University of Bremen
Institute of Environmental Physics (IUP)

Constraining uncertainties in multi-model projections of future climate with observations

Dissertation

Author:
Manuel Schlund

Supervisors:
Prof. Dr. Veronika Eyring
Prof. Dr. Pierre Gentine

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Abstract (English version)

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Abstract (German version)

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Contents

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1. Introduction

1.1. Structure of the thesis

Parts of this thesis are published in multiple peer-reviewed publications (two first-author studies and six co-author studies). If applicable, this is clearly stated at the beginning of each chapter. Chapter 2 introduces the scientific background for this thesis. This includes relevant literature that is used as a baseline for this thesis. Chapter 3 gives an overview over the contributions made to the Earth System Model Evaluation Tool (ESMValTool), an open-source software for the analysis of ESMs. These contributions helped improving the routine evaluation of ESMs which is useful for the whole scientific community and lead to co-authorship in four peer-reviewed studies (Eyring et al., 2020; Lauer et al., 2020; Righi et al., 2020; Weigel et al., 2020). Chapter 4 covers the assessment of policy-relevant climate metrics like the Equilibrium Climate Sensitivity (ECS) and the Transient Climate Response (TCR) in the latest generation of ESMs. This work is already published in two scientific publications (Bock et al., 2020; Meehl et al., 2020). Since the ECS and TCR are considerably higher in this new climate model generation, chapter 5 describes the assessment of emergent constraints (a technique to reduce uncertainties in climate model projections, see section 2.4 on page 13) on the ECS for these ESMs. The contents of this chapter are published in *Earth System Dynamics* (Schlund, Lauer, et al., 2020). Chapter 6 focuses on a new method to reduce climate model uncertainties based on Machine Learning (ML). As an example, the method is applied to the photosynthesis rate at the end of the 21st century, which is already published in the *Journal of Geophysical Research: Biogeosciences* (Schlund, Eyring, et al., 2020). Finally, chapter 7 provides a summary of the results of this thesis and gives an outlook of possible future works.

2. Scientific Background

This chapter introduces the scientific background of this thesis. First, basic concepts of climate model simulations and associated uncertainties are introduced. Next, the fundamental biogeochemical processes of the global carbon cycle and important metrics describing climate change are presented. Finally, state-of-the art techniques used reduce uncertainties in projections of the future climate are shown. These methods form the basis for the new techniques developed in this thesis.

2.1. Earth System Models: Simulations and Analysis

2.1.1. Numerical Climate Modeling

In contrast to other fields of science, researching the future evolution of the Earth's climate cannot be purely done by performing experiments in a laboratory. Due to the immense complexity of the Earth system (including physical, biological and chemical processes on various temporal and spatial scales and their mutual interactions), we do not have access to a tiny replica of the Earth that we can analyze when exposed to different external conditions (Flato, 2011). While observing the current state of the Earth System is (relatively) straightforward, gaining evidence about the future evolution of the climate by only considering present-day observations is rather difficult.

A possible way out is given by numerical climate models, which offer the possibility to simulate the Earth's climate on a computer. The first numerical climate models came up in the 1960s and were based on weather prediction models (Flato, 2011). Early models from the 1970s simulated only the physical components of the climate system: atmosphere, land surface, ocean and sea

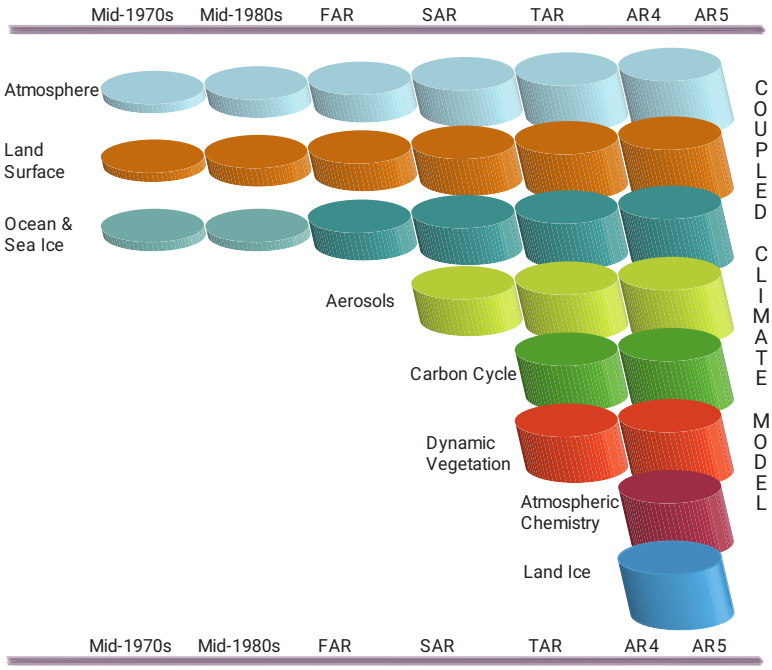

Figure 2.1.: Historical evolution of coupled climate models over the last 45 years. In early days, these models were so-called Atmosphere-Ocean General Circulation Models (AOGCMs) and only included three components: the atmosphere, the land surface and the ocean. Over the time, the individual components grew in complexity and included a wider range of processes (illustrated by the growing cylinders). Eventually, more and more components (aerosols, carbon cycle, etc.) were added to the coupled system, forming the modern Earth System Models (ESMs). Taken from Cubasch et al. (2013).

ice (see figure 2.1). The basis of these so-called AOGCMs (Flato et al., 2013) is the numerical solving of the differential equations describing the exchange of energy and matter between these physical components.

Over the course of the years, climate models became more and more complex by including a wider range of processes within the components, but also by introducing new components to the coupled system. Examples of these are aerosols, the carbon cycle, a dynamic vegetation, atmospheric chemistry and land ice (see figure 2.1). AOGCMs coupled to these additional components are called Earth System Models (ESMs), which are the current state-of-the-art models that allow the most sophisticated simulations of the Earth's climate. In contrast to

AOGCMs, ESMs enable the simulation of biological and chemical processes in addition to the dynamics of the physical components of the Earth system. Especially in the context of anthropogenic climate change, these additional processes are of uttermost importance for realistic climate model simulations, since the anthropogenic interference with the Earth system directly influences the various biogeochemical cycles of the Earth. For example, the emission of the most prominent Greenhouse Gas (GHG), carbon dioxide (CO_2), immediately impacts the global carbon cycle by inserting additional carbon into the system (for details see section 2.3). Further examples include land use changes like the deforestation of tropical rainforests, which also directly influences several biogeochemical cycles (e.g. carbon cycle, nitrogen cycle, phosphorus cycle, etc.) by altering respective sinks and sources.

Due to the complex interactions between the different components of the Earth system, these changes in the biogeochemical processes also affect the physical properties of the climate system. For example, due to the global carbon cycle, only about 50 % of the emitted CO_2 by humankind remains in the atmosphere (Friedlingstein et al., 2019). The residual part is absorbed by the two other main carbon sinks of the planet, the terrestrial biosphere and the ocean. Since only atmospheric CO_2 can act as GHG by introducing an additional radiative forcing to the Earth System leading to increasing surface temperatures, this uptake of CO_2 by the carbon cycle slows down global warming.

2.1.2. CMIP

Due to the complex nature of the Earth system itself, numerical models of it consist of hundreds of thousands of lines of computer code. Thus, a standardization to a certain degree is crucial for the various research groups developing ESMs all around the world in order to obtain comparable output and to facilitate model analysis. For this reason, the Working Group on Coupled Modelling (WGCM) of the World Climate Research Programme (WCRP) initiated the Coupled Model Intercomparison Project (CMIP) in 1995, with the objective to "better understand past, present and future climate changes arising from natural, unforced variability or in response to changes in radiative forcing in a

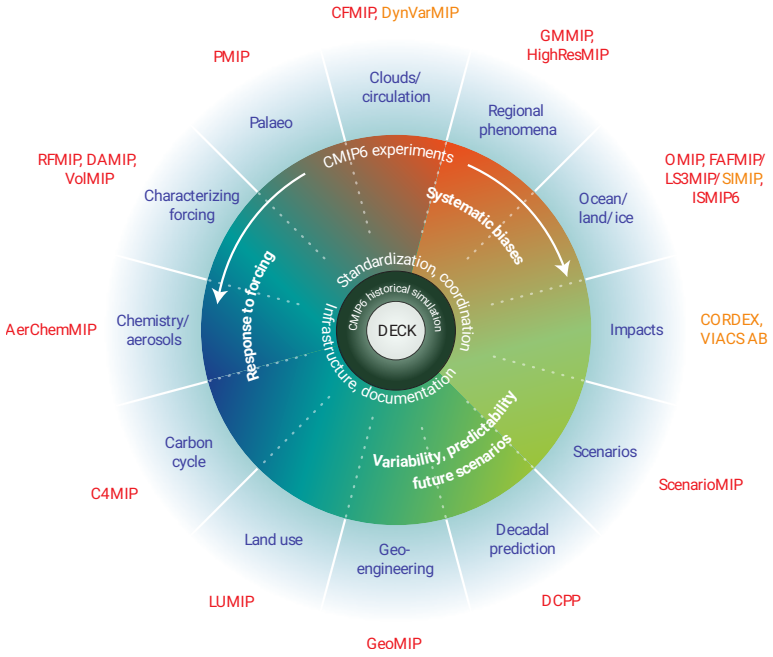

Figure 2.2.: Schematic of the experiment design of Phase 6 of the Coupled Model Intercomparison Project (CMIP6). The center of the circle illustrates the four DECK (Diagnostic, Evaluation, and Characterisation of Klima) experiments and the CMIP6 historical simulation. The circular sectors show additional science themes that can be explored through the 21 CMIP6-Endorsed Model Intercomparison Projects (MIPs). Taken from Simpkins (2017).

multi-model context" (WCRP, 2020). One major element of CMIP is to establish common standards, coordination, infrastructure, and documentation in order to facilitate the distribution of climate model output (Eyring et al., 2016).

A further main aspect is to provide a set of standardized experiments for global climate model simulations. To participate in the latest phase of CMIP, CMIP6, climate models need to run a *historical* simulation of the period 1850–2014 and the so-called Diagnostic, Evaluation, and Characterisation of Klima (DECK) experiments, which include a pre-industrial control run (*piControl*), a historical Atmospheric MIP simulation (*amip*), a simulation forced with an abrupt quadrupling of CO_2 (*abrupt-4xCO2*) and a simulation forced with a 1 % per year increase of the atmospheric CO_2 concentration (*1pctCO2*) (Eyring et al., 2016).

This is shown in the center of figure 2.2, which illustrates the experimental design of CMIP6.

To increase diversity and answer more scientific questions, CMIP6 models can participate in the so-called CMIP6-Endorsed MIPs, of which CMIP6 offers 21 (see circular sectors in figure 2.2). Some MIPs offer additional experiments to explore specific aspects of the Earth system, like the Coupled Climate-Carbon Cycle Model Intercomparison Project (C4MIP) which focuses on the carbon cycle (Jones et al., 2016) or the Cloud Feedback Model Intercomparison Project (CFMIP) which focuses on the evaluation of cloud feedbacks (Webb et al., 2017). Other MIPs allow the assessment of future climate change. An example is the Scenario Model Intercomparison Project (ScenarioMIP), which provides common experiments that simulate different possible futures (O'Neill et al., 2016). These experiments are based on the so-called Shared Socioeconomic Pathways (SSPs), a set of alternative pathways of future societal development (O'Neill et al., 2017; O'Neill et al., 2013). For each experiment, a set of emissions and land use changes is calculated from the SSPs (Riahi et al., 2017) which are then used to force the global climate models. For ScenarioMIP, five different SSPs are considered, ranging from SSP1 (sustainability) to SSP5 (fossil-fuel development). Each SSP is combined with a climate outcome (measured as radiative forcing in the year 2100) based on a particular forcing pathway that Integrated Assessment Modelss (IAMs) have shown to be feasible. For example, SSP5-8.5 represents a scenario based on a fossil-fuel development with a radiative forcing of $8.5\,\mathrm{Wm}^{-2}$ in 2100 while SSP1-2.6 represents a sustainable future with a radiative forcing of $2.6\,\mathrm{Wm}^{-2}$ in the year 2100. The two other main scenarios (called *Tier 1* experiments in ScenarioMIP) are the SSP2-4.5 and SSP3-7.0 scenarios. In contrast to the ScenarioMIP experiments, the corresponding CMIP5 counterparts (Taylor et al., 2012), the so-called Representative Concentration Pathways (RCPs), only used the radiative forcing in 2100 as only dimension to describe the possible futures (e.g. RCP8.5, RCP4.5, RCP2.6, etc.).

In this thesis, climate model data from the two most recent CMIP generations is used, CMIP5 and CMIP6. More detailed information about the specific variables and experiments analyzed is given in the corresponding chapters.

2.1.3. Sources of Uncertainties in Climate Model Projections

- anthropogenic forcing vs. natural forcing (volcanoes, solar cycle, etc.)
  - basic physics of greenhouse gases (vibration modes, etc.)
  - historical vs. future: in historical (future), uncertainty in forcing low (high)
  - definition of feedbacks, examples

2.2. Climate Sensitivity

- Physical Feedbacks (ECS)
  - Equations for feedbacks + decomposition
  - ocean heat uptake (TCR)
  - different between effective climate sensitivity and equilibrium version
  - equations for ECS and TCR

2.3. The Global Carbon Cycle

Since one study presented in this thesis aims to reduce uncertainties in carbon cycle-related processes (Schlund, Eyring, et al., 2020; see chapter 6), this chapter introduces the scientific background of the global carbon cycle.

2.3.1. Overview

A schematic overview of the global carbon cycle is shown in figure 2.3. To quantify the carbon cycle, common units are parts per million (ppm) for the atmospheric trace gas concentrations (dry-air mole fraction) and gigatonnes of carbon (GtC) or GtC yr^{-1} for the reservoirs masses or exchange fluxes, respectively. The carbon exchange processes between the different carbon reservoirs run on a wide range of time scales. Conceptually, one can distinguish between two domains of the global carbon cycle: a slow and a fast domain. The slow domain with turnover times (reservoir mass of carbon divided by exchange flux) of more than 10000 years consists of the large carbon stores in rocks and sediments which are connected to the rapid domain of the carbon cycle through volcanic

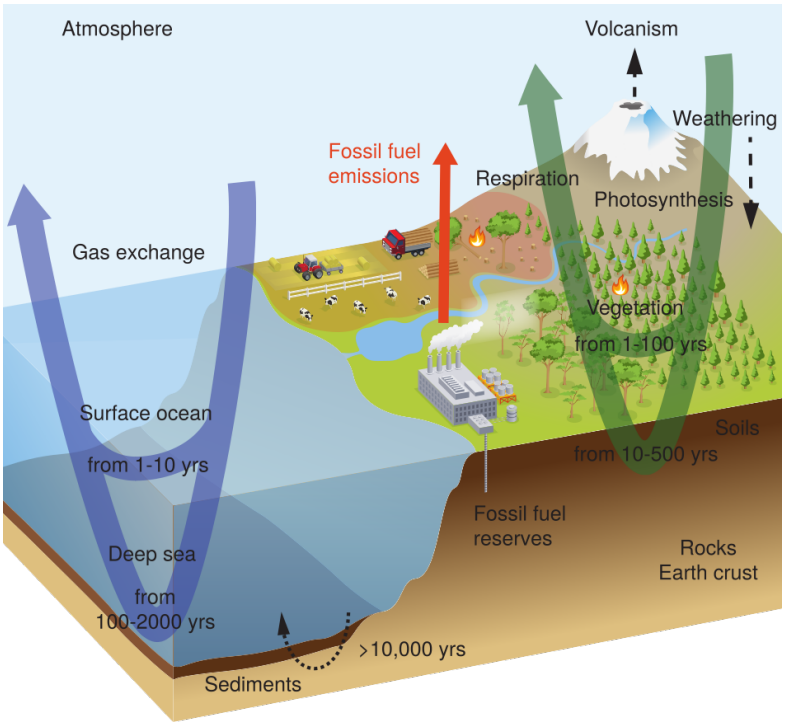

Figure 2.3.: Simplified schematic of the global carbon cycle including the typical turnover time scales for carbon transfers through the major reservoirs (atmosphere, land surface and ocean). Taken from Ciais et al. (2013).

emissions of CO_2, chemical weathering, erosion and sediment formation on the sea floor. These natural exchange fluxes between the slow and the fast domain are comparatively small ($< 0.3\,\mathrm{GtC\,yr^{-1}}$) and can be assumed as approximately constant in time over the last few centuries (Ciais et al., 2013).

The fast domain of the global carbon cycle consists of three main carbon reservoirs: the atmosphere, the terrestrial biosphere and the ocean. In the atmosphere, carbon is mainly stored in trace gases, with CO_2 as the major component with a current (2019) concentration of about 410 ppm (Friedlingstein et al., 2019). Additional contributors to the atmospheric carbon content are the trace gas methane (CH_4), the trace gas carbon monoxide (CO), hydrocarbons, black carbon aerosols and organic compounds (Ciais et al., 2013). Carbon in the terrestrial biosphere is mainly stored as organic compounds, with about 450–650 GtC in the living vegetation biomass, 1500–2400 GtC in dead organic matter in litter and soils and about 1700 GtC in permafrost soils (Ciais et al., 2013). The

main component of the oceanic carbon reservoir is dissolved inorganic carbon (carbonic acid, bicarbonate ions and carbonate ions) with about 38000 GtC. Further carbon is stored as dissolved organic carbon (about 700 GtC), in surface sediments (about 1750 GtC) and in marine biota (about 3 GtC, predominantly phytoplankton and other microorganisms) (Ciais et al., 2013; Friedlingstein et al., 2019).

In the fast domain of the global carbon cycle, reservoir turnover times range from seconds to millennia. In contrast to the slow domain, the carbon exchange fluxes within the fast domain of the carbon cycle are much higher. One major group of exchange processes in the fast domain connects the atmosphere and the terrestrial biosphere. CO_2 is removed from the atmosphere by plant photosynthesis with about 120 GtC yr^{-1} (Ciais et al., 2013). This process is also known as Gross Primary Productivity (GPP). The carbon fixed into plants can be released back into the atmosphere by autotrophic (plant) and heterotrophic (soil microbial and animal) respiration and additional disturbance processes like fires (Ciais et al., 2013). Since the land CO_2 uptake by photosynthesis occurs only during the growing season, whereas respiration occurs nearly all year, the larger amount of vegetation in the Northern hemisphere (due to the larger land mass) gives rise to a seasonal cycle of the atmospheric CO_2 concentration (Keeling et al., 1995). This seasonal cycle reflects the phase of the global carbon cycle and shows a maximum of the atmospheric CO_2 concentration in the Northern hemisphere winter (net CO_2 flux into atmosphere due to respiration) and a minimum during the Northern hemisphere summer (net CO_2 flux into the land due to photosynthesis). Another major carbon exchange process connects the atmosphere and the ocean. Atmospheric CO_2 is exchanged with the surface ocean through gas exchange, which is driven by the partial CO_2 pressure difference between the air and the sea (Ciais et al., 2013).

2.3.2. Anthropogenic Perturbations

Before the Industrial Era, the global carbon cycle was roughly in a dynamic equilibrium, which means that exchange fluxes balanced each other and the amount of carbon in the different reservoirs did neither increase nor decrease. This

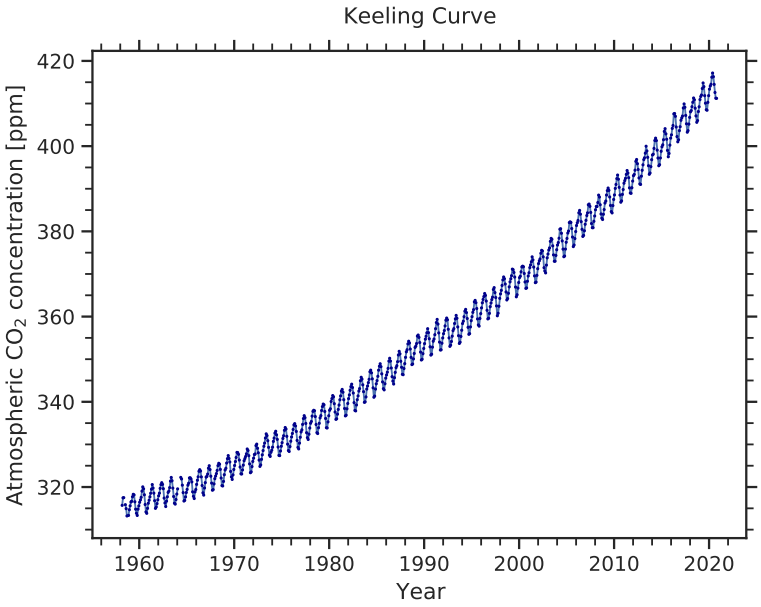

Figure 2.4.: The Keeling Curve: monthly-mean atmospheric CO_2 concentration at the Mauna Loa Observatory, Hawaii (19.5 °N, 155.6 °W; elevation: 3397 m) from 1958 to 2019 (Keeling et al., 2005). The steady increase of the atmospheric CO_2 concentration is superimposed with a seasonal oscillation caused by the seasonal CO_2 cycle (see section 2.3.1).

can be inferred from ice core measurements, which show an almost constant atmospheric CO_2 concentration over the last several thousand years before the Industrial Revolution in the 19th century (Ciais et al., 2013). Since the beginning of the Industrial Era, humanity is constantly emitting carbon-based GHGs (e.g. CO_2 and CH_4) into the atmosphere. Especially the atmospheric CO_2 concentration has substantially increased, which has already been shown by Charles D. Keeling in 1976 by his continuous CO_2 measurements at Mauna Loa, Hawaii that started in 1958 (Keeling et al., 1976; see figure 2.4). From 1958, the atmospheric CO_2 concentration at Mauna Loa has steadily increased by about 100 ppm to 410 ppm in the year 2019 (Keeling et al., 2005). In addition to the steady increase, the so-called *Keeling Curve* is further superimposed with the seasonal CO_2 cycle, which gives rise to local maxima of the atmospheric CO_2 concentration in the Northern hemisphere winter and local minima in the Northern hemisphere summer (Keeling et al., 1995; see section 2.3.1). Due to its location in

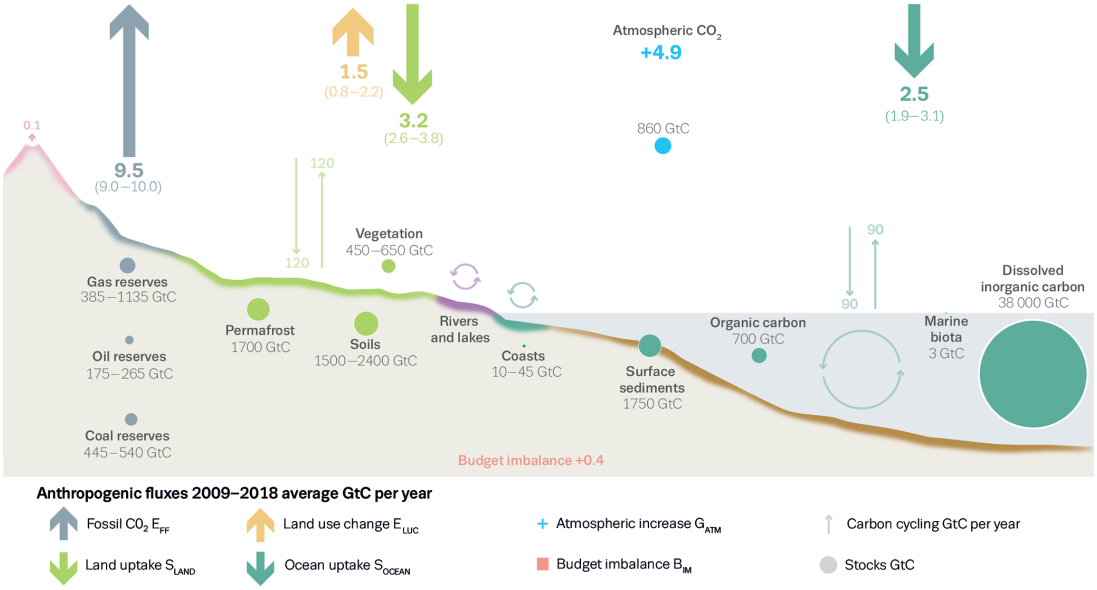

Figure 2.5.: Schematic representation of the overall perturbation of the global carbon cycle caused by anthropogenic activities, averaged globally for the decade 2009–2018. Arrows represent carbon exchange fluxes; circles carbon reservoirs. More details are given in the legend of this figure. Taken from Friedlingstein et al. (2019).

the middle of the Pacific Ocean, the Mauna Loa Observatory offers perfect conditions for CO_2 measurements by being far away from big population centers. Moreover, its elevation of more than 3000 m provides access to the well-mixed air of the Pacific Ocean in high altitudes, which prevents any interference from the vegetation present on the Hawaiian Islands.

Apart from warming the Earth by altering its radiation budget, the anthropogenically emitted CO_2 directly influences the carbon exchange fluxes of the global carbon cycle. Due to the excessive carbon in the atmosphere, there is now a net carbon flux from the atmosphere into the land and ocean reservoirs (see figure 2.5). Thus, the carbon cycle is not in a steady state anymore. In the decade 2009–2018, anthropogenic activities caused net carbon fluxes of $3.2\,\mathrm{GtC\,yr^{-1}}$ from the atmosphere into the terrestrial biosphere due to increased plant photosynthesis and $2.5\,\mathrm{GtC\,yr^{-1}}$ from the atmosphere into the ocean due to increase dissolution of CO_2 into the sea (Friedlingstein et al., 2019). In the same time, the amount of carbon in the atmosphere reservoir increased with a

rate of 4.9 GtC yr^{-1}, indicating that only about half of the anthropogenic CO_2 emissions in the last decade remained in the atmosphere (Friedlingstein et al., 2019) where they can act as GHG.

Thus, this removal of CO_2 from the atmosphere actively slows down global warming. However, whether this benefit will persist in the future remains unclear, which is primarily linked to two feedback processes connecting the climate system and the global carbon cycle: the *concentration-carbon feedback* and the *climate-carbon feedback* (Collins et al., 2013; Friedlingstein et al., 2006; Gregory et al., 2009). For the terrestrial biosphere, the concentration-carbon feedback is connected to the *CO_2 fertilization effect* (Walker et al., 2020), that causes an increase of photosynthesis rates when the atmospheric CO_2 concentration increases, which in turns removes CO_2 from the atmosphere, forming a negative feedback. For the ocean, the concentration-carbon feedback is negative as well. In this case, an elevated atmospheric CO_2 concentration causes an increased dissolution of CO_2 into the sea, which increases the ocean carbon uptake. On the other hand, the climate-carbon feedback is thought to be positive for both the terrestrial biosphere and the ocean (Gregory et al., 2009). In the first case, temperature and precipitation changes due to anthropogenic activities decrease the land carbon uptake because of increased temperature and water stress on photosynthesis and higher ecosystem respiration costs, which accelerates global warming due to more CO_2 that remains in the atmosphere. For the ocean, increased temperatures lead to a reduction of vertical transport in the ocean resulting from increased stability and reduced solubility of CO_2 in the sea, which reduces the ocean carbon uptake and enhances climate change (Gregory et al., 2009).

2.4. Techniques to reduce Uncertainties in Climate Model Projections

- Process-based weighting (Knutti + MDER)
  - emergent constraints
  - Wenzel et al., Nature (2016) as example (refer to carbon cycle chapter)

- Review of ECS emergent constraints is given in chapter on Schlund et al., ESD (2020)

3. Improving Routine Climate Model Evaluation

TBA.

4. Assessment of Policy-relevant Climate Metrics in CMIP6

TBA.

5. Evaluation of Emergent Constraints on the Equilibrium Climate Sensitivity in CMIP6

TBA.

6. Constraining Uncertainties in future Gross Primary Productivity with Machine Learning

TBA.

7. Summary and Outlook

TBA.

Appendix

A. TBA

A.1. test

test

hi The Equilibrium Climate Sensitivity (ECS) is really cool. I like it very much!

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E.g.blaa. E.g. blaaaa. i.e.blaaaa, i.e. blaa.

These are really cool papers: (Schlund, Lauer, et al., 2020; Schlund, Eyring, et al., 2020)

autocite: (Lauer et al., 2018)

cite: Lauer et al., 2010 (Anav et al., 2015) (Anav et al., 2013) (Allen & Ingram, 2002)

textcite: Lauer et al. (2010)

And this one, too: (Lauer et al., 2020)

This is a reference to the equation: equation (1)

Three authors: (Bao et al., 2020)

Many many authors: (Eyring et al., 2020)

```
input <iostream>
```

$$c_{k_1,k_2} := 1200 \log_2 \left(\frac{f_1^{(k_2)}}{f_1^{(k_1)}} \right) \text{ cents.} \tag{1}$$

Table 1.: The effects of treatments X and Y on the four groups studied.

Groups	**Treatment X**	**Treatment Y**
1	0.2	0.8
2	0.17	0.7
3	0.24	0.75
4	0.68	0.3

Semitones	Interval	c / cents (ET)	c / cents (JI)
0	Perfect unison	0	0
1	Minor second	100	112
2	Major second	200	204
3	Minor third	300	316
4	Major third	400	386
5	Perfect fourth	500	498
6	Augmented fourth	600	590
7	Perfect fifth	700	702
8	Minor sixth	800	814
9	Major sixth	900	884
10	Minor seventh	1000	996
11	Major seventh	1100	1088
12	Perfect octave	1200	1200

Table 2.: Logarithmic frequency ratios c of certain intervals in the equal temperament (ET) and the just intonation (JI). x cents correspond to a frequency ratio of $2^{x/1200}$.

B. TBA

TBA.

List of Acronyms

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Declaration of Authorship

I assure that this thesis is a result of my personal work and that no other than the indicated aids have been used for its completion. Furthermore I assure that all quotations and statements that have been inferred literally or in a general manner from published or unpublished writings are marked as such. Beyond this I assure that the work has not been used, neither completely nor in parts, to pass any previous examination.

Oberpfaffenhofen, March 2021

Manuel Schlund