DGVM. Therefore the table

also shows the budget imbalance, which provides a measure of the discrepancies among the nearly
 independent estimates. Its uncertainty exceeds ± 60 GtC. The method used here does not capture the loss

independent estimates. Its uncertainty exceeds ± 60 GtC. The method used here does not capture the loss
of additional sink capacity from reduced forest cover, which is about 20 GtC and would exacerbate the

budget imbalance (see Section 2.7.3). All values are rounded to the nearest 5 GtC and therefore columns

8 do not necessarily add to zero.

Units of GtC	1750-2017	1850-2005	1850-2014	1959-2017	1870-2017	1870-2018ª
Emissions						
Fossil CO ₂ emissions (E _{FF})	430 ± 20	320 ± 15	400 ± 20	350 ± 20	425 ± 20	435 ± 20
Land-use change CO_2 emissions (E_{LU}	c) 235 ± 95	185 ± 70	195 ± 75	80 ± 40	190 ± 75	190 ± 75
Total emissions	660 ± 95	500 ± 75	595 ± 80	430 ± 45	615 ± 80	625 ± 80
Partitioning						
Growth rate in atmospheric CO_2 concentration (G_{ATM})	275 ± 5	200 ± 5	235 ± 5	190 ± 5	250 ± 5	255 ± 5
Ocean sink (S _{OCEAN})	165 ± 20	125 ± 20 ^b	150 ± 20	100 ± 20	150 ± 20	155 ± 20
Terrestrial sink (S _{LAND})	215 ± 50	160 ± 45	185 ± 50	130 ± 30	190 ± 50	195 ± 50
Budget imbalance						
B _{IM} = E _{FF} +E _{LUC} - (G _{ATM} +S _{OCEAN} +S _{LAND})	(5)	(20)	(25)	(10)	(25)	(25)

9 ^aUsing projections for year 2018 (Sect. 3.3).

10 ^bThis value was incorrectly reported as 145 in Le Quéré et al. (2018).

1 Table 9. Major known sources of uncertainties in each component of the Global Carbon Budget,

2 defined as input data or processes that have a demonstrated effect of at least ±0.3 GtC yr⁻¹.

3

Source of uncertainty	Time scale (years)	Location	Status	Evidence
Fossil CO ₂ emissions (E _{FF} ; Se	ction 2.1)			
energy statistics	annual to decadal	mainly China	see Sect. 2.1	(Korsbakken et al., 2016)
carbon content of coal	decadal	mainly China	see Sect. 2.1	(Liu et al., 2015)
Emissions from land-use cha				
land-cover and land-use change statistics	continuous	global; in particular tropics	see Sect. 2.2	(Houghton et al., 2012)
sub-grid-scale transitions	annual to decadal	global	see Table A1	(Wilkenskjeld et al., 2014)
vegetation biomass	annual to decadal	global; in particular tropics	see Table A1	(Houghton et al., 2012)
wood and crop harvest	annual to decadal	global; SE Asia	see Table A1	(Arneth et al., 2017)
peat burning ^a	multi-decadal trend	global	see Table A1	(van der Werf et al., 2010)
loss of additional sink capacity	multi-decadal trend	global	not included; Section 2.7.3	(Gitz and Ciais, 2003)

Atmospheric growth rate (G_{ATM}) \rightarrow no demonstrated uncertainties larger than ±0.3 GtC yr^{-1, b}

Ocean sink (S _{OCEAN})				
variability in oceanic circulation ^c	semi-decadal to decadal	global; in particular Southern Ocean	see Sect. 2.4.2	(DeVries et al., 2017)
Internal variability	annual to decadal	high latitudes; Equatorial Pacific	no ensembles/ coarse resolution	(McKinley et al., 2016)
anthropogenic changes in nutrient supply	multi-decadal trend	global	not included	(Duce et al., 2008)
Land sink (S _{LAND})				
strength of CO ₂ fertilisation	multi-decadal trend	global	see Sect. 2.5	(Wenzel et al., 2016)
response to variability in temperature and rainfall	annual to decadal	global; in particular tropics	see Sect. 2.5	(Cox et al., 2013)
nutrient limitation and supply	multi-decadal trend	global	see Sect. 2.5	(Zaehle et al., 2011)
response to diffuse radiation	annual	global	see Sect. 2.5	(Mercado et al., 2009)

4 ^aAs result of interactions between land-use and climate

5 ^bThe uncertainties in G_{ATM} 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.

6 Could in part be due to uncertainties in atmospheric forcing (Swart et al., 2014)
1 Appendix A. Supplementary tables.

2 **Table A1.** Comparison of the processes included (Y) or not (N) in the bookkeeping and Dynamic

3 Global Vegetation Models for their estimates of ELUC and SLAND. See Table 4 for model references.

- 4 All models include deforestation and forest regrowth after abandonment of agriculture (or from
- 5 afforestation activities on agricultural land).

	bookke mod	eping lels									DG	VMs						
	H&N2017	BLUE	CABLE-POP	CLASS-CTEM	CLM5.0	DLEM	ISAM	JSBACH ⁱ	JULES	LPJ-GUESS	LPJ	LPX-Bern	OCN	Orchidee-CNP	Orchidee-Trunk	SDGVM	SURFEX	VISIT
Processes relevant for ELUC																		
Wood harvest and forest degradation ^a	Y	Y	Y	N	Y	Y	Y	Y	N	Y	Y	N ^d	Y	N	Y	Ν	N	Y
Shifting cultivation / subgrid scale transitions	N ^b	Y	Y	N	Y	N	Ν	Y	N	Y	Y	N ^d	N	Ν	N	Ν	N	Y
Cropland harvest (removed, r, or added to litter, l)	Y(r) ^h	Y(r) ^h	Y(r)	Y(I)	Y(r)	Y	Y	Y(r,l)	N	Y(r)	Y(I)	Y(r)	Y(r,l)	Y(r)	Y(r)	Y(r)	N	Y(r)
Peat fires	Y	Y	Ν	Ν	Y	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν
Fire as a management tool	Y ^h	\mathbf{Y}^{h}	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν
N fertilization	Y ^h	\mathbf{Y}^{h}	N	Ν	Y	Y	Y	Ν	Ν	Y	Ν	Y	Y	Y	Ν	Ν	Ν	Ν
Tillage	Y ^h	\mathbf{Y}^{h}	Y	Ye	Ν	Ν	Ν	Ν	N	Y	Ν	Ν	Ν	Ν	Yg	Ν	Ν	Ν
Irrigation	Y ^h	\mathbf{Y}^{h}	N	Ν	Y	Y	Y	Ν	N	Y	Ν	Ν	Ν	Ν	Ν	Ν	Yg	Ν
Wetland drainage	Y ^h	Y^h	N	Ν	Ν	Ν	Ν	Ν	N	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	N
Erosion	Y ^h	Y ^h	N	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	Ν	N	Ν	Ν	Ν	Y
Southaast Asia peat drainage	Y	Y	N	Ν	Ν	Ν	Ν	Ν	N	N	Ν	N	Ν	Ν	N	Ν	Ν	N
Grazing and mowing harvest (removed, r, or added to litter, l)	Y(r) ^h	Y(r) ^h	Y(r)	Ν	Ν	Ν	Y(I)	Y(I)	N	Y(r)	Y(I)	N	Y(r,l)	Ν	N	Ν	N	Ν
Processes relevant also for $\ensuremath{S_{LAND}}$																		
Fire simulation	US only	Ν	N	Y	Y	Y	Ν	Y	Ν	Y	Y	Y	Ν	N	Ν	Y	Y	Y
Climate and variability	N	Ν	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CO ₂ fertilisation	N ^f	N^f	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Ye	Y	Y	Y
Carbon-nitrogen interactions, including N deposition	N ^h	N ^h	Y	N ^d	Y	Y	Y	Y	N	Y	N	Y	Y	Y	N	Yc	Ni	N

^a Refers to the routine harvest of established managed forests rather than pools of harvested products.

7 ^b No back- and forth-transitions between vegetation types at the country-level, but if forest loss based on FRA

8 exceeded agricultural expansion based on FAO, then this amount of area is interpreted as shifting cultivation.

9 ^c Limited. Nitrogen uptake is simulated as a function of soil C, and photosynthesis is directly related to canopy N. Does

10 not consider N deposition.

^d Although C-N cycle interactions are not represented, the model includes a parameterization of down-regulation of

12 photosynthesis as CO₂ increases to emulate nutrient constraints (Arora et al., 2009)

^e Tillage is represented over croplands by increased soil carbon decomposition rate and reduced humification of litter
 to soil carbon.

¹⁵ ^f Bookkeeping models include effect of CO₂-fertilization as captured by observed carbon densities, but not as an effect

16 transient in time.

- 1 ^g 20% reduction of active soil organic carbon (SOC) pool turnover time for C3 crop and 40% reduction for C4 crops
- 2 ^h Process captured implicitly by use of observed carbon densities.
- Simple parameterization of nitrogen limitation based on Yin (2002; assessed on FACE experiments).

Table A2. Comparison of the processes and model set up for the Global Ocean Biogeochemistry

2 Models for their estimates of S_{OCEAN}. See Table 4 for model references.

	CCSM-BEC	NorESM-OC	MITgcm- REcoM2	MPIOM - HAMOCC	NEMO3.6- PISCESv2-gas (CNRM)	NEMO-PISCES (IPSL)	NEMO- PlankTOM5
Atmospheric forcing	NCEP	CORE-I (spin up) / NCEP with CORE-II corrections	JRA55	NCEP / NCEP+ERA-20C (spin-up)	NCEP	NCEP	NCEP
Initialisation of carbon chemistry	GLODAP	GLODAP v1 + spin up 1000 years	GLODAP, then spin-up 116 years (2 cycles JRA55)	spin-up with ERA20C	GLODAPv2 + 300 years online	GLODAP from 1948 onwards	GLODAP + spin up 30 years
Physical ocean model	POP Version 1.4.3	MICOM	MITgcm 65n	MPIOM	NEMOv3.6- GELATOv6- eORCA1L75	NEMOv3.2- ORCA2L31	NEMOv2.3- ORCA2
Resolution	3.6° lon, 0.8 to 1.8° lat	1° lon, 0.17 to 0.25 lat; 51 isopycnic layers + 2 bulk mixed layer	2° lon, 0.38-2° lat, 30 levels	1.5°; 40 levels	1° lon, 0.3 to 1° lat 75 levels, 1m at surface	2º lon, 0.3 to 1.5º lat; 31 levels	2º lon, 0.3 to 1.5º lat; 31 levels

1 **Table A3.** Comparison of the inversion set up and input fields for the atmospheric inversions.

2 Atmospheric inversions see the full CO₂ fluxes, including the anthropogenic and pre-industrial

- 3 fluxes. Hence they need to be adjusted for the pre-industrial flux of CO₂ from the land to the
- 4 ocean that is part of the natural carbon cycle before they can be compared with S_{OCEAN} and S_{LAND}
- 5 from process models. See Table 4 for references.

	CarbonTracker Europe (CTE)	Jena CarboScope	CAMS	MIROC
Version number	CTE2018	s85oc_v4.2	v17r1	tdi84_2018
Observations				
Atmospheric observations	Hourly resolution (well-mixed conditions) OBSPACK GLOBALVIEWplus v3.2 & NRTv4.2 ^a	Flasks and hourly (outliers removed by 2-sigma criterion)	Daily averages of well- mixed conditions - OBSPACK GLOBALVIEWplus v3.2ª & NRT v4.2, WDCGG, RAMCES and ICOS ATC	Flask and continuous data at remote sites from ObsPack GLOBALVIEWplus v3.2 and v4.0
Prior fluxes				
Biosphere and fires	SiBCASA-GFED4s ^b	No prior	ORCHIDEE (climatological), GFEDv4 & GFAS	Climatological CASA with 3-hourly downscaling
Ocean	Ocean inversion by Jacobson et al. (2007)	pCO ₂ -based ocean flux product oc_v1.6 (update of Rödenbeck et al., 2014)	Landschützer et al. (2015)	Takahashi et al. (2009)
Fossil fuels	EDGAR+IER, scaled to CDIAC	CDIAC (extended after 2013 with GCP totals)	EDGAR scaled to CDIAC	EDGARv4.3.2 (2012 map after 2013)
Transport and o	optimization			
Transport model	TM5	TM3	LMDZ v5A	MIROC4-ACTM
Weather forcing	ECMWF	NCEP	ECMWF	JRA55
Resolution (degrees)	Global: 3° x 2°, Europe: 1° x 1°, North America: 1° x 1°	Global: 4° x 5°	Global: 3.75° x 1.875°	Global: 2.8∘ × 2.8∘
Optimization	Ensemble Kalman filter	Conjugate gradient (re-ortho- normalization) ^c	Variational	Matrix Method, 84 regions

6 ^a(GLOBALVIEW, 2016;Carbontracker Team, 2017)

7 ^b(van der Velde et al., 2014)

8 ^cocean prior not optimised

Table A4 Attribution of fCO₂ measurements for the year 2017 included in SOCAT v6 (Bakker et al., 2016) to inform ocean pCO₂-based flux

2 products.

Platform	Regions	No. of	Principal Investigators	No. of data sets
Allure of the Seas	Tropical Atlantic	127007	Wanninkhof, R. : Pierrot, D.	51
Atlantic Cartier	North Atlantic	33565	Steinhoff, T. : Koertzinger, A. : Wallace, D.	7
Aurora Australis	Southern Ocean	64481	Tilbrook, B.: Neill, C.: Akl, J.	3
Benguela Stream	North Atlantic; Tropical Atlantic	105517	Schuster, U. : Watson, A.J.	17
BOBOA_90E_15N	Indian Ocean	66	Sutton, A. : O Brien, C. : Hermes, R.	1
Cap san Lorenzo	North Atlantic; Tropical Atlantic	33901	Lefevre, N.: Diverres, D.	7
Colibri	North Atlantic; Tropical Atlantic	9334	Lefevre, N.: Diverres, D.	2
Discovery	North Atlantic	2540	Kitidis, V.	1
Equinox	Tropical Atlantic	114369	Wanninkhof, R. : Pierrot, D.	42
Finnmaid	North Atlantic	128793	Rehder, G. : Glockzin, M.	11
G.O. Sars	North Atlantic	99028	Skjelvan, I.	7
Gordon Gunter	North Atlantic; Tropical Atlantic	60213	Wanninkhof, R. : Pierrot, D.	12
Henry B. Bigelow	North Atlantic	40703	Wanninkhof, R. : Pierrot, D.	7
Heron Island	Tropical Pacific	2775	Tilbrook, B.: van Ooijen, E.: Passmore, A.	2
Investigator	Southern Ocean; Tropical Pacific	98081	Tilbrook, B.: Neill, C.: Akl, J.	6
Kangaroo Island	Southern Ocean	1650	Tilbrook, B.: van Ooijen, E.: Passmore, A.	1
Laurence M. Gould	Southern Ocean	41657	Sweeney, C. : Takahashi, T. : Newberger, T. : Sutherland, S.C. : Munro, D.R.	7
Maria Island	Southern Ocean	3023	Tilbrook, B.: van Ooijen, E.: Passmore, A.	2
Marion Dufresne	Indian Ocean; Southern Ocean	6641	Metzl, N. : Lo Monaco, C.	1
MSC Marianna	North Atlantic; Tropical Atlantic	2823	Gonzalez-Davila, M. : Santana-Casiano, J.M.	1
New Century 2	North Atlantic; North Pacific; Tropical Atlantic; Tropical Pacific	28604	Nakaoka, S.	13
Nuka Arctica	North Atlantic	139842	Becker, M. : Olsen, A.: Johannessen, T.	29
Polarstern	Arctic, North Atlantic, Southern Ocean; Tropical Atlantic	135031	van Heuven, S. : Hoppema, M.	6
Ronald H. Brown	Southern Ocean; Tropical Atlantic, Tropical Pacific	45510	Wanninkhof, R. : Pierrot, D.	4
S.A. Agulhas II	Southern Ocean	8990	Monteiro, P.M.S. : Gregor, L.	1
Simon Stevin	North Atlantic	12189	Gkritzalis, T. : Theetaert, H.	3
Soyo Maru	North Pacific	49613	Ono, T.	3
TAO110W_0N	Tropical Pacific	825	Sutton, A.	2
Trans Future 5	North Pacific, Southern Ocean; Tropical Pacific	22596	Nakaoka, S. : Nojiri, Y.	21
Victor Angelescu	North Atlantic, Southern Ocean, Tropical Atlantic	4624	Negri, R.: Padin, X.A.	1
Wakmatha	Tropical Pacific	20496	Tilbrook, B.: Neill, C.: Akl, J.	6

Table A5. Funding supporting the production of the various components of the global carbon

2 budget in addition to the authors' supporting institutions (see also acknowledgements).

budget in dualion to the dutions supporting institutions (see diso deknowed	agements).
Funder and grant number (where relevant)	author initials
Australia, Great Barrier Reef Foundation	BT, CN
Australia, Integrated Marine Observing System (IMOS)	BT, CN
Australian Government National Environment Science Program (NESP)	JGC, VH
EC H2020 (AtlantOS: grant no 633211)	AO, US
EC H2020 (CRESCENDO: grant no. 641816)	MF, PF, RS, TI
EC H2020 European Research Council (ERC) Synergy grant (IMBALANCE-P; grant no. ERC- 2013-SyG-610028)	DSG
EC H2020 ERC (QUINCY; grant no. 647204).	SZ
EC H2020 (RINGO: grant no. 730944; FixO3: grant no. 312463).	US
EC H2020 project (VERIFY: grant no. 776810)	CLQ, GPP, IH, JIK, RMA, PP, PC
FRA, MOE	ТО
French Institut National des Sciences de l'Univers (INSU) and Institut Paul Emile Victor (IPEV), Sorbonne Universités (UPMC, Univ Paris 06)	NM
German Federal Ministry for Education and Research (BMBF)	GR, MH, TS
German Federal Ministry of Transport and Digital Infrastructure (BMVI)	GR, MH, TS
German Helmholtz Association in its ATMO programme	AA
German Helmholtz Association Innovation and Network Fund (VH-NG-1301)	JH
German Research Foundation's Emmy Noether Programme (grant no. PO1751/1-1)	JP
Integrated Carbon Observation System (ICOS) RI	GR, MH, NL, TG, TJ, TS, IS, US
French Institut de Recherche pour le Développement (IRD)	NL
Japan Environment Research and Technology Development Fund of the Ministry of the Environment (grant no. 2-1701)	РКР
Japan Fisheries Research and Education Agency (FREA), Ministry of Environment (MOE)	ТО
Japan National Institute for Environmental Studies (NIES), Ministry of Environment (MOE)	SN
Netherlands Organization for Scientific Research (NWO; grant no. SH-312, 16666)	lvdLL
Norwegian Research Council (grant no. 229771)	JS
Norwegian Research Council (grant no. ICOS 245927)	IS, TJ, BP
Norwegian Research Council (grant no. 209701)	RMA, JIK, GPP
The Netherlands, Research Foundation – Flanders (FWO contract no. G0H3317N)	TG
The Copernicus Atmosphere Monitoring Service, implemented by the European Centre for Medium-Range Weather Forecasts (ECMWF) on behalf of the European Commission	FC
Swiss National Science Foundation (grant no. 200020_172476)	SL
UK BEIS/Defra Met Office Hadley Centre Climate Programme (grant no. GA01101)	CDJ
UK Natural Environment Research Council (SONATA: grant no. NE/P021417/1)	CLQ, US
UK NERC (RAGNARoCC: grant no. NE/K002473/1)	US
UK Newton Fund, Met Office Climate Science for Service Partnership Brazil (CSSP Brazil)	AW
USA Climate Program Office of NOAA (grant no. NA13OAR4310219)	LR
USA Department of Agriculture, National Institute of Food and Agriculture (grants no. 2015-67003-23489 and 2015-67003-23485)	DLL
USA Department of Commerce, NOAA/OAR's Global Ocean Monitoring & Observing Program	AS, LB, DP
USA Department of Commerce, NOAA/OAR's Ocean Acidification Program	AS, DP, LB

USA Department of Energy, Oak Ridge National Laboratory (contract no. DE-AC05- 00OR22725)	APW
USA Department of Energy, Office of Science and BER prg. (grant no. DE-SC000 0016323)	ATJ
USA Department of Energy (grants no. DE-FC03-97ER62402/A010 and DE-SC0012972)	DLL
USA NASA Interdisciplinary Research in Earth Science Program.	BP
Computing resources	
Norway UNINETT Sigma2, National Infrastructure for High Performance Computing and	IC
Data Storage in Norway (NN2980K/NS2980K)	12
TGCC under allocations 2017-A0030102201 and 2017-A0030106328 made by GENCI	FC, NV
Japan National Institute for Environmental Studies computational resources	EK
UEA High Performance Computing Cluster, UK	RW, CLQ
Support for aircraft measurements in Obspack	

Support for aircraft measurements in Obspack

L. V. Gatti, M. Gloor, J.B. Miller: AMAZONICA consorcium project was funded by NERC (NE/F005806/1), FAPESP (08/58120-3), GEOCARBON project (283080)

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Jeff Peischl of the University of Colorado/CIRES for the NOAA WP-3D aircraft vertical profile data

- 1 **Table A6.** Aircraft measurement programs archived by Cooperative Global Atmospheric Data
- 2 Integration Project (CGADIP, 2017) that contribute to the evaluation of the atmospheric inversions

3 (Figure B3).

Measurement program name in Obspack	Specific doi	Data providers
Airborne Aerosol Observatory, Bondville, Illinois		Wanninkhof, R. : Pierrot, D.
Alaska Coast Guard		Sweeney, C.; McKain, K.; Karion, A.; Dlugokencky, E.J.
Atmospheric Carbon and Transport -	https://doi.org/10.333	Davis, K.J.; Digangi, J.P.; Yang, M.
America Atmospheric Carbon and Transport - America Alta Floresta	4/OKNEDAAC/1556	Davis, K.J.; Sweeney, C.; Dlugokencky, E.J.; Yang, M. Gatti, L.V.; Gloor, E.; Miller, J.B.;
Aircraft Observation of Atmospheric trace gases by JMA		ghg_obs@met.kishou.go.jp
Aerosol, Radiation, and Cloud Processes affecting Arctic Climate 2008 (air campaign)		Ryerson, T.B.; Peischl, J.; Aikin, K.C.
LARC - NASA Langley Research Center Aircraft Campaign	https://doi.org/10.333 4/ORNLDAAC/1556	Chen, G.; Digangi, J.P.
Beaver Crossing, Nebraska		Sweeney, C.; Dlugokencky, E.J.
California Nexus 2010 (air campaign)		Ryerson, T.B.; Peischl, J.; Aikin, K.C.
Briggsdale, Colorado		Sweeney, C.; Dlugokencky, E.J.
Cape May, New Jersey		Sweeney, C.; Dlugokencky, E.J.
CONTRAIL (Comprehensive Observation Network for TRace gases by AIrLiner) Carbon in Arctic Reservoirs Vulnerability	http://dx.doi.org/10.17 595/20180208.001	Machida, T.; Matsueda, H.; Sawa, Y. Niwa, Y. Sweeney, C.; Karion, A.; Miller, J.B.;
Experiment (CARVE)	https://doi.org/10.222	Miller, C.E.; Dlugokencky, E.J.
Aircraft Campaign	4/ORNLDAAC/1556	Chen, G.; Digangi, J.P.; Beyersdorf, A.
LARC - NASA Langley Research Center Aircraft Campaign	https://doi.org/10.333 4/ORNLDAAC/1556	Chen, G.; Digangi, J.P.; Yang, M.
Dahlen, North Dakota		Sweeney, C.; Dlugokencky, E.J.
Estevan Point, British Columbia		Sweeney, C.; Dlugokencky, E.J.
East Trout Lake, Saskatchewan		Sweeney, C.; Dlugokencky, E.J.
Molokai Island, Hawaii		Sweeney, C.; Dlugokencky, E.J.
Homer, Illinois		Sweeney, C.; Dlugokencky, E.J.
HIPPO (HIAPER Pole-to-Pole Observations)	https://doi.org/10.333 4/CDIAC/HIPPO_010	Wofsy, S.C.; Stephens, B.B.; Elkins, J.W.; Hintsa, E.J.; Moore, F.
INFLUX (Indianapolis Flux Experiment)		Sweeney, C.; Dlugokencky, E.J.; Shepson, P.B.; Turnbull, J.
Park Falls, Wisconsin		Sweeney, C.; Dlugokencky, E.J.
Mid Continent Intensive		Sweeney, C.; Dlugokencky, E.J.
Marcellus Pennsylvania		Sweeney, C.; Dlugokencky, E.J.
Worcester, Massachusetts		Sweeney, C.; Dlugokencky, E.J.
ORCAS (O2/N2 Ratio and CO2 Airborne Southern Ocean Study)	https://doi.org/10.506 5/D6SB445X	Stephens, B.B.; Sweeney, C.; McKain, K.; Kort, E.A.
Poker Flat, Alaska		Sweeney, C.; Dlugokencky, E.J.
Rio Branco		Gatti, L.V.; Gloor, E.; Miller, J.B.
Rarotonga		Sweeney, C.; Dlugokencky, E.J.
Montzka		Sweeney, C.; Dlugokencky, E.J.

	Santarem		Sweeney, C.; Dlugokencky, E.J.
	Charleston, South Carolina		Sweeney, C.; Dlugokencky, E.J.
	LARC - NASA Langley Research Center Aircraft Campaign	https://doi.org/10.333 4/ORNLDAAC/1556	Chen, G.; Digangi, J.P.; Beyersdorf, A.
	Southeast Nexus 2013 (air campaign)		Ryerson, T.B.; Peischl, J.; Aikin, K.C.
	Southern Great Plains, Oklahoma		Sweeney, C.; Dlugokencky, E.J.; Biraud, S.
	Shale Oil and Natural Gas Nexus 2015 (air campaign)		Ryerson, T.B.; Peischl, J.; Aikin, K.C.
	Harvard University Aircraft Campaign		Wofsy, S.C.
	Tabatinga		Gatti, L.V.; Gloor, E.; Miller, J.B.
	Sinton, Texas		Sweeney, C.; Dlugokencky, E.J.
	Trinidad Head, California		Sweeney, C.; Dlugokencky, E.J.
	Atmospheric Tomography Mission (ATom)		McKain, K.; Sweeney, C.
	Ulaanbaatar		Sweeney, C.; Dlugokencky, E.J.
	West Branch, Iowa		Sweeney, C.; Dlugokencky, E.J.
1			

1 Figure Captions





3 Figure 1. Surface average atmospheric CO₂ concentration (ppm). The 1980-2018 monthly data are from NOAA/ESRL (Dlugokencky and Tans, 2018) and are based on an average of direct 4 5 atmospheric CO₂ measurements from multiple stations in the marine boundary layer (Masarie and 6 Tans, 1995). The 1958-1979 monthly data are from the Scripps Institution of Oceanography, based 7 on an average of direct atmospheric CO₂ measurements from the Mauna Loa and South Pole 8 stations (Keeling et al., 1976). To take into account the difference of mean CO₂ and seasonality 9 between the NOAA/ESRL and the Scripps station networks used here, the Scripps surface average (from two stations) was deseasonalised and harmonised to match the NOAA/ESRL surface average 10 (from multiple stations) by adding the mean difference of 0.542 ppm, calculated here from 11 12 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 2008-2017. See legends for the corresponding arrows and units. The uncertainty in the atmospheric CO_2 growth rate is very small (±0.02 Gt C 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 Ciais et al. (2013) for all numbers, with the ocean fluxes updated to 90 GtC yr⁻¹ to account for the increase in atmospheric CO_2 since publication, and except for the carbon stocks in coasts which is from a literature review of coastal marine sediments (Price and Warren, 2016).





2 Figure 3. Combined components of the global carbon budget illustrated in Fig. 2 as a function of time, for fossil CO₂ emissions (E_{FF}; grey) and emissions from land-use change (E_{LUC}; brown), as well 3 4 as their partitioning among the atmosphere (GATM; purple), ocean (SOCEAN; blue), and land (SLAND; 5 green). The partitioning is based on nearly independent estimates from observations (for G_{ATM}) and from process model ensembles constrained by data (for SOCEAN and SLAND), and does not 6 7 exactly add up to the sum of the emissions, resulting in a budget imbalance which is represented 8 by the difference between the bottom pink line (reflecting total emissions) and the sum of the ocean, land and atmosphere. All time series are in GtC yr⁻¹. G_{ATM} and S_{OCEAN} prior to 1959 are 9 based on different methods. E_{FF} are primarily from Boden et al. (2017), with uncertainty of about 10 11 $\pm 5\%$ ($\pm 1\sigma$); E_{LUC} are from two bookkeeping models (Table 2) with uncertainties of about $\pm 50\%$; 12 G_{ATM} prior to 1959 is from Joos and Spahni (2008) with uncertainties equivalent to about ±0.1-0.15 GtC yr⁻¹, and from Dlugokencky and Tans (2018) from 1959 with uncertainties of about ±0.2 GtC 13 yr⁻¹; S_{OCEAN} prior to 1959 is averaged from Khatiwala et al. (2013) and DeVries (2014) with 14 uncertainty of about ±30%, and from a multi-model mean (Table 4) from 1959 with uncertainties 15 of about ±0.5 GtC yr⁻¹; S_{LAND} is a multi-model mean (Table 4) with uncertainties of about ±0.9 GtC 16 yr⁻¹. See the text for more details of each component and their uncertainties. 17



2 presented individually for (a) fossil CO₂ emissions (E_{FF}), (b) emissions from land-use change (E_{LUC}), 3 4 (c) the budget imbalance that is not accounted for by the other terms, (d) growth rate in 5 atmospheric CO₂ concentration (G_{ATM}), and (e) the land CO₂ sink (S_{LAND}, positive indicates a flux 6 from the atmosphere to the land), (f) the ocean CO_2 sink (S_{OCEAN}, positive indicates a flux from the 7 atmosphere to the ocean). All time series are in GtC yr⁻¹ with the uncertainty bounds representing 8 $\pm 1\sigma$ in shaded colour. Data sources are as in Fig. 3. The black dots in (a) show values for 2015-9 2017 that originate from a different data set to the remainder of the data (see text). The dashed 10 line in (b) identifies the pre-satellite period before the inclusion of peatland burning.





2 Figure 5. Fossil CO₂ emissions for (a) the globe, including an uncertainty of ± 5% (grey shading), 3 and the emissions extrapolated using BP energy statistics (black dots), (b) global emissions by fuel 4 type, including coal (salmon), oil (olive), gas (turquoise), and cement (purple), and excluding gas 5 flaring which is small (0.6% in 2013), (c) territorial (solid lines) and consumption (dashed lines) 6 emissions for the top three country emitters (USA - olive; China - salmon; India - purple) and for the European Union (EU; turquoise for the 28 member states of the EU as of 2012), and (d) per-7 8 capita emissions for the top three country emitters and the EU (all colours as in panel (c)) and the 9 world (black). In (b-c), the dots show the data that were extrapolated from BP energy statistics for 2014-2016. All time series are in GtC yr⁻¹ except the per-capita emissions (d), which are in tonnes 10 11 of carbon per person per year (tC person⁻¹ yr⁻¹). Territorial emissions are primarily from Boden et 12 al. (2017) except national data for the USA and EU28 (the 28 member states of the EU) for 1990-2016, which are reported by the countries to the UNFCCC as detailed in the text; consumption-13 14 based emissions are updated from Peters et al. (2011a). See Sect. 2.1.1 for details of the calculations and data sources. 15





Figure 6. CO₂ exchanges between the atmosphere and the terrestrial biosphere as used in the
global carbon budget (black with ±1o uncertainty in grey shading), for (a) CO₂ emissions from
land-use change (E_{LUC}), showing also individually the two bookkeeping models (two brown lines)
and the DGVM model results (green) and their multi-model mean (dark green). The dashed line
identifies the pre-satellite period before the inclusion of peatland burning; (b) Land CO₂ sink
(S_{LAND}) with individual DGVMs (green); (c) Total land CO₂ fluxes (b minus a) with individual DGVMs
(green) and their multi-model mean (dark green).





Figure 7. Comparison of the anthropogenic atmosphere-ocean CO₂ flux showing the budget values
of S_{OCEAN} (black; with ±1σ uncertainty in grey shading), individual ocean models (blue), and the two
ocean pCO₂-based flux products (dark blue; see Table 4). Both pCO₂-based flux products were
adjusted for the preindustrial ocean source of CO₂ from river input to the ocean, which is not
present in the ocean models, by adding a sink of 0.78 GtC yr⁻¹ (Resplandy et al., 2018), to make
them comparable to S_{OCEAN}. This adjustment does not take into account the anthropogenic
contribution to river fluxes (see Sect. 2.7.3).







bands for the (top) globe (2nd row) north (north of 30°N), (3rd row) tropics (30°S-30°N), and 4

5 (bottom) south (south of 30°S), and (left) total, (middle) land only (SLAND – ELUC) and (right) ocean

6 only. Positive values indicate a flux from the atmosphere to the land and/or ocean.

7 Estimates from the combination of the process models for the land and oceans are shown (black

8 for the total, green for the land, blue for the ocean) with $\pm 1\sigma$ of the model ensemble (in grey).

9 Results from the atmospheric inversions are also shown (pink lines), and from the pCO₂-based flux

10 products (dark blue lines).



3 Figure 9. Cumulative changes during 1870-2017 and mean fluxes during 2008-2017 for the

4 anthropogenic perturbation as defined in the legend.

1 Appendix B. Supplementary figures.



Figure B1. Evaluation of the GOBMs and flux products using the interannual mismatch metric for
the period 1985 to 2017, as proposed by Rödenbeck et al. (2015) and the SOCAT v6 database,
versus the amplitude of the annual variability (taken as the annual standard deviation). Results are
presented for the globe, north (>30°N), tropics (30°S-30°N), and south (<30°S) for the GOBMs
(circles) and for the pCO₂-based flux products (star symbols). The two pCO₂-based flux products
use the SOCAT database and therefore are not fully independent from the data (See section
2.4.1).



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3 Figure B2. Evaluation of the DGVM using the International Land Model Benchmarking system 4 (ILAMB; Collier et al., 2018). (left) absolute skill scores, (right) skill scores relative to other models. 5 The benchmarking is done with observations for vegetation biomass (Saatchi et al., 2011; and GlobalCarbon unpublished data; Avitabile et al., 2016), GPP (Jung et al., 2010; Lasslop et al., 2010), 6 7 leaf area index (De Kauwe et al., 2011; Myneni et al., 1997), net ecosystem exchange (Jung et al., 8 2010; Lasslop et al., 2010), ecosystem respiration (Jung et al., 2010; Lasslop et al., 2010), soil 9 carbon (Hugelius et al., 2013;Todd-Brown et al., 2013), evapotranspiration (De Kauwe et al., 10 2011), and runoff (Dai and Trenberth, 2002). For each model-observation comparison a series of error metrics are calculated, scores are then calculated as an exponential function of each error 11 metric, finally for each variable the multiple scores from different metrics and observational data 12 sets are combined to give the overall variable scores shown in the left panel. The set of error 13 metrics vary with data set and can include metrics based on the period mean, bias, root mean 14 15 squared error, spatial distribution, interannual variability and seasonal cycle. The relative skill score shown in the right panel is a Z-score, which indicates in units of standard deviation the 16 17 model scores relative to the multi-model mean score for a given variable. Grey boxes represent missing model data. 18

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2 Figure B3. Evaluation of the atmospheric inversion products. The mean of the absolute model 3 minus observed is shown for four latitude bands. The four models are compared to independent CO₂ measurements made onboard aircraft over many places of the world between 1 and 7 km 4 above sea level. All data between 2008 and 2016 archived in Cooperative Global Atmospheric 5 Data Integration Project (CGADIP, 2017) have been used to compute the biases of the differences 6 7 in four 45-degree latitude bins. Land of ocean data are used without distinction. The number of data for each latitude band is: 16,000 (90°S-45°S), 53,000 (45°S-0), 64,000 (0-45°N), 122,000 8 9 (45°N-90°N), rounded off to nearest thousand. 10



2

3 Figure B4. Comparison of global carbon budget components released annually by GCP since 2006. CO₂ emissions from (a) fossil CO₂ emissions (E_{FF}), and (b) land-use change (E_{LUC}), as well as their 4 5 partitioning among (c) the atmosphere (G_{ATM}), (d) the land (S_{LAND}), and (e) the ocean (S_{OCEAN}). See 6 legend for the corresponding years, and Table 3 for references. The budget year corresponds to the year when the budget was first released. All values are in GtC yr⁻¹. Grey shading shows the 7 uncertainty bounds representing $\pm 1\sigma$ of the current global carbon budget. 8