

Emissions and CO₂ Concentration—An Evidence Based Approach

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Abstract: The relation between CO₂ emissions and atmospheric CO₂ concentration has traditionally been treated with more or less complex models with several boxes. Our approach is motivated by the question of how much CO₂ must necessarily be absorbed by sinks. This is determined by accepted measurements and the global carbon budget. Observations lead to the model assumption that carbon sinks, similar to oceans or the biosphere, are linearly dependent on CO₂ concentration on a decadal scale. In particular, this implies the falsifiable hypothesis that oceanic and biological CO₂ buffers have not significantly changed in the past 70 years and are not saturated in the foreseeable future. A statistical model with two parameters is built from the global carbon budget and two testable assumptions. This model explains the relation between CO₂ emission and historical CO₂ concentration data very well. The model gives estimates of the natural emissions, the pre-industrial CO₂ equilibrium concentration levels, the half-life time of an emission pulse, and the future CO₂ concentration level from a given emission scenario. It is validated by an ex-post forecast of the last 20 years. The important result is that, with the stated policies emission scenario of the International Energy Agency (IEA), the future CO₂ concentrations will not rise above 475 ppm. The model is compared with the carbon module of the Bern model, mapping their complex impulse response functions (IRFs) to a single time variant absorption parameter.

Keywords: carbon sinks; equilibrium concentration; emission pulse; peak emissions; Bern model; net zero



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1. Introduction—A New Way of Looking at the Problem

Climate science is usually concerned about the question “*How much CO₂ remains in the atmosphere?*”, given the anthropogenic emissions and the limited capability of oceans and biosphere to absorb the surplus CO₂ concentration [1–4]. This has led to conclusions of the kind that a certain increasing part of anthropogenic emissions will remain in the atmosphere forever. The frequently used notion of “airborne fraction” [5,6], which is the part of anthropogenic emissions remaining in the atmosphere, seems to suggest this. The Bern model explicitly includes a term that represents the fraction of the emissions remaining in the atmosphere forever [4].

We change the focus of attention by posing the logically equivalent question “*How much CO₂ does not remain in the atmosphere?*”. Why is this so different? The amount of CO₂ that does not remain in the atmosphere can be calculated from direct measurements. We do not have to discuss each absorption mechanism from the atmosphere into oceans or plants. From the known global concentration changes and the known global emissions, we have a good estimate of the sum of actual yearly absorptions. These are related to the CO₂ concentration, motivating the guiding hypothesis for a linear model of absorption. It turns out that we do not need to know the actual coefficients of the individual absorption mechanisms—it is sufficient to assume their linear dependence on the current CO₂ concentration.

Additionally, by changing the focus of attention from “how much remains in the atmosphere” to “how much is absorbed annually”, the formally equivalent estimation equations become much better conditioned. Both the known previous investigations based

on a linear absorption model [7,8] had computational stability problems, which were noticeable in the large error bars of the resulting equilibrium concentration. Although the publications omit the computation of error bars, they can be reproduced from their data and equations. A third paper with a linear absorption model [9] uses apparently similar equations, but separates the estimation of the oceanic and biosphere absorption constants from the contribution of the anthropogenic emissions, which leads to the strange phenomenon that their main equation has no remaining free parameters to account for emission changes explicitly. We will discuss their approach in the appendix (Appendix B).

Overview of Methods

As a first step, we will derive the effective absorption from CO₂ concentration growth and emissions based on the global carbon budget (Section 2.1). The plausibility and testability of the two model hypotheses are discussed (Sections 2.3 and 2.4). Relating effective absorption to CO₂ concentration by means of these hypotheses leads us to a statistical absorption model that can be estimated by ordinary least squares, providing robust parameter and error estimates (Section 2.5). Furthermore, model variations with temperature dependency or indirect temperature dependency via CO₂ proxy are explored (Section 2.5.1). The model, which includes CO₂ concentration at two different times, is applied to recursively predict future CO₂ concentrations from current concentration and future emissions. Predicting the concentration of the last 20 years from prior data validates the model and shows its predictive quality (Section 2.5.4). This recursion is also applied to calculate the carbon pulse response and the CO₂ adjustment time (Section 2.5.3 and Appendix A.1.1). A time-dependent generalization of the model is shown to be equivalent to the Bern model. This is proven in the appendix (Appendix A). While temperature prediction is not the main focus of the paper, a measurement based CO₂ concentration proxy is estimated from the temperature and CO₂ concentration data of the last 170 years as an upper bound temperature dependence on CO₂ (Section 2.3.2). This allows for a maximum temperature estimate of future CO₂ concentrations (Section 3.1).

2. The Absorption Model

2.1. Mass Conservation

From the Global Carbon Project [10], we obtain the emission and concentration data. A global mass balance representation of the yearly atmospheric CO₂ flow is created, as it has been performed in [11], where they prove that the CO₂ adjustment time is much larger than the CO₂ residence time. The analysis of the airborne fraction and sink rate of anthropogenic emissions by [6] is also based on this global carbon budget (their Equation (1)).

For our purposes the components of the global carbon budget equation are

- C_i the CO₂ concentration of the atmosphere at the end of year i ,
- E_i the global emissions of human origin during year i ,
- L_i the global land use net emissions during year i ,
- N_i the global natural net emissions during year i ,
- S_i other special causes of emissions, such as El Nino, volcanos, etc.,
- A_i the global net absorption of CO₂ during year i into the oceans and biosphere ($0 \leq i < n$):

$$C_i = C_{i-1} + E_i + L_i + S_i + N_i - A_i \quad (1)$$

Without explicit external information, S_i cannot be discriminated from L_i or N_i . Therefore, we set S_i to 0 and include all inferred special causes in the unknown N_i in this investigation. With $S_i = 0$, the equation becomes

$$E_i + L_i - (C_i - C_{i-1}) = A_i - N_i \quad (2)$$

This is not a model, but the formulation of the necessary mass conservation as seen from the atmosphere, similar to a bank account with cumulative yearly deposits and withdrawals, not directly dealing with the daily ups and downs or with the exact nature of the earning and spending processes. As a matter of fact, Equation (2) must be fulfilled at all time scales.

For consistency, all quantities have to be converted to the same unit (1 ppm = 2.124 GtC, 1 GtC = 3.664 Gt CO₂ [10]). Here, all calculations are performed with the unit “ppm”. All CO₂-related data, emissions, land use change, and CO₂ concentration growth are from the Global Carbon Budget 2021, covering the years 1850–2020. Land use change data are subject to considerable uncertainty, with an error range of ±0.4 ppm.

We assume a value for land use change emission that is 0.2 ppm lower than the published mean value, as discussed further below. This is well within the error range and, therefore, justifiable.

Figure 1 shows that the total emissions ($E_i + L_i$, blue) come to exceed the yearly CO₂ concentration growth ($C_i - C_{i-1}$, green), indicating that we have an increasingly effective absorption ($A_i - N_i$, red) with growing CO₂ concentration.

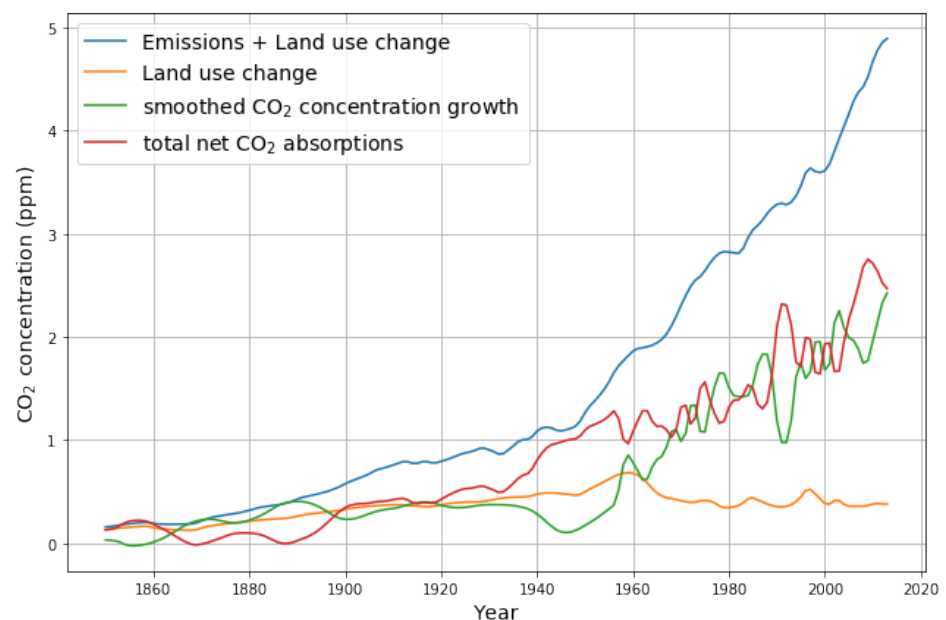


Figure 1. Emissions, land use change, and CO₂ concentration change.

Another benefit of displaying these raw data is that, before 1900, the anthropogenic emissions were considerably smaller than other variations, such as land use change. In fact, there are roughly four historical phases:

- The phase before 1900, where explicit emissions are smaller than implicit ones, due to land use change; however, there is a small, but increasing, CO₂ concentration growth.
- The phase between 1900 and 1950 with growing emissions, but approximately constant CO₂ concentration growth and slightly increasing land use change.
- The phase from 1950 to 2010 with growing emissions and growing concentration growth.
- Recent publications indicate that emissions have remained approximately constant since 2010 [12] and are expected to remain approximately constant for the foreseeable future [13] (their Figure 2, stated policies scenario). The challenge is to estimate reasonable projections of CO₂ concentration based on these emission assumptions.

2.2. Exploratory Analysis

As a first exploratory analysis of these data, the scatter plot in Figure 2 relates the effective CO₂ absorption to the CO₂ concentration.

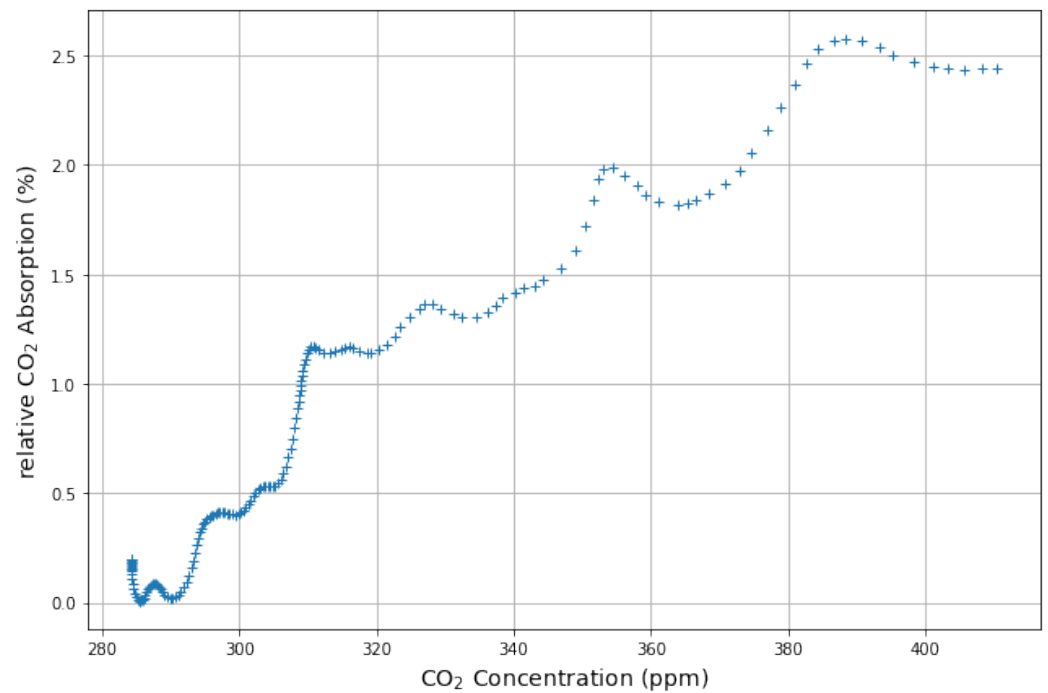


Figure 2. Effective absorption vs CO₂ concentration.

Qualitatively, we see a long-term linear dependence of the effective absorption on the atmospheric CO₂ concentration with significant short-term deviations, where the effective zero-absorption line is crossed at approx. 280 ppm. This is considered to be the pre-industrial equilibrium CO₂ concentration, where natural yearly emissions are balanced by the yearly absorptions. The average yearly absorption is approx. 2.5% of the CO₂ concentration exceeding 280 ppm.

While the correlation coefficient of 0.97 is very high, there are clear non-random deviations from an ideal linear behaviour. With the large uncertainty of the land use change and contingent effects, such as volcano eruptions and influences such as ENSO (El Nino Southern Oscillation), it is not surprising that there are systematic deviations from a perfect line [8].

Regarding the predictions of future CO₂ concentration, the key question is whether the deviations are averaging out or whether there is a systematic saturation trend that is limiting the absorption of CO₂. Some climate researchers claim that the absorption will decline [14], but there are other papers providing evidence of increasing absorption [15].

We can see from these data that a reliable estimate of the historical equilibrium concentration requires the whole data range. An estimation based on all data above 310 ppm (year 1950) results in a smaller equilibrium value of 245 ppm.

Starting from the mass conservation Equation (2), above, on the basis of the preceding considerations, we state two hypotheses, from which the actual model is derived:

2.3. Hypothesis 1: The Absorption A_i Is Proportional to Previous CO₂ Concentration

Formally this is

$$A_i = a \cdot C_{i-1} \quad (3)$$

The physical justification for this assumption is the fact that the partial pressure of CO₂, which is relevant for absorption processes, increases in proportion to concentration. It is also known that C₃ plants, representing the majority of all plants, have a linear absorption property. The absorption property of C₄ plants is nearly flat, but also linear in the range of 280–560 ppm, resulting in a linear behaviour when averaging over all plants. Halparin [7]

analysed the different processes of gas transport into the ocean, with the conclusion that all relevant processes can be linearised (his Equation (14)):

- Net primary production of plants,
- Phytoplankton production, a smaller effect of dead biomass sinking to large depths of the ocean,
- Gas exchange with the deep ocean.

Assuming that there are different absorption constants for oceanic (a_{Ocean}), phytoplankton ($a_{Phytoplankton}$), and biospheric absorption ($a_{Biosphere}$), under the linearity assumption, they can be added to a single constant a :

$$a = a_{Ocean} + a_{Phytoplankton} + a_{Biosphere} \quad (4)$$

Both the oceanic and biospheric processes may consist of multiple sub-processes, e.g., the photosynthesis of C_3 plants has a much larger proportionality constant to that of C_4 plants in the relevant CO_2 concentration range of 280.. 560 ppm. As long as linearity holds, the net absorption constant is reflected by the sum of all elementary absorption constants.

This is a radical simplification of the box-diffusion model [16] referred to in [1]. Instead of assuming separate boxes for the mixed layer and for the biosphere, we assume a one-dimensional diffusion process between the atmosphere, ocean, and biosphere, with a single diffusion constant, making no explicit assumptions about the properties of the mixed layer nor the mechanism of the absorption in the biosphere. The advantage of this model is that we do not have to make any speculative assumptions about numerous possible model parameters, some of which are quite arbitrary (e.g., the thickness of the mixed layer), but instead, restrict the whole model to a single absorption parameter and an additive constant, both of which are estimated from measured data. While we do not know the contributing components, we can measure their total effect over time.

The authors of the Bern model claim that the “net primary production of the land biosphere and the surface ocean carbon uptake depend on atmospheric CO_2 and surface temperature in a nonlinear way” [4] by assuming a superposition of four absorption processes. This statement contradicts our assumption of a single absorption process. We will show in the appendix that the impulse response functions of the Bern model ([4], their Equation (21)), can be mapped into the form of our model with a time varying absorption parameter, a (Appendix A). Statistical tests will decide if there is a need to actually introduce this time dependence or whether it is more appropriate to assume a constant absorption parameter, making relative absorption a linear function of CO_2 concentration. Any deviations from the validity of a linear model will show up in the residual error. This gives our model a method of intrinsic validation, and the model can be extended when required.

2.3.1. Temperature Dependence of the Absorption Parameter

We have to consider the possibility that the absorption parameter, a , depends on temperature. Investigations of ice core data clearly indicate a temperature dependency of CO_2 concentration [17]. The open question is whether there is a measurable dependency during the time scale and the temperature scale of our investigation. We will hypothetically test the temperature dependence of absorption parameter a with a linear dependency on sea surface temperature anomaly T with the HadSST2 temperature dataset T_i [18]. The linear dependence of the absorption parameter on the temperature anomaly is assumed, as in the Bern model [4]:

$$a_i = a_0 + a_1 \cdot T_i \quad (5)$$

2.3.2. CO_2 Concentration as a Hypothetical Proxy for Temperature

When we make predictions with hypothetical future CO_2 emissions, we do not know the future temperatures. Without diving into the problematic discussion about the degree,

how strong the influence of CO₂ concentration is on temperature [19], we assume the “worst case” of full predictability of temperature effects by CO₂ concentration (Figure 3).

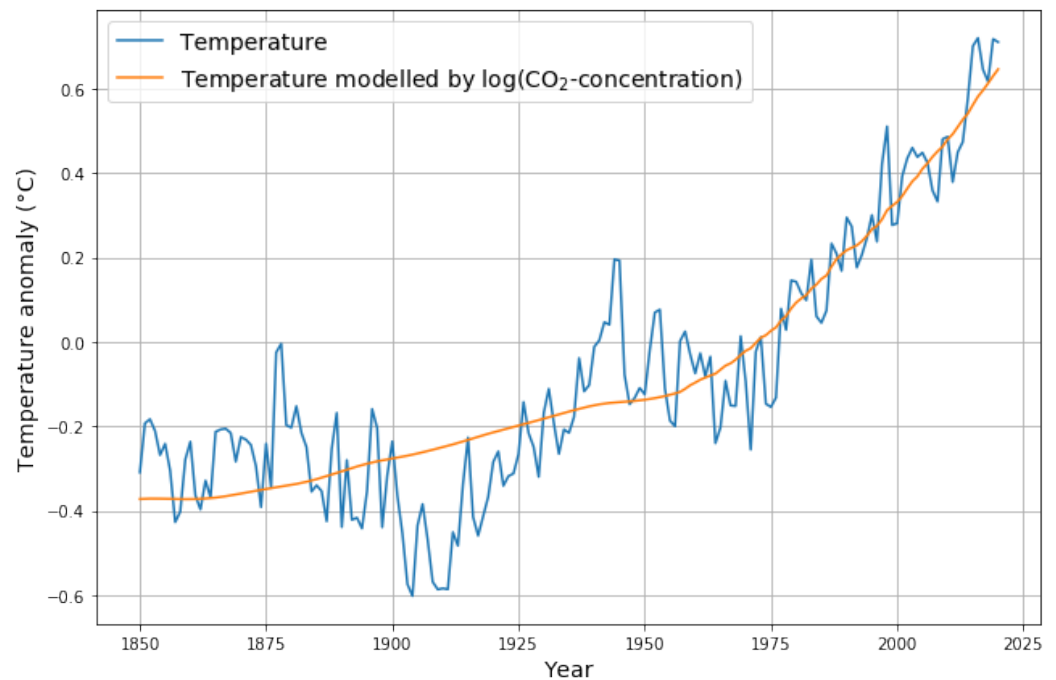


Figure 3. CO₂ concentration as a proxy for global temperature.

Without making any assumptions about $C_{i-1} \rightarrow T_i$ causality, the estimated functional dependence of the temperature proxy from the regression on CO₂ concentration was found to be

$$T_i^{proxy} = -16.0 + 2.77 \cdot \ln(C_{i-1}) \quad (6)$$

We are aware that this is a very incomplete model. It ignores the obvious, significant, trend-reversing deviations between 1900 and 1975, and it also ignores the dominant contribution of cloud albedo reduction to global warming [20], whereby 80% of recent warming is caused by albedo reduction and only 20% by increase of CO₂ concentration. Nevertheless, the proxy is still a suitable tool for estimating an upper bound of temperature dependence on CO₂ concentration. Based on measured data, it avoids speculations and discussions about hypothetical feedback factors of CO₂ sensitivity.

2.3.3. Corollary: Carbon Sinks Are Not Expected to Be Saturated in the Near Future

This is related to, and is a consequence of, the linearity assumption. Much of the debate about carbon sinks is concerned with numerous details about the possible saturation of various “boxes” in the models [21]. There are strong reasons to consider the atmosphere and the mixed layer, i.e., the top 75 m of the ocean as a single “box”, which exchanges gases with the deep ocean and the biosphere [7]. Due to the fact that the deep ocean contains more than 50 times the CO₂ of the atmosphere, or 4000 times the yearly global emissions, this means that the whole atmospheric content is just about 2% of the ocean content. Therefore, we do not expect this huge “box” to be saturated any time soon.

There are four indications supporting the assumption that the up-taking reservoirs are not saturated:

- (1) We can test the past 70 years for linearity. If there was any sign of saturation, this would have shown up as a deviation from the linearity assumption. We will see that, in the residual deviations from the model, if the actual absorption parameter

decreased with time, the real CO₂ concentration at the end would be larger than estimated by the model.

- (2) The global carbon budget [10] clearly shows an increasing trend in both the ocean sink, as well as the (biosphere) land sink.
- (3) A recent article revised the estimates of the ocean-atmosphere CO₂ flux [15], making it consistent with the increasing ocean sink found in the global carbon budget.
- (4) We can make a rough estimation of the expected ocean uptake. The ocean has a total carbon inventory of 38,000 GtC \approx 140,000 Gt CO₂. If we assume the realistic scenario of constant future emissions at today's level (37 Gt CO₂ per year) and we assume that they are all absorbed by the ocean, by 2100 that would be approx. 3000 Gt CO₂, just about 2% of the current ocean inventory.

Whatever our subjective opinion may be regarding future absorption, the measured data provide us with the current trend and its potential changes in the near future.

2.4. Hypothesis 2: Natural Emissions and Absorptions Are Balanced

This implies that, without anthropogenic emissions, $C_i = C_{i-1} = C_0$, resulting in a constant equilibrium concentration C_0 . Equations (1)–(3) imply that global natural emissions are constant:

$$N_i = a \cdot C_0 \quad (7)$$

This relation makes a falsifiable statement about the magnitude of those natural emissions, which are not compensated by absorptions within the time unit of measurement, which is a year in this investigation. The statement of assumed constant equilibrium concentration requires further clarification. We know, e.g., from ice core investigations that historical CO₂ concentration is not constant and most likely depends on temperature. A linear dependence on temperature can be mapped onto a linear dependence of the absorption parameter a on temperature, which is covered by Equation (5).

As we know, there are causes for systematic changes in the natural emissions, e.g., volcanic eruptions, ocean cycles, and changes of land use. We will see from the residual deviations of the measured data how significant these influences are and if the model needs to be adapted. For the time being, we initially assume no changes of natural emissions within the investigated time range 1850–2020. As with the previous assumption, the residual error of the model will lead to possible further fine-tuning of the model. Three possible deviations are possible:

- A systematic “trend” in the natural emissions. This would either increase or decrease the estimated absorption factor and the equilibrium concentration given a constant model of natural emissions,
- Short-term zero centered variations within a year. These variations do not show up in our model, due to the one year sampling interval,
- Long-term variations of more than a year are not averaged out. They are visible in the residual error of the predicted CO₂ content.

2.5. The Modelling Equations

From Equations (2), (3), and (7), we obtain the final regression equation for an assumed constant absorption parameter, a :

$$E_i + L_i - (C_i - C_{i-1}) = a \cdot C_{i-1} - a \cdot C_0 + R_i \quad (8)$$

where the innovation or residual, R_i , is an unselfcorrelated random variable with zero mean. Equation (8) emphasises the fact that the effective absorption depends linearly on the difference between the actual and the equilibrium CO₂ concentration C_0 . This implicitly includes the natural carbon cycle, described by the equilibrium concentration C_0 . Initially, we estimate $a \cdot C_0$ as the constant natural emissions simultaneously with a in this regression

equation, for estimating temperature-dependent models we assume a fixed known value for the equilibrium CO₂ concentration C₀ and estimate the absorption function *a*.

Starting with the available data, from emissions *E_i*, land use change, *L_i*, CO₂ growth, and the absorptions are modelled according to Equation (8) for the time interval 1850–2014,

For *L_i*, the emission change per year due to land use, the uncertainty is considerable [10]. Therefore, we have a certain amount of freedom to adapt its value, in order to satisfy other given constraints.

The absorption constant, *a*, and the natural equilibrium concentration C₀ in a given time interval are obtained through estimation with the least squares method, where the dependent variable is the left hand side of Equation (8), and the independent variable is C_{*i*−1}, by means of the Python module OLS (statsmodel-OLS-0.13.5). The results are shown in Table 1.

Table 1. The result table of the Python linear regression model displays, for each regression variable, its estimated value (“Coef.”), its estimated standard error, the t-statistic for the variable being non-zero, and the error probability under the null hypothesis that the variable is non-zero. The last two columns show the error bounds, i.e., the 95% interval of the variable’s value.

	Coef.	Std.Err.	t	<i>P</i> > <i>t</i>	[0.025	0.975]
− <i>a</i> · C ₀	−6.8952	0.2640	−26.1142	0.00	−7.4166	−6.3738
<i>a</i>	0.0247	0.0008	29.3485	0.00	0.0230	0.0264

This results in C₀ = 279 ppm, with error bounds [277, 282] ppm, and a half-life time of an emission pulse $t_{1/2} = \frac{\ln(2)}{a} = 28$ years, with error bounds [26, 30] years.

C₀ is very close, and its error bounds contain the widely accepted pre-industrial equilibrium CO₂ concentration of 280 ppm. As can be seen from model Equation (8), we can substitute global variations of *L_i* and C₀ :

$$\Delta C_0 = -\frac{1}{a} \Delta L \tag{9}$$

When using the center value of the land use change error band, i.e., on average 0.55 ppm, the calculated C₀ would have been 271 ± 2 ppm, which we consider to be too small to be compatible with the accepted value of 280 ppm. Therefore, in the face of the large uncertainty of land use change estimates, we prefer to assume slightly lower average land use change-caused emissions (average 0.35 ppm) over an inconsistent equilibrium concentration. This substitution, however, only changes the equilibrium concentration.

Modelling the raw, noisy differential absorption data with this—simplest possible—model shows a fairly good approximation over the whole time span. The residual

$$R_i = E_i + L_i - (C_i - C_{i-1}) - a \cdot (C_{i-1} - C_0) \tag{10}$$

shows variations, but no systematic trend over the time span 1850–2014 (Figure 4).

The blue differential effective absorption data are approximated by the orange model curve, and the green curve shows the residual deviations. The standard deviation of the residuum is 0.2 ppm, the same order of magnitude as the uncertainty of emission and concentration measurements, in particular, *L_i*. We can, therefore, safely assume that the residual error reflects zero mean deviations of land use change or natural emissions, as discussed in [8].

We notice that, before 1900, the absorptions are smaller than this error, which means that analysing absorption values at times before 1900 is not meaningful. We also observe that, after 1950, when the quality of measurements dramatically increased, there is much more variability in the differential measurements of CO₂ concentration. This justifies doubts about the data quality before 1950 and justifies a separate analysis of the much more reliable data after 1950.

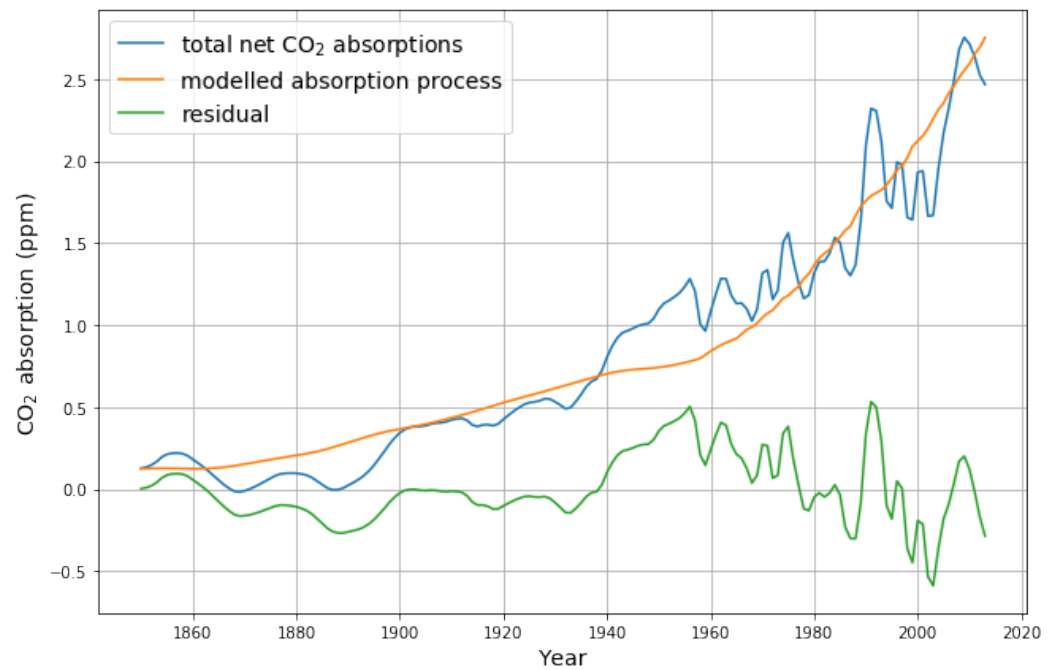


Figure 4. Linear model of CO₂ absorption.

Next, we investigate the possible dependence of the absorption parameter a on the sea surface temperature from the data set HadSST2 [18]. Using Equation (8) with temperature-dependent variable a from Equation (5) leads to a more complex three parameter estimation problem:

$$E_i + L_i - (C_i - C_{i-1}) = (a_0 + a_1 \cdot T_i) \cdot (C_{i-1} - C_0) + R_i \tag{11}$$

This cannot be easily solved in closed form when C_0 is variable. After showing that the data are consistent with $C_0 = 280$ ppm in the case for constant absorption a , we assume C_0 to be constant as an *a priori* condition and simplify the model equation by fixing C_0 to this value and only estimate the absorption parameters a_0 and a_1 from the data. Implicitly, this means that we make use of the assumption that the equilibrium concentration is constant. The results of the temperature-dependent, two-parameter absorption estimation problem are displayed in Table 2.

Table 2. Estimation of temperature dependent absorption parameters with measured data from 1850 to 2014.

	Coef.	Std.Err.	t	$P > t $	[0.025	0.975]
a_0	0.0263	0.0007	39.6674	0.00	0.0250	0.0276
a_1	-0.0082	0.0025	-3.2074	0.00	-0.0132	-0.0031

The temperature-dependent parameter a_1 is statistically significant, and we obtain a slightly negative trend of the absorption parameter with increasing sea surface temperature since 1900.

The negative temperature dependence tells us that, before 1900, the absorption has no identifiable trend and that, between 1900 and 2000, the absorption appears to have decreased. The relative absorption in 1900 of 3% corresponds to the half-life time of 23 years for an emission pulse. However, in 2014, the relative absorption is still larger than 2.3% of the CO₂ concentration, which corresponds to a half-life time of 30 years for an emission pulse. The fact that the absorption parameter changes with time in this model variant prohibits the use of a time-invariant convolution kernel for computing the CO₂

concentration from emissions. Before we draw conclusions from this result, we need to validate the estimation.

2.5.1. Prediction and Model Validation

In order to validate the model, we are in the comfortable situation, in that there is a long time series, so we can perform an ex-post predictions by restricting the training data of the model to the year 2000 and make predictions of the CO₂ concentration of the years 2001–2020, which are available for comparison.

In the validation process, we compare all 3 discussed model variants:

- Assumed constant absorption parameter;
- Assumed temperature-dependent absorption parameter;
- Assumed absorption parameter dependent on temperature modelled by CO₂ concentration.

2.5.2. Estimation with Limited Data Range and Model Validation

The estimation results based on historical data may depend, to a certain extent, on the selected time interval, in particular, when we let the value of the equilibrium concentration of CO₂ be determined from the data. This explains why previous authors arrive at such different results for the equilibrium concentration [7,8]. There are several reasons for constraining the data range:

- As stated above, there is no large variability of both CO₂ emissions and CO₂ concentration before the year 1900. Moreover, the measurements at that time were not really reliable. Therefore, the signal-to-noise ratio is so large that, for the determination of concentration changes as a function of CO₂ emissions, it is better to dispense with these data.
- We want to evaluate the predictive quality of the data model. Therefore, we limit the training data to 1999 and compare the predicted CO₂ concentration of the years 2000 to 2020 with the actual measurements.
- We further argue that the data of the first part of the 20th century are also not really reliable, indicated, e.g., by the nearly constant yearly change of CO₂ concentration, despite growing emissions, as well as the extreme uncertainty of land use change data. We also know that CO₂ concentration measurement methods have greatly improved in the 1950s [22]. We will, therefore, make an evaluation with training data from 1950 to 1999 and build the model based on these data.

We allow the investigated data interval to have its own equilibrium concentration, according to the available data. The equilibrium concentration is determined by the initial model with constant absorption parameter *a*.

2.5.3. Estimation Based on Data from 1950 to 2000

The much better CO₂ concentration measurements after 1950, in conjunction with the fact that the overwhelming bulk of anthropogenic emissions were released after 1950, justify investigating the second half of the 20th century separately. The result of the parameter estimation is displayed in Table 3.

Table 3. Estimation of constant absorption parameters with measured data from 1950 to 2000.

	Coef.	Std.Err.	t	<i>P</i> > <i>t</i>	[0.025	0.975]
$-a \cdot C_0$	-3.8188	0.2640	-14.4670	0.00	-4.3496	-3.2881
<i>a</i>	0.0158	0.0008	19.7789	0.00	0.0142	0.0174

This implies an equilibrium CO₂ concentration of $C_0 = 242$ ppm with the error bounds [232, 251]. The half-life time of an emission pulse is 44 years with the 95% error bounds [39, 48].

The temperature-dependent estimation, according to Equation (11), with fixed $C_0 = 242$ ppm, leads to the results of Table 4.

Table 4. Estimation of temperature dependent absorption parameters with measured data from 1950 to 2000.

	Coef.	Std.Err.	t	$P > t $	[0.025	0.975]
a_0	0.0157	0.0002	92.4536	0.00	0.0154	0.0161
a_T	0.0005	0.0008	0.6142	0.54	−0.0011	0.0021

The temperature-dependent part of the absorption is clearly not significantly different from 0. When using the CO_2 temperature proxy from Equation (6), we obtain the results in Table 5.

Table 5. Estimation of absorption parameters depending on CO_2 temperature proxy with measured data from 1950 to 2000.

	Coef.	Std.Err.	t	$P > t $	[0.025	0.975]
a_0	0.0157	0.0002	90.0473	0.00	0.0154	0.0161
a_C	0.0005	0.0010	0.4667	0.64	−0.0016	0.0025

Using the CO_2 proxy for temperature, there is also no significant temperature dependence. Therefore, we are forced to take the model with constant absorption parameter as the best possible absorption model for the 50 years from 1950 to 2000 (Figure 5).

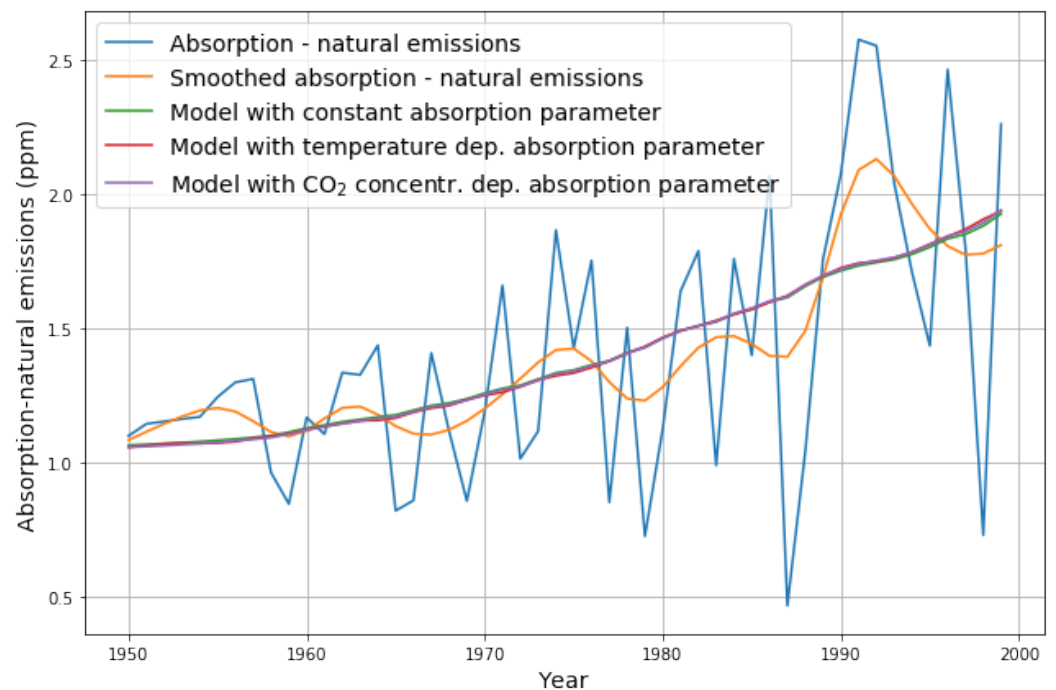


Figure 5. Comparing absorption models 1950–2000.

The diagram in Figure 5 confirms that there is no deviation from the constant absorption parameter curve when assuming a hypothetical temperature dependence.

2.5.4. Validation Based on Data from 1950 to 2000

Based on the model parameters from the 1950–2000 data, recursive evaluation of Equation (8) with future emission and land use data allows the prediction of future CO₂ concentrations C_i from C_{i-1} .

Figure 6 shows an excellent prediction in the center of the 95% gray error bar. There are small apparently periodical variations between the predictions and the actual data. Spencer [8] has explained these systematic deviations of up to 1 ppm with the Multivariate ENSO Index [23], further improving the already excellent fit. For projections of future emission scenarios, these small deviations, which are symmetric with respect to zero, do not play a significant role. Spencer also identifies volcanic activities, e.g., the Pinatubo eruption, but also these small deviations do not change the functional dependency between anthropogenic emissions and CO₂ concentration in a significant way.

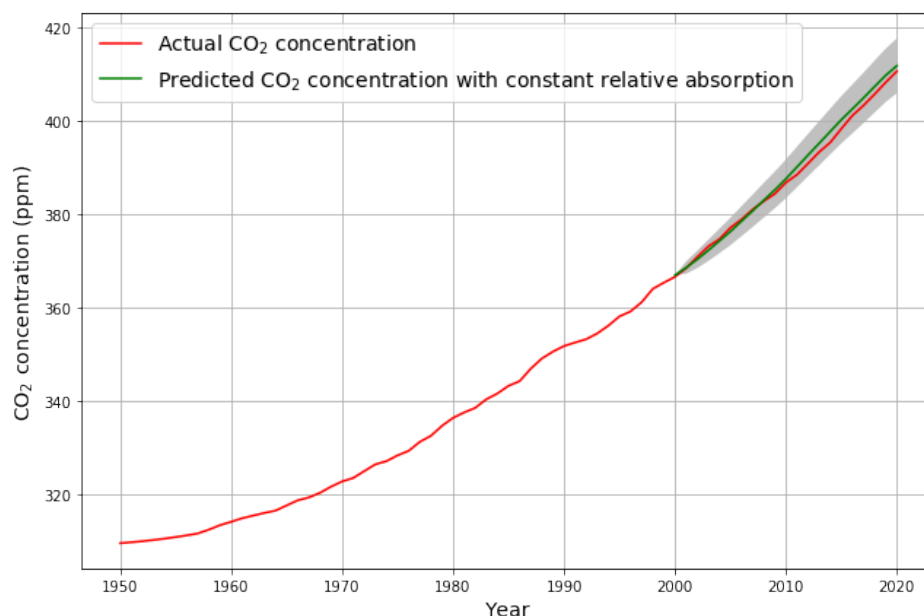


Figure 6. Actual (1950–2020) and predicted (2000–2020) CO₂ concentration.

3. Prediction and Future Scenario

Due to the small error and excellent fit, the prediction of the future concentrations is based on model with constant absorption parameter, which is not temperature-dependent with data after 1950. The reproduction of the actual data is so good that we can trust this model not only within the 50 year time range of the measurements, but also due to the excellent ex post prediction of the concentrations of the last 20 years and the small residual error, we can confidently predict future concentrations.

For future predictions we expand the training data and use the full 70 years data range from 1950–2020 for the determination of the model parameters, as shown in Table 6.

Table 6. Estimation of constant absorption parameters with measured data from 1950 to 2020.

	Coef.	Std.Err.	t	$P > t $	[0.025	0.975]
$-a \cdot C_0$	-4.0355	0.1684	-23.9655	0.00	-4.3714	-3.6996
a	0.0165	0.0005	34.0113	0.00	0.0155	0.0174

This corresponds to an equilibrium concentration $C_0 = 245$ ppm with 95% error bounds [239, 251], respectively, yearly net natural emissions of 4 ppm and a half-life time of 42 years for an emission pulse with the 95% error bounds [40, 45] years. This is consistent with the half-life time of 44 years from the 50 year time interval data.

3.1. Prediction of 2021–2100 CO₂ Concentration on the Basis of the 2021–2050 IEA Stated Policies Emission Scenario

To evaluate policy decisions, this model is applied to predict future CO₂ levels based on the—most conservative and most likely—stated policies scenario of the International Energy Agency (IEA). This essentially means that the current energy consumption is continued, without significant further emission reductions beyond normal efficiency improvements. The stated policies scenarios can be regarded as the most realistic prediction, because it is based on policies that are actually in effect.

This scenario assumes global emissions remain approximately at the current maximum of 37 Gt/yr = 4.6 ppm, with a slight reduction of 3% per decade. Total budget to 2100: 2640 Gt CO₂, then 29 Gt/yr (excluding land use change). The actually used data set for a realistic future projection is created by trend extrapolating the stated policies beyond 2050 and assuming that the land use change data will follow the current trend and decrease to 0 by the year 2100 (Figure 7). Emissions will not be reduced to zero in the year 2100, but will remain close to the 2005 level.

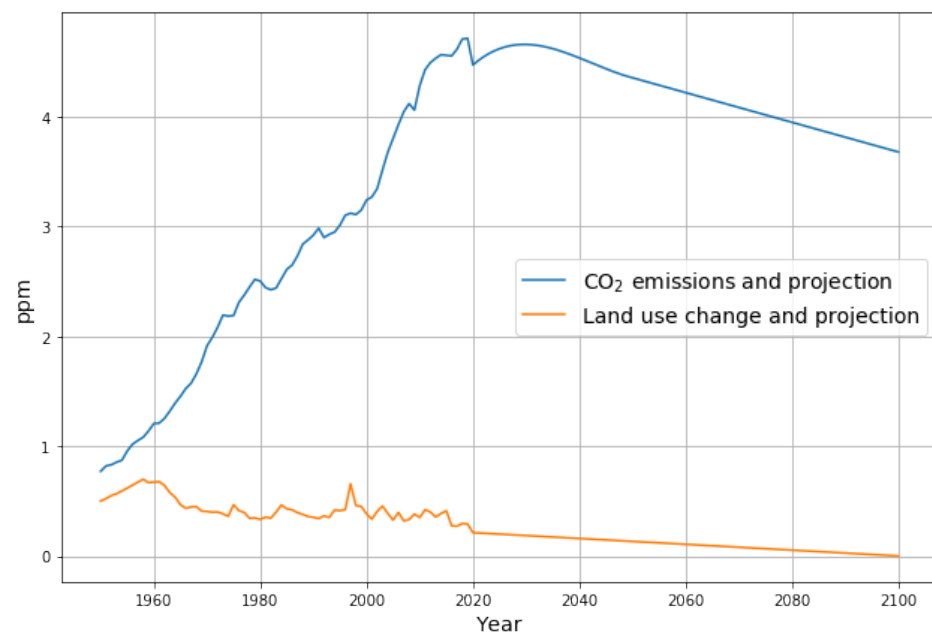


Figure 7. Emissions 1950–2020, IEA emission scenario 2021–2050, and extension to 2100.

The prediction for the CO₂ concentration is based on the recursion of Equation (8) with the parameter $a = 0.0165$ and $C_0 = 245$ ppm and $R = 0$, derived from the constant absorption parameter estimation with the 1950–2020 data and hypothetical emission data from the discussed extended IEA scenario.

Figure 8 shows that the IEA stated policies scenario, i.e., no special CO₂ reduction policies, which implies that a CO₂ concentration equilibrium of approx. 475 ppm will be reached during the second half of this century, with an 95% range of [463, 488] ppm. Based on the empirical CO₂ temperature proxy Equation (6), this increase of the CO₂ concentration from 410 ppm (in 2020) to 475 ppm corresponds to a temperature increase of 0.4 °C from 2020, or 1.4 °C from 1850.

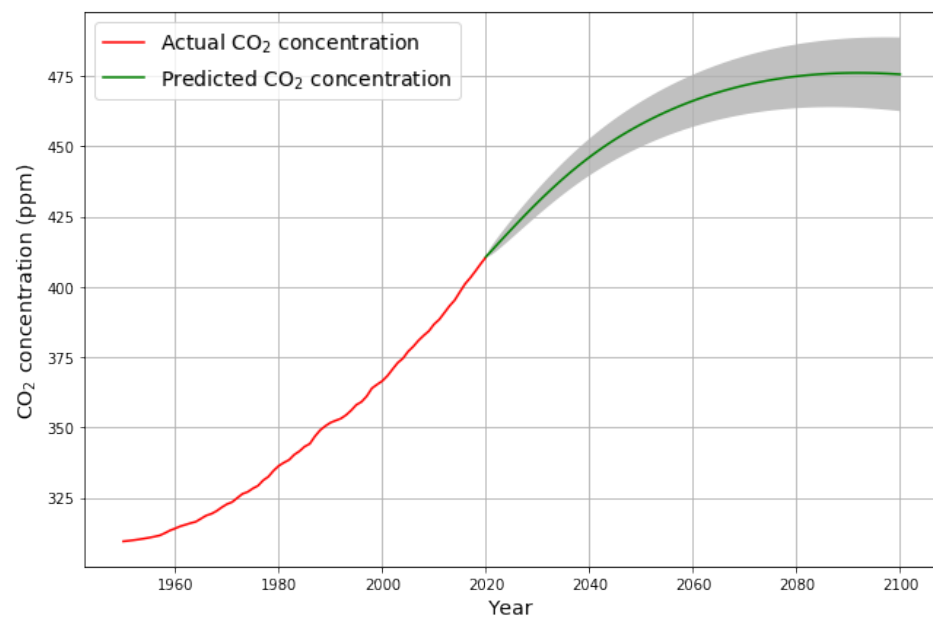


Figure 8. Actual (1950–2020) and predicted (2021–2100) CO₂ concentration for IEA stated policies scenario.

4. Conclusions

The model and results derived in this paper are based on very general assumptions:

- The undeniable mass conservation of CO₂,
- The assumption of approximate linearity of the relevant absorption processes w.r.t. CO₂ concentration. This assumption has been relaxed to allow for temperature-dependent absorption,
- The assumption that CO₂ concentration can be used as an upper limit proxy for temperature, i.e., a part of the temperature changes that can be explained by CO₂ concentration,
- The assumption of constant natural emissions is within the time period of measurement. We observed, however, apparent changes of natural emissions in the first half of the 20th century, resulting in a large prediction uncertainty. Further investigations are required for a better understanding, because these changes cannot be distinguished from land use changes, which also have a large uncertainty.

Although the model allows for varying absorptions over time, the data of the last 70 years, which is the period of the bulk anthropogenic CO₂ emissions, leads to the conclusion that relative CO₂ absorption has no significant temperature or other time-dependent component, and a current CO₂ emission pulse is absorbed with a 42 year half-life time.

The ex post validation of our model indicates that it predicts future CO₂ concentration very well, on the basis of known emissions. In contrast, more than 40 years after their article was written, we see now that Oeschger's complicated model, which explained the C₁₄ content, including bomb test data, quite well, but failed badly for predicting future CO₂ levels. Their predicted 2020 additional CO₂ concentration beyond their assumed pre-industrial level of 295 ppm was more than 150% larger (590 ppm = 295 ppm + 295 ppm) than the actual additional concentration (410 ppm = 295 ppm + 115 ppm). It remains to be analyzed in detail whether the failure is due to overestimated emissions based on the unrealistic assumption of exponential emission growth or whether it is caused by the model itself.

The main conclusion of this evaluation is that, for the most likely IEA emission scenario of approximately constant, slightly decreasing global emissions, we can expect a maximum CO₂ concentration level of approximately 475 ppm in the second half of this century. At

this point, the emissions will be fully balanced by the absorptions, which is by definition the “net zero” situation.

Assuming the unlikely worst case that CO₂ concentration is fully responsible for all global temperature changes, the maximum expected rise of global temperature caused by the expected CO₂ concentration rise is 0.4 °C from now or 1.4 °C from the beginning of industrialisation.

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Appendix A. Relation to the Bern Model

Our model relates to other papers that have been dealing with the relation between carbon emissions and CO₂ concentration. For the sake of clarity, we separate the details of the relation to other concepts from the main thread of the paper.

The Bern model (Strassmann-2018) is a kind of accepted standard for climate science. We describe here how our model relates to the Bern model and discuss the differences of representation.

Appendix A.1. Data Transformation of the Linear CO₂ Concentration Model

The foregoing considerations confirm that within the time range of the measurements

- The linearity assumption of the absorptions;
- The assumption of constant natural emissions.

is reasonably valid. For showing the correspondence to the well-known Bern model (Strassmann-2018), we begin by using the temperature independent Equation (8). We show how this maps to a single component of the Bern model. Eventually, we show how the temperature-dependent model maps to the multi-component Bern model.

We transform the model, in order to eliminate the assumed constant natural emissions by defining the “excessive CO₂ concentration” C_i^E caused by anthropogenic emissions

$$C_i^E = C_i - C_0 \quad (\text{A1})$$

and total anthropogenic emissions E_i^A by adding land use change to carbon emissions:

$$E_i^A = E_i + L_i \quad (\text{A2})$$

With this substitution Equation (8) becomes

$$C_i^E = E_i^A + C_{i-1}^E - a \cdot C_{i-1}^E \quad (\text{A3})$$

or

$$C_i^E = E_i^A + (1 - a) \cdot C_{i-1}^E \tag{A4}$$

This is the key equation to describe the relation between anthropogenic emissions, E_i , and the resulting atmospheric excessive concentration. This relation explains why the “natural” pre-industrial CO₂ level of approx. A total of 280 ppm is taken as the reference line, and anthropogenic and natural emissions are treated separately.

In order to solve the equation analytically, i.e., describe the excessive concentration as a function of the emissions, we recursively substitute C_{i-1}^E , starting with

$$C_i^E = E_i^A + (1 - a) \cdot (E_{i-1}^A + (1 - a) \cdot C_{i-2}^E) \tag{A5}$$

Assuming $C_i^E = 0$ and $E_i = 0$ for $i < 0$, this sum is finite

$$C_i^E = \sum_{j=0}^i (1 - a)^j \cdot E_{i-j}^A \tag{A6}$$

which is equivalent to

$$C_i^E = \sum_{j=0}^i (1 - a)^{i-j} \cdot E_j^A \tag{A7}$$

Appendix A.1.1. Relation to the Impulse Response Model, the Carbon Cycle Component of the Bern Model

Equation (A7) says that any single unit carbon emission pulse ($E_j = \delta(j)$) will decay, similar to a geometric series,

$$C_i^{Pulse} = \sum_{j=0}^i (1 - a)^{i-j} \cdot \delta(j) \tag{A8}$$

$$C_i^{Pulse} = (1 - a)^i \tag{A9}$$

For $a = 0.0165$, the half-life time $t_{0.5}$ of a unit pulse is reached after

$$t_{0.5} = \frac{\ln 0.5}{\ln(1 - a)} \approx 42(\text{years}) \tag{A10}$$

In order to show the correspondence of this model to the impulse response function of (Maier-Reimer-1987), we convert the discrete model to a continuous model.

With $\tau = \frac{1}{a}$ we get

$$C_i^E = C_{i-1}^E + E_i^A - \frac{C_{i-1}^E}{\tau} \tag{A11}$$

This is a discrete approximation of the differential equation

$$\frac{dC^E(t)}{dt} = E^A(t) - \frac{C^E(t)}{\tau} \tag{A12}$$

This equation is solved by means of the Green’s function $G(t) = e^{-\frac{t}{\tau}}$

$$C^E(t) = \int_0^t G(t - t') \cdot E^A(t') dt' \tag{A13}$$

$$C^E(t) = \int_0^t e^{-\frac{t-t'}{\tau}} \cdot E^A(t') dt' \tag{A14}$$

This gives τ the meaning of a time constant in an exponential decay. Approximating Equation (A14) with discrete samples is the sum

$$C_i^E = \sum_{j=0}^i e^{-\frac{i-j}{\tau}} \cdot E_j^A \tag{A15}$$

This is equivalent to Equation (A7), with the approximation

$$\ln(1 - a) = \ln\left(1 - \frac{1}{\tau}\right) \approx \frac{1}{\tau}$$

, which is valid for $a < 0.1$.

We will now show that this is formally equivalent to the full Bern model, where the general form of the impulse response function (IRF) is (Strassmann-2018, equation (19)):

$$G^H = A_0 + \sum_{j=1}^N A_j \cdot e^{-\frac{t}{\tau_j}} \tag{A16}$$

with the constraint

$$\sum_{j=0}^N A_j = 1 \tag{A17}$$

The correspondence can best be seen when we start with the differential form of the pulse response equation (Strassmann-2018, Equation (21), variables renamed). Instead of the infinitely long time constant, we assume a very large one, so all terms can be written in the same form

$$\frac{dC_k^E}{dt} = E^A(t) \cdot A_k - \frac{C_k^E}{\tau_k} \tag{A18}$$

with

$$\sum_{k=0}^N A_k = 1 \tag{A19}$$

and

$$\sum_{k=0}^N C_k(t) = C^E(t) \tag{A20}$$

When we substitute $a_k(t) = \frac{C_k(t)}{\tau \cdot C^E(t)}$, we obtain

$$\frac{dC_k}{dt} = E^A(t) \cdot A_k - a_k(t) \cdot C^E(t) \tag{A21}$$

and with (30) and (31)

$$\frac{dC^E}{dt} = E^A(t) - \sum_{k=0}^N a_k(t) \cdot C^E(t) \tag{A22}$$

Apart from the time dependence of $a(t)$, this is identical to Equation (24), with

$$a(t) = \sum_{k=0}^N a_k(t) \tag{A23}$$

With these transformations, we have shown that the IRFs of the Bern model can be mapped to a simple univariate model with a time varying coupling variable. The time dependency of the coupling variable $a(t)$ creates the nonlinearity that Strassmann and Joos

(Strassmann-2018, chapter 2) talked about. The simplest possible time dependence of a is a linear time dependence, which can easily, and in a statistically robust way, be tested by testing for a linear trend in a :

$$a(t) = a_0 + a_1 \cdot t \quad (\text{A24})$$

Time dependence of absorption is not directly physically meaningful; at best, it is a proxy for other physical processes that are time-dependent. Looking at the short time ranges where measurements are available, changes caused by temperature are the most relevant. Therefore, replacing the time dependence by temperature dependence is a meaningful heuristic.

Appendix B. Discussion of the Paper from Weber, Lüdecke and Weiss

The paper “A simple model of the anthropogenically forced CO₂ cycle” [9] also applies a linear model, but separates the oceanic and biospheric contribution. Their Equation (3) can be related to our Equation (8), in combination with our Equation (4), where their yearly emissions are noted with $n_{tot}(t)$ ($E_i + L_i$ in our model), with the difference being that their biospheric absorption $n_b(t)$ is not considered to be proportional to the CO₂ concentration $N_a(t)$ ($=C_i$ in our model) as in our model, but to its concentration growth $n_a(t)$ ($=C_i - C_{i-1}$ in our model). The behaviour of C_3 , as well as C_4 , plants clearly indicate that the absorption is proportional to the absolute CO₂ concentration within the relevant CO₂ concentration range of 280.. 600 ppm. The main problem of the different definitions of oceanic and biospheric absorption is that it is not possible to easily merge the different processes for the determination of the global CO₂ retention time. Contrary to this, in our model, all individual absorption constants add up to the total absorption constant. We question the physical meaning of the subsequent denominator $(1 + b)$ in their Equation (7). Intuitively, we would expect another sink to increase the difference between emissions and oceanic absorption and not make it smaller, as in their Equation (7). This may explain the discrepancy between our time constant of 42 years with theirs of 100 years.

Another difference of their approach to ours is that they estimate the 2 absorption constants (Equations (8) and (9) in their paper) completely unrelated from their main Equation (7), which leads to the strange phenomenon, that their main Equation (7) does not contain any free parameters. This raises the question regarding how the system is able to react to changing emission scenarios. In our understanding, $N_a(t)$ should be a measured input variable in the phase of parameter estimation, whereas in their Equation (7), $N_a(t)$ appears to be the unknown output variable.

Appendix C. Discussion of Harde’s Paper and Its Critics

Equation (A4) is formally identical to equation 11 in Harde’s publication “Scrutinizing the carbon cycle and CO₂ residence time in the atmosphere” [24]. His paper, as a whole, and in particular, this formula, have been heavily criticised [25]. This makes it necessary to discuss some issues raised in this discussion. Formally, the criticism that one equation is not enough to describe the CO₂ concentration in the atmosphere (“1-box model”) as a function of emissions is not justified because

- The mass conservation of CO₂ can hardly be disputed, see Equation (1).
- The linear dependence of absorption from concentration (Equation (3)) has been extensively discussed above, and the deviations from this assumption in the measured data are so statistically insignificant, that it is not justified to dismiss a model assuming constant a .
- The assumption of a state of equilibrium between natural emissions and absorptions (his Equation (7)) during recent pre-industrial centuries is in my understanding scientific consensus (paleo-climate and its CO₂ variability is not the issue here), and most mainstream publications explicitly or implicitly assume a constant pre-industrial CO₂ concentration of approx. 280 ppm.

- Given the measured anthropogenic emissions, as well as the measured CO₂ concentrations, the equation is well-posed and, therefore, can be solved without further equations.
- The remaining small residual errors have been recognized and discussed as being caused by e.g., the El Niño southern oscillation and volcanic eruptions [8], the systematic deviations in the first part of the 20th century remain to be fully evaluated.

Harde's approach to solve the equation in question is flawed, however. He claimed the total anthropogenic and natural emissions to be 97.2 ppm/yr, most of which are assumed to be natural emissions. Contrary to his assumption, the data from 1950 to 2020 force us to the conclusion that the yearly net natural emissions are 4.0 ppm (95% interval is [3.7, 4.4]), which are fully compensated by absorption. Obviously, the total amount of emitted and absorbed CO₂ is much larger, but all emissions, which are compensated by daily or seasonal absorptions, i.e., within the year, are invisible in the yearly balance and do not count for the emission/concentration relation. The difference between residence time and adjustment time was thoroughly discussed in [11].

Therefore, the anthropogenic emissions are indeed a key control knob of the resulting excess CO₂ concentration in the atmosphere, but the data lead us to a relatively short half-life time of approx. 42 years, with no "eternal" CO₂ remaining beyond the natural equilibrium level.

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