

Article

Evaluating the Effectiveness of Natural Carbon Sinks Through a Temperature-Dependent Model

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Abstract: Articles have recently been circulating in the media around the world, claiming that natural CO₂ sinks have “suddenly and unexpectedly” ceased to function. It turned out that these articles were based on a single preprint of a meanwhile published article. Its reasoning is essentially based on the large spike of CO₂ concentration growth in 2023 despite constant anthropogenic emissions. However, there are no obvious indications that photosynthesis or oceanic sinks have decreased. In this paper, it is shown that besides the natural sink systems of the land plants and oceans, the variability of natural emissions has to be considered. Based on a previous publication, it is made evident that natural emissions are temperature-dependent. Therefore, the careful analysis of monthly sea surface temperature and CO₂-concentration data for 2023 and 2024 gives a consistent explanation for the rise in atmospheric carbon concentration growth without referring to the implausible hypothesis of failing carbon sinks. The temperature dependence of natural CO₂ emissions indicates a clear causality from temperature to CO₂ concentration. This is confirmed by the time shift between temperature and the subsequent concentration change. This suggests a new component in climate models with implications for climate policies.

Keywords: natural CO₂ sinks; climate change; natural emissions; temperature dependence



Academic Editor: Marco Aurelio dos Santos

Received: 28 April 2025

Revised: 7 June 2025

Accepted: 16 June 2025

Published: 19 June 2025

Citation: Dengler, J. Evaluating the Effectiveness of Natural Carbon Sinks Through a Temperature-Dependent Model. *Appl. Sci.* **2025**, *15*, 6907. <https://doi.org/10.3390/app15126907>

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1. Introduction

Articles are currently being circulated in the media claiming that natural CO₂ sinks have “suddenly and unexpectedly” ceased to function. The natural CO₂ reservoirs are the biota, consisting of all living organisms, plants, animals and humans. In addition, the oceans store around 50 times the amount of atmospheric CO₂. It is known and has been proven for many decades that both the biota and the oceans are strong CO₂ sinks. Currently, more than half of all anthropogenic emissions are absorbed by the two major sink systems, ocean and land plants, as reported in [1].

What has happened that suddenly the sink effect is supposedly diminishing? Even at first glance, the diagram (Figure 3) in [1] reveals that the sink effect, which is attributed to land plants, is subject to extraordinarily strong fluctuations, much more so than in the case of the oceans, for example. This should immediately make us suspicious when we talk about a “one-off” event within the past year.

The scientific basis and trigger for the current discussion is the recent article: “Low latency carbon budget analysis reveals a large decline of the land carbon sink in 2023” [2]. The publication essentially states that anthropogenic emissions have been more or less constant over the recent years, but atmospheric CO₂ concentration grew much more than usual in 2023, while between 2016 and 2022 concentration growth was steadily declining. Their conclusion from this observation is that the systems responsible for CO₂ absorption, such as land plants or cold oceans, must have been failing. Another publication

from the Alfred Wegener Institute (AWI) in Germany investigated the ocean uptake of CO₂ since 1958 [3]. They came to the conclusion that the ocean sink is diminishing; besides wind, they identified increasing temperature as a sink-diminishing factor.

Other investigations have found convincing evidence that land sinks have, in fact, significantly increased due to CO₂ fertilization, particularly in tropical forest regions and reduced cold-limitations due to elevated temperature, primarily at higher latitudes [4]. Moreover, this overview article gives good reasons for the future increase of land sinks. In particular, the CMIP6 climate models predict increasing land sinks for at least the next 30 years in the RCP2.6 and higher scenarios [5]. In a recent publication, it was discovered by means of a new analysis that, in fact, the gross primary production (GPP) is 25% larger than previously assumed [6], and in particular, the GPP is 5% larger than soil respiration.

Such evidence suggests that there may be a forgotten factor in the understanding of the carbon cycle. We may have to look for another explanation causing changes in CO₂ concentration growth. Evaluating the literature on carbon sinks gives some hints on where to look for an answer for the apparent deviations. Roy Spencer introduced El Niño as a possible cause to balance the apparently declining carbon sink activity [7]. Ferdinand Engelbeen used a similar argument to explain short-term atmospheric CO₂ concentration changes depending on temperature anomalies [8], but from that publication, it is not clear exactly what he means by temperature anomaly. In an earlier publication on his blog [9], he indicates (in the legend of the first graph) that his understanding of temperature anomaly is the time derivative of temperature, contrary to the standard definition of temperature anomaly, defined it as the temperature difference to a fixed earlier baseline temperature.

Outline of the Article

A previous paper [10] introduced the global sea surface temperature irrespective of the CO₂ concentration as an additional predictor of the carbon sink effect, resolving the contradiction between the apparent temperature trend independence of the sink effect and the obvious temperature trend of global temperature anomalies as a consequence of the high correlation between the global temperature anomaly and CO₂ concentration.

The described model could only make statements about the difference between absorptions and natural emissions because only their difference can be easily measured from available global data. It could not tell whether a specific reduction in the measured sink effect was due to a reduction in absorption or an increase in natural emissions.

Previous publications were restricted by yearly data. The fast change in CO₂ concentration growth over 2023 and 2024 motivates a higher resolution. In particular, the potential time lag between temperature change and change in the sink effect will have to be investigated—it is expected to be several months.

This article includes additional evidence from two more sources. The decay of the atmospheric ¹⁴C concentration after the nuclear test ban treaty 1963 gives an indication of the absorption rate. This will help to separate the downwelling carbon flow from the upwelling emissions.

The other source of additional evidence is studies investigating the temperature dependence of natural emissions by the two main emitters, the biological decay and the outgassing from oceans.

This article brings together different sources of evidence in order to develop a consistent model of the atmospheric carbon cycle. This will help to clarify the recent anomalies of the atmospheric concentration growth of CO₂.

2. Materials and Methods

The approach taken here is not to investigate possible individual sources or sinks and their specific mechanism, that would be the bottom-up approach. Instead, a top-down approach is taken. The sources of information are global measurable data, notably CO₂ concentration measured at Mauna Loa [11], the global anthropogenic emissions, as defined in the Global Carbon Budget [1], and the global average sea surface temperature [12].

For validation purposes, other sources of information are included. One of them, the ¹⁴C concentration data after the bomb test treaty in 1963, is also a global data set [13].

All types of emissions, except explicit anthropogenic emissions, are considered here to be part of the unknown natural emissions, in particular, the land use change emissions. This decision has been discussed in [10]. The variability of these natural emissions is constrained by the residual of the introduced models.

In the publications “Emissions and CO₂ Concentration—An Evidence Based Approach” [14] and “Improvements and Extension of the Linear Carbon Sink Model” [10], the relationship among yearly data of emissions, concentration increase, and sink effect was analyzed and a robust, simple model of the sink effect was developed that not only reproduces the measurement data of the last 70 years very accurately but also allows reliable forecasts. For example, the concentration data for the years 2000–2020 were predicted with extremely high accuracy from the emissions and the model parameters determined before the year 2000. However, the most recent series of measurements used in the publications ended in December 2022 and annual averages were used, so the phenomena that are currently causing so much excitement were not yet taken into account.

This article builds on the evidence gained by these previous papers and develops the models further by introducing monthly data resolution and considering time shifts between temperature change and its effect.

2.1. The Top-Down Carbon Sink Model from the Continuity Equation

The continuity equation based on the conservation of mass implies that the atmospheric concentration growth G_i in year i results from the difference between the total emissions and all absorptions A_i [14], whereby the total emissions are the sum of the anthropogenic emissions E_i and the natural emissions N_i , i.e.,

$$G_i = E_i + N_i - A_i \quad (1)$$

The effective sink capacity S_i is calculated as the difference between the anthropogenic emissions E_i and the concentration growth G_i , i.e.,

$$S_i = E_i - G_i \quad (2)$$

Following the continuity equation above, the effective sink capacity S_i , therefore, is the difference of ocean and plant absorptions A_i and natural emissions N_i :

$$S_i = A_i - N_i \quad (3)$$

It is important to note that the sink effect consists of two components, the actual absorptions and the natural emissions. When measuring the sink effect, we do not know anything about the actual absorptions A_i nor about the natural emissions N_i . All models for the sink effect S_i have this conceptual deficit. Nevertheless, they are the starting point of this investigation.

A simple linear sink model for Equation (3) has been developed by several researchers [7,14–18], where the sink effect of the yearly data model only depended on the

CO₂ concentration of the previous year C_{i-1} with an offset C^0 , representing an equilibrium concentration:

$$\hat{S}_i(C) = a' \cdot (C_{i-1} - C^0) \quad (4)$$

$$= a' \cdot C_{i-1} - n \quad (5)$$

The parameters a' and n are determined by minimizing the sums of squares between measured data from Equation (2) and the sink model of Equation (5) over all known years i :

$$\min_{a',n} \sum_i (E_i - G_i - (a' \cdot C_{i-1} - n))^2 \quad (6)$$

All statistical evaluations, in particular, the ordinary least squares optimization, were conducted with the Python package Statmodels, version 0.13.5 [19], and the graphs were created with the Python package Matplotlib, version 3.7.0 [20].

$n = a' \cdot C^0$ represents the assumed constant natural net emissions per year. Obviously, this is a very crude model because with the constant n it is not possible to represent any systematic variability.

Questions about the principle validity of this model for multiple sinks have made it necessary to again clarify a point that has been discussed before [14,16]. The total sink effect is composed of the sum of several linearized components, which may have different equilibrium concentrations. Let us pick ocean, phytoplankton, C₃ plants, and C₄ plants [21]:

$$\hat{S}_i(C) = a_{ocean} \cdot (C_i - C_{ocean}^0) + a_{phyto} \cdot (C_i - C_{phyto}^0) + a_{C3} \cdot (C_i - C_{C3}^0) + a_{C4} \cdot (C_i - C_{C4}^0) \quad (7)$$

As this is a linear form, it maps perfectly into the form of Equation (5). The individual sink rates or their equilibrium value remain unknown, only their combined effect is determined.

Land use change effects are not considered here as anthropogenic. They are assumed to be part of the unknown natural emissions. In a previous publication, land use change emissions have been included as part of the anthropogenic emissions [14], pulling down the resulting equilibrium concentration to 242 ppm. This contradicts the accepted consensus that the pre-industrial equilibrium concentration was between 270 ppm and 290 ppm. Furthermore, [10] demonstrated that prediction quality improves when land use change emissions are discarded as explicit anthropogenic emissions during the time since 1959. Land use change emissions might have had a significant role in the first half of the 20th century [10], this will be subject to future research.

2.1.1. Finding the Appropriate Data Resolution

There are two aspects that motivate the observation of monthly data. Primarily, the rise in concentration growth happened within a short time interval in 2023. Working with monthly data also opens the possibility to investigate time lags. In the simple yearly model of Equation (4), there is an implicit time lag of 1 year between a change in concentration and a change in concentration growth. Using monthly data can make it possible to actually estimate the optimal time lag.

On the other hand, there is much more noise at the monthly scale, with the undesirable consequence that any model with only a few parameters will only explain a small fraction of the total variance, making it difficult to evaluate the quality of a statistical model.

In order to balance both criteria, the data of year i are decomposed into data of month k the following way. The monthly anthropogenic emissions add up during the year:

$$E_i^{year} = \sum_{k=12i}^{12i+11} E_k^{month} \quad (8)$$

Concentrations of 12 consecutive months are averaged and thus are automatically deseasonalized:

$$C_i^{year} = \frac{1}{12} \sum_{k=12i}^{12i+11} C_k^{month} \quad (9)$$

The time lag of 1 year transforms into 12 months

$$C_{i-1}^{year} = \frac{1}{12} \sum_{k=12i}^{12i+11} C_{k-12}^{month} \quad (10)$$

and therefore concentration growth is

$$G_i^{year} = \frac{1}{12} \sum_{k=12i}^{12i+11} (C_k^{month} - C_{k-12}^{month}) \quad (11)$$

With substitutions from Equations (8)–(11) and replacing the fixed concentration time lag 12 with $lagC$, the ordinary least squares minimization becomes

$$\min_{a',n} \sum_i \left(\sum_{k=12i}^{12i+11} \left(E_k^{month} - \frac{1}{12} (C_k^{month} - C_{k-12}^{month}) \right) - \hat{S}_i(C) \right)^2 \quad (12)$$

with the sink model

$$\hat{S}_i(C) = a' \cdot \sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-lagC}^{month} - n \quad (13)$$

2.1.2. The Extended Linear Sink Model

It is generally known and a consequence of Henry's Law that the gas exchange between the sea and the atmosphere depends on the sea surface temperature. Increased CO₂ emissions from the oceans are, therefore, expected as the temperature rises, like in a glass of beer on a warm day. It is also possible that absorptions are diminished as temperature rises.

Similarly, the decay of biological matter and organisms is related to van't Hoff's rule, which states an increase in decay rate and, thus, natural emissions with an increase in temperature. Of course, the sustainable availability of decayable substances depends on photosynthesis. But photosynthesis also scales with sunlight hours and temperature up to 30 °C besides scaling with CO₂ concentration and thus CO₂ fertilization. CO₂ fertilization dominates the greening of the earth, which has been more than 30% since 1900 [22]. So, it is logical that absorption dominantly scales with CO₂ concentration, while biological decay scales with temperature. When both are correlated as they have been for the last 65 years, a balanced growth of both is expected.

These considerations motivate the introduction of temperature as a model parameter in the description of the effective sink capacity. This model extension has been first introduced in a previous publication [10]. But here, the model is refined by applying it to monthly data in conjunction with an optimization of the time lag between temperature and CO₂ concentration change.

The extended sink model has two components. Absorptions are proportional to the CO₂ concentration preceding by $lagC$ time units, with an offset C^0 , while natural emissions are proportional to temperature preceding by $lagT$ time units, with an offset T^0 . The introduction of a potential time lag between temperature and change of CO₂ concentration is motivated by the fact that decay processes take time, typically a few months. The existence of a time lag in the relation between temperature change and CO₂ concentration change has also been observed in another investigation [23]. Humlum's publication has been criticized because of the suppression of the long-term trend in both CO₂ concentration and temperature [24]. CO₂ concentration or temperature is not manipulated in such a way here, but their actually measured values are used in the regression model. Following the logic of Equation (13), the extended sink model becomes

$$\hat{S}_i(C, T) = a \cdot \left(\sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-lagC}^{month} - C^0 \right) + b \cdot \left(\sum_{k=12i}^{12i+11} \frac{1}{12} T_{k-lagT}^{month} - T^0 \right) \quad (14)$$

$$= a \cdot \sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-lagC}^{month} + b \cdot \sum_{k=12i}^{12i+11} \frac{1}{12} T_{k-lagT}^{model} + c \quad (15)$$

with $c = -a \cdot C^0 - b \cdot T^0$ capturing all offsets of concentration or temperature measurements. With the special choice

$$\hat{C}^0 = \frac{-c}{a} \quad (16)$$

(see Equation (22) in [10]), which implies $T^0 = 0$, the extended sink model takes a simplified form:

$$\hat{S}_i(C, T) = a \cdot \left(\sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-lagC}^{month} - \hat{C}^0 \right) + b \cdot \sum_{k=12i}^{12i+11} \frac{1}{12} T_{k-lagT}^{month} \quad (17)$$

It must be noted that $\hat{C}^0$ here is not the estimated preindustrial concentration, but the estimated hypothetical equilibrium concentration for zero anthropogenic emissions and the temperature anomaly $T = 0$.

This means that with an expected negative value of b , there is a reduction in the observed sink effect with rising temperature, but this is overcompensated by the increasing sink effect through the rising concentration as long as the temperature and concentration are correlated, as they have been over the last 60 years. This strong correlation between CO₂ concentration and sea surface temperature is demonstrated in Figure 1, irrespective of any assumed causality direction.

The monthly timeshift $lagC$ and $lagT$ are unknown; therefore, different timeshifts have to be tested. The best model is determined by the R^2 measure, which measures the ratio of the variance explained by the model with the total variance.

The model is strictly linear for both concentration and temperature. Strict linearity is, in fact, a precondition for using global data like average sea surface temperature. The reason is simple. When input variables of a local process can be averaged, and output variables are also averaged, then the process must necessarily be linear. Therefore, by definition, nonlinearities can be neglected in this investigation. When nonlinear processes like the temperature dependence in Henry's law are involved, the effect of interest has to be linearized, and the scope of the model is restricted to the linear part.

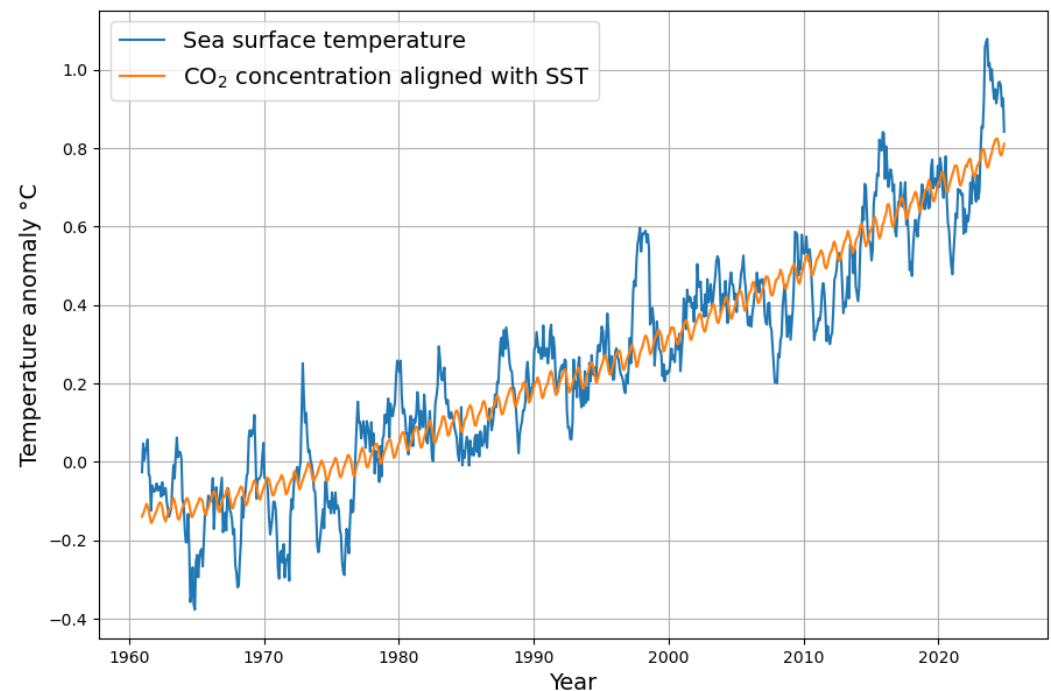


Figure 1. Sea surface temperature, original (blue) [12]. Temperature modeled with CO₂ (orange) [11].

2.1.3. Other Approaches That Relate Temperature to Sink Effect

There have been suggestions that the sink effect and, as a consequence, the concentration growth, should depend on the time derivative of temperature instead of temperature itself [9].

This is not a good idea. Not only are both mentioned natural laws, Henry's law and van't Hoff's rule relate natural emission to temperature and not to its derivative. Also, a simple thought experiment rules out the derivative: Let us assume a single temperature jump of 1 °C at the sea surface, then temperature remains at the elevated level for a long time. If the temperature effect depended on the time derivative of temperature, there would only be a single pulse of natural emissions during the very first time interval. But, in reality, temperature as a thermodynamic state variable triggers increased natural emissions at all times following the temperature step.

Roy Spencer has related the short-term variability of the sink effect to the Multivariate ENSO index (MEI) [7]. This is, in fact, highly related to the approach described here. Two of the five components of the MEI are regional sea surface temperature and regional air temperature anomalies. The anomalies are determined by subtracting the 30-year average from the temperature. This removes the trend from the temperature [25]. The temperature of the temperature-dependent model described here can be decomposed into a linear function of CO₂ concentration containing the temperature trend and a residual temperature [10]. The zero mean residual temperature has structural similarities with the MEI signal. When sea surface temperature is indeed a physical driving force of the sink effect and CO₂ concentration growth, it can be expected that MEI has a significant influence on the sink effect. In that case, we would, however, expect that the model based explicitly on sea surface temperature would explain the observed data better than the model with the complex MEI index. We invite Roy Spencer and others to determine the R^2 value when MEI is used as a predictor.

2.2. Separating Absorptions and Natural Emissions

In the extended sink model, the net sink effect is a linear function of both concentration and temperature. The net sink effect includes both absorptions and natural emissions. We

expect the a , the coefficient of C_i , to represent the absorptions and b , the coefficient of T_{i-lag} , to represent the temperature trend of natural emissions. In order to evaluate the validity of this assumption, we need evidence of plausibility.

Optimally, we would like to find distinct methods of measurement or physical laws for the determination of the absorption and the natural emissions separately instead of their net difference.

In fact, there are two kinds of evidence. The pure absorption effect is measured from the “bomb test data”, the atmospheric decay of ^{14}C after the nuclear test ban treaty in 1963.

The influence of temperature on natural emissions is to evaluate the plausibility of the temperature effect on both ocean outgassing and plant growth and decay.

2.2.1. Estimating CO_2 Absorption by Means of the Bomb Test Data

The nuclear bomb tests beginning in the 1950s stopped rather suddenly in 1963 with the nuclear test ban treaty. This provides a close-to-ideal identifiable carbon emission pulse of ^{14}C that has been thoroughly investigated for more than 40 years [13]. The data series is the global data sequence from 1950 to 2019 from the supplements of [13]. The relative deviation from the preindustrial zero level of ^{14}C concentration, $\Delta^{14}\text{C}$, is displayed as the blue graph in Figure 2.

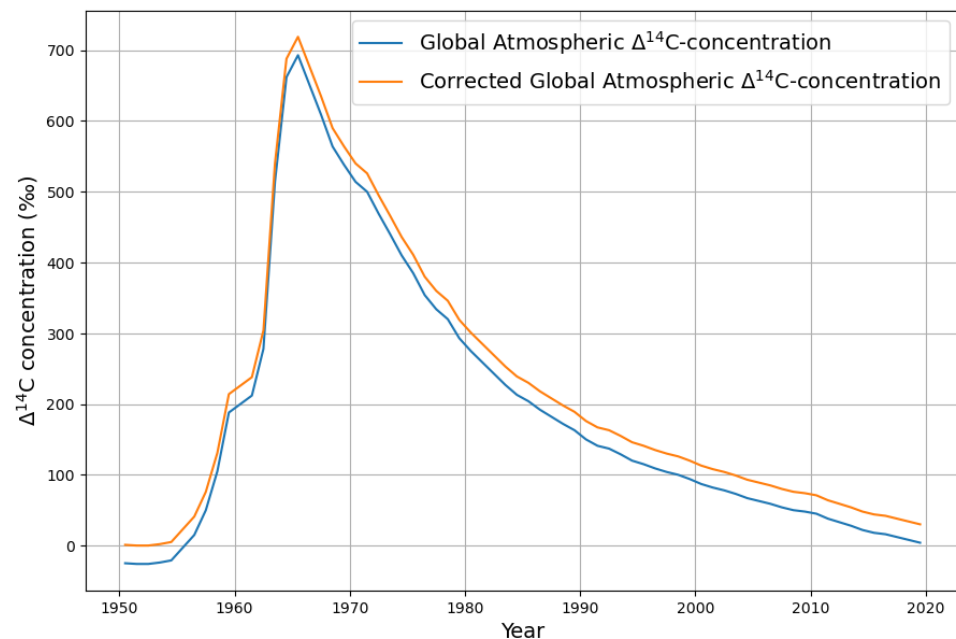


Figure 2. The decay of the global atmospheric $\Delta^{14}\text{C}$ after 1965 [13]. Published data are blue, and adjusted data are orange.

Why is this concentration decay representing “pure” absorptions? The CO_2 emissions from the oceans have the much lower ^{14}C concentration of the long-term equilibrium before the bomb tests; therefore, the upwelling ^{14}C can be neglected.

The primary purpose of the publication from Hua et al. [13] was to provide a data set usable for correcting carbon dating measurements. Therefore, the zero concentration reference level is the preindustrial level before 1900. The purpose here, however, is a completely different one. We want to determine the time constant of the atmospheric decay of $\Delta^{14}\text{C}$ caused by ocean sinks and long-living plants. Therefore, we have to preprocess the data by treating the ^{14}C dilution in the atmosphere caused by fossil fuels that do not contain ^{14}C , the so-called Suess effect [26], in a different way than required by carbon dating.

In order to deal with the Suess effect properly, we need to look at the definition of the provided data. They are calculated in the $\Delta^{14}\text{C}$ convention [27–29], which is defined as follows:

$$\Delta^{14}\text{C}(t) = \left(\frac{{}^{14}\text{C}_{\text{Atm}}(t)/{}^{12}\text{C}(t)}{{}^{14}\text{C}_{\text{Std}}/{}^{12}\text{C}_{\text{Std}}} - 1 \right) \cdot 1000 \quad (18)$$

$\Delta^{14}\text{C}(t)$ are the relative deviations from the pre-industrial reference concentration level of ${}^{14}\text{C}$. This contains all deviations from the pre-industrial standard, both the Suess effect and the bomb test anomaly. But because we want to model the post-bomb test ${}^{14}\text{C}$ data as an exponential decay, the fact that the $\Delta^{14}\text{C}(t)$ data are negative in the years before the bomb tests due to the Suess effect requires an adjustment. In the definition of $\Delta^{14}\text{C}(t)$, the pre-industrial zero level had been fixed in order to meet the needs of carbon dating, but in order to measure the decay of the bomb test ${}^{14}\text{C}$ concentration, the zero level has to be the level just before the bomb test, that is, just before the sharp rise.

The resulting decreasing atmospheric ${}^{14}\text{C}$ concentration shows, over a more than 40-year time period, that the contributing absorption sink processes exhibit an undistorted exponential decay of a first-order linear differential equation; see Figure 3.

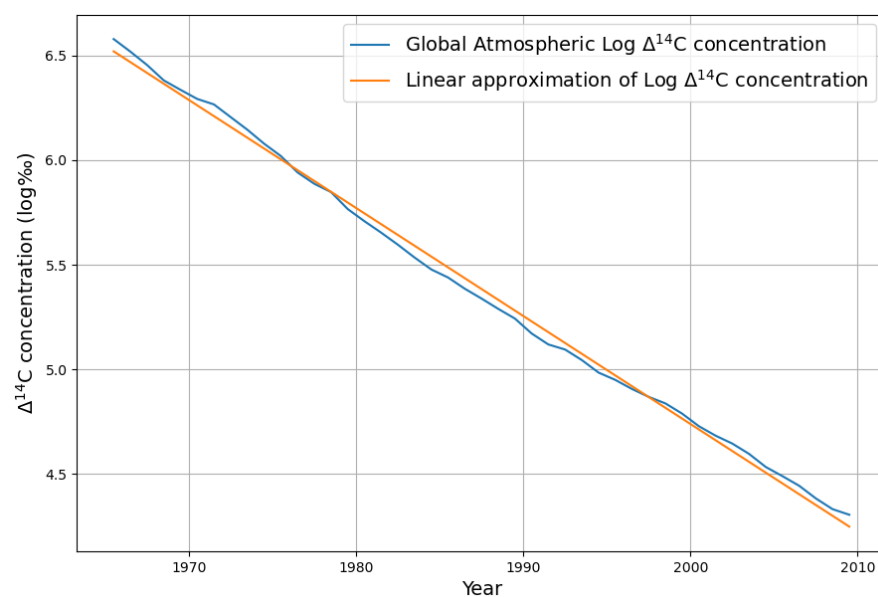


Figure 3. Determination of the ${}^{14}\text{C}$ decay rate by a logarithmic transformation.

This decay includes both the decay of ${}^{14}\text{C}$ concentration into the sinks and the Suess effect due to atmospheric concentration change of ${}^{12}\text{C}$ by anthropogenic emissions. For the determination of the Suess effect, we take the 25 years from 1965 to 1990, where we have a good ${}^{14}\text{C}$ decay signal.

The upper bound of the diluting Suess effect due to fossil fuels is obtained by pretending there is no sink effect, thus adding the cumulative emissions of 60 ppm (=127 GtC) between 1965 and 1990 to the 1965 CO_2 concentration of 320 ppm. The yearly diluting contribution is calculated by

$$\Delta C_{\text{Suess}} = \sqrt[25]{\frac{320 + 60}{320}} = 1.0069$$

This means that the Suess effect contributes 0.69% per year to the decline of $\Delta^{14}\text{C}$. The regression parameter for the slope in Figure 3 is -0.058 , with the 95% confidence interval $[-0.054, -0.063]$. When this is reduced by 0.0069, the real absorption constant of ${}^{14}\text{C}$ is -0.051 , with a corresponding confidence interval. This means that around 5.1% of the surplus ${}^{14}\text{C}$ is absorbed by oceans and long-living plants each year. The 5.1% corresponds to a time constant of 19 years, which is close to and definitively within the error range—the value that was also determined by Burton [8,30] based on the data provided from [31].

It is a basic fact of physics that neither absorption into the ocean nor photosynthesis can differentiate between the isotopes ^{14}C and ^{12}C . Therefore, we have to assume that this high rate of absorption applies to all the CO_2 . This number will have to be related to the result of the extended sink model. The deviation to the measured sink effect must necessarily be caused by natural emissions.

2.2.2. Estimating the Temperature Effect on Natural Emissions from Land Plants and Oceans

As stated above, photosynthesis is the primary driver of the following processes of plant decay and soil respiration. In a recent article, it was confirmed that the Gross Primary Production (GPP) in absolute numbers is 5% larger than soil respiration [6]. In [32], the Net Primary Production (NPP) during the time interval from 1982 to 1999 was investigated. They found a yearly increase of 3.4 GtC of NPP over 18 years. During this time, the temperature increased by 0.25°C . This would imply a 13.6 GtC increase of bound carbon per $^\circ\text{C}$ and year. According to the article, this was not only due to the increase of CO_2 fertilization but also, to a large degree, to the reduction of cloud cover over the Amazon rainforest and an increase in solar radiation, which directly influences photosynthetic processes more than CO_2 concentration and temperature. A later reported decline of yearly NPP by 0.55 GtC in the years 2000–2009 [33] adjusts this exorbitantly high yearly number to $2.85 \text{ GtC} / 0.5^\circ\text{C} = 5.7 \text{ GtC}/^\circ\text{C}$.

According to [34], during the 19 years from 1989 to 2008, the natural emissions from soil respiration R_S have risen by 0.1 GtC per year, i.e., 1.9 GtC during the whole investigation period. During this time, the global temperature has risen by 0.3°C see, e.g., Figure 4. Therefore, we have a temperature dependency of R_S per year:

$$\frac{\Delta R_S}{\Delta T} = \frac{1.9}{0.3} \text{ GtC}/^\circ\text{C} = 6.33 \text{ GtC}/^\circ\text{C}$$

An R_S increase of $3.3 \text{ GtC}/^\circ\text{C}$ per year is reported by [35]. According to [36], there is considerable uncertainty in the determination of the temperature sensitivity of soil respiration.

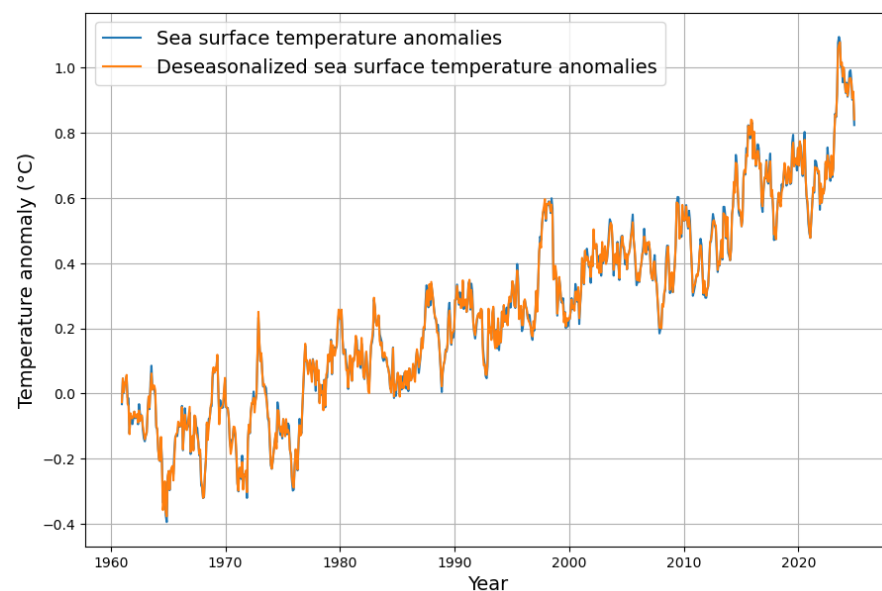


Figure 4. Monthly global sea surface temperature time series [12] and deseasonalized monthly global sea surface temperature data.

Regarding the temperature dependence of the emissions from the oceans, we begin with the baseline of yearly emissions from oceans of 80–100 GtC [1]. According to [37], the relative change in CO_2 partial pressure in seawater is 0.0423 per $^\circ\text{C}$ for a wide range of

temperatures from 2 °C to 28 °C. Therefore, the yearly increase in terms of absolute mass would be in the range between $80 \text{ GtC} \cdot 0.042/^\circ\text{C} = 3.4 \text{ GtC}/^\circ\text{C}$ and $100 \text{ GtC} \cdot 0.042/^\circ\text{C} = 4.2 \text{ GtC}/^\circ\text{C}$. It is noteworthy that F. Engelbeen in the “Conclusions” of [9] agrees in principle with yearly rates ranging from 3 to 5 $\text{GtC}/^\circ\text{C}$, but he restricts the validity of this process to just a few subsequent years, most likely as a consequence of his assumption that the temperature time derivative is the driving parameter, an assumption I do not share.

Adding the collected evidence for temperature dependency of both soil respiration and ocean emissions results in a total range from $3.3 + 3.4 = 6.7 \text{ GtC}/^\circ\text{C}$ to $6.3 + 4.2 = 10.5 \text{ GtC}/^\circ\text{C}$ per year. This is based only on a few investigations, requiring further research. But it gives an indication of what we can realistically expect.

3. Results and Discussion

Since details of the last two years are now relevant, the calculations are performed with monthly data up to December 2024 in order to obtain a clear picture and minimize the effect of boundary conditions. The starting point is the original monthly Mauna Loa measurement time series, which is shown in Figure 5.

The monthly data are subject to seasonal fluctuations caused by the uneven distribution of land mass between the Northern and Southern Hemisphere. Therefore, the first processing step is to remove the seasonal influences, i.e., all periodic changes with a period of 1 year [38]. Due to the 12-month averaging in the Equations (8)–(11), deseasonalization is done implicitly. Only for the purpose of display, deseasonalization has to be done explicitly. Specifically, this was done with a third-order trend component and a cyclical component of sine and cosine terms up to the second order. The details are described in Appendix A. The results of the deseasonalized CO_2 concentrations are displayed in Figure 5 (orange color).

The global sea surface temperature is also subject to seasonal fluctuations, but to a much lesser extent, as shown in Figure 4.

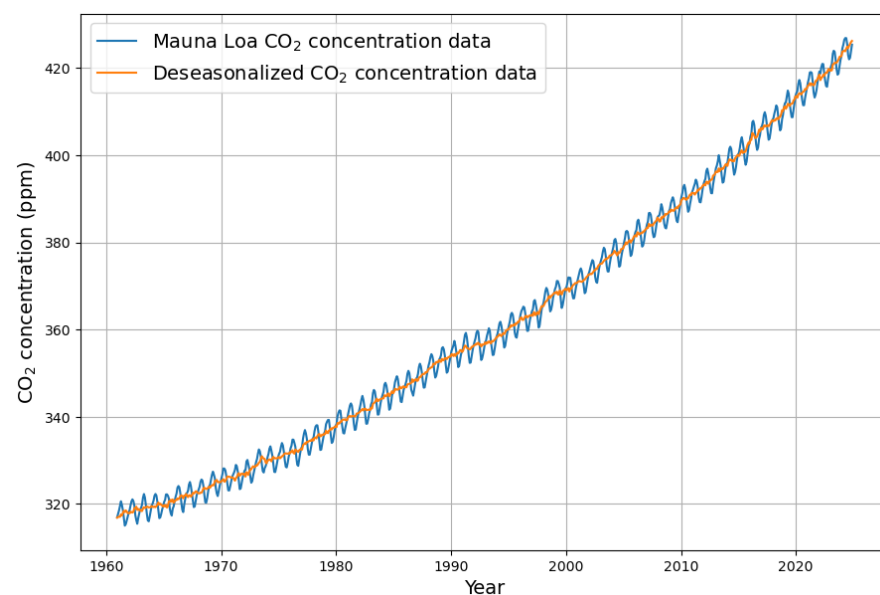


Figure 5. Monthly Mauna Loa time series of CO_2 concentration (blue) [11] and deseasonalized monthly CO_2 concentration data (orange).

3.1. Formation and Analysis of the Monthly Increase in Concentration

The deseasonalized increase in concentration is calculated according to Equation (11), and the results are displayed in Figure 6.

The monthly fluctuations of concentration growth indicate that the high peak at the end of 2023 is by no means a singular event. In 2016, there was a similarly large spike and a trend of decline until 2022. The 2023 spike is interpreted as a decrease in sink performance in the current media discussion. The diagram, however, shows a gradually increasing trend with similar spikes from time to time.

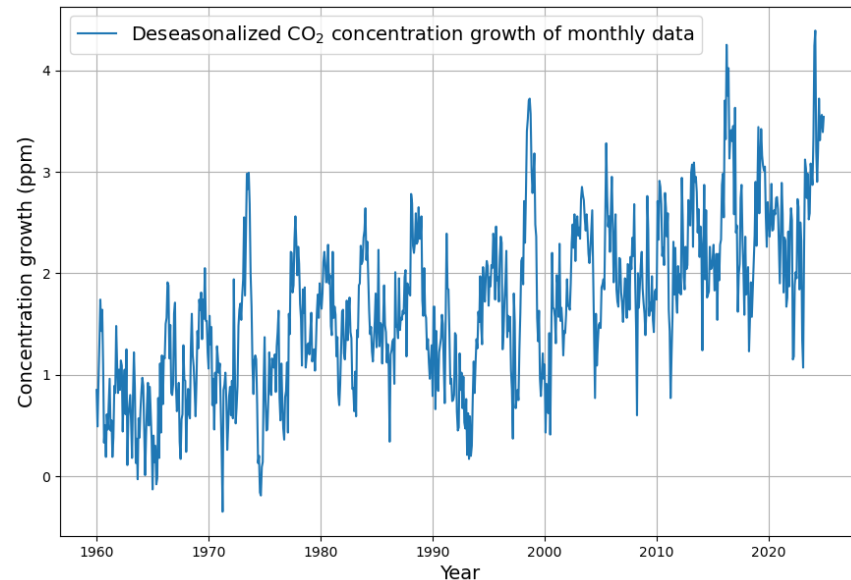


Figure 6. Monthly deseasonalized concentration growth.

3.2. Evaluation of the Two Sink Models

Figure 7 shows the effective sink capacity (green) from the difference between anthropogenic emissions (blue) and concentration growth (orange). The sink capacity is displayed with a negative sign in order to separate it visually from the concentration growth. The sink capacity is increasing with time, not decreasing.

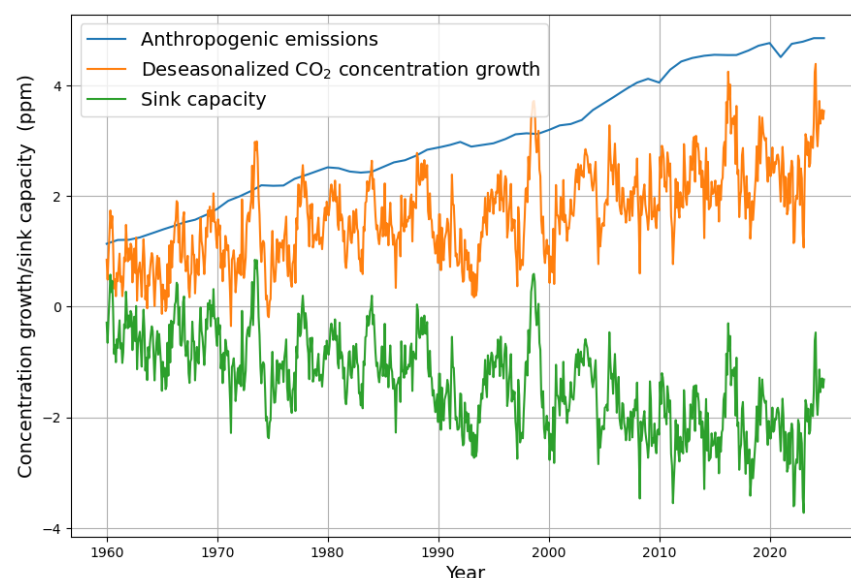


Figure 7. Anthropogenic emissions (blue) [1], CO₂ deseasonalized concentration growth (orange), and corresponding sink capacity (green). The sink capacity after 2000 is always larger than 0, and it has an approximately linear increasing trend. In 2023 and 2024 there is a reduction to nearly 0. This corresponds with a rise in concentration growth nearly reaching the anthropogenic emissions. Such situations occurred multiple times in the past.

It is easy to see that the effective sink capacity does not fall below 0 at the right-hand edge of Figure 7; these rare situations only occurred before 1999. However, it was actually decreasing in 2023–2024.

3.2.1. Evaluation with the Simple Concentration-Dependent Sink Model

The design of the simple concentration model has been extended compared to previous papers by allowing a time shift of the CO₂ concentration in least squares optimization (Equation (12)). The optimization is conducted for all time shifts between 0 and 22 months. The explained variance ratio R^2 of the model is shown in Figure 8. After optimization for the two parameters a and n , the R^2 value of the regression has a maximum of nearly 0.59 at the optimal time shift of 16 months. This means that the simple model explains, at most, 59% of the original data variability.

Table 1 displays the most relevant time shift dependent values, the explained variance ratio R^2 , the sink parameter a , the model constant n , and the equilibrium CO₂ concentration C^0 .

The estimated model parameters a' and n are not very sensitive to the applied time shift, but a maximum of the explained variance is clearly visible. As there are several underlying causal processes involved, the visible maximum is an indication of the most dominant process. Determining the mechanism in nature that causes this time delay is the subject of further research.

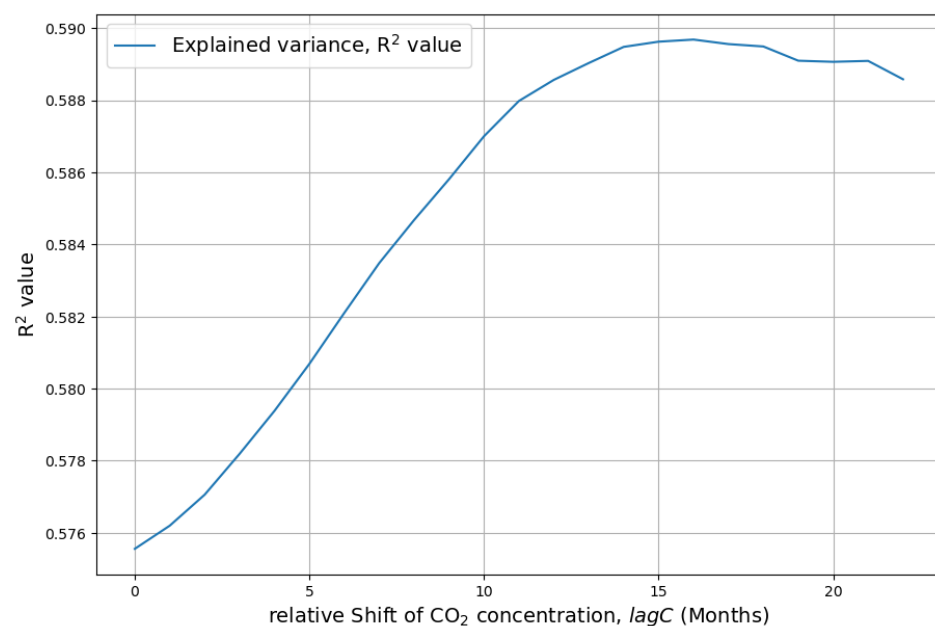


Figure 8. Explained variance of simple sink model as a function of CO₂ concentration shift $lagC$, measured in months.

Table 1. Shift and corresponding metrics (R^2 , a' , n , and C^0).

Metric	Shift							
	11	12	13	14	15	16	17	18
R^2	0.5880	0.5886	0.5890	0.5895	0.5896	0.5897	0.5896	0.5895
a'	0.0175	0.0176	0.0176	0.0176	0.0176	0.0177	0.0177	0.0177
n	−4.93	−4.94	−4.95	−4.96	−4.97	−4.97	−4.98	−4.99
C^0	282.2	282.7	283.2	283.7	284.1	284.5	284.9	285.2

With the optimal concentration time shift, the model Equation (4) becomes:

$$\hat{S}_i(C) = 0.018 \cdot \left(\sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-16}^{\text{month}} - 285 \text{ ppm} \right) \quad (19)$$

The value $C^0 = 285$ ppm can be interpreted as the effective preindustrial equilibrium concentration. The 95% confidence interval for the absorption parameter a' is [0.014, 0.021]. The 95% confidence interval for C^0 is [192, 379] and is, therefore, very large. But it is plausible: when the relative error of a is about 10% and the relative error for n is 13%, then the relative error of their ratio is 17%. Therefore, it is not surprising that different authors arrive at different values depending on their data selection and model design.

3.2.2. Evaluation with the Extended Concentration and Temperature-Dependent Sink Model

The extended sink model $\hat{S}(C, T)$, Equation (14), is replacing $\hat{S}(C)$ in the least squares optimization (Equation (12)). Using the CO₂ concentration time shift of 16, the optimization is conducted for temperature time shifts from 0 to 12 months. Figure 9 shows that the explained variance ratio R^2 has a rather clear maximum of more than 0.8 at a time shift of 4 months. This is a quite remarkable increase in the explained variance ratio, leaving only 20% of the total variance unexplained. Table 2 displays the dependence of R^2 , the absorption value a , the temperature coefficient b , the constant c , and the equilibrium concentration $\hat{C}^0$ on the temperature time shift.

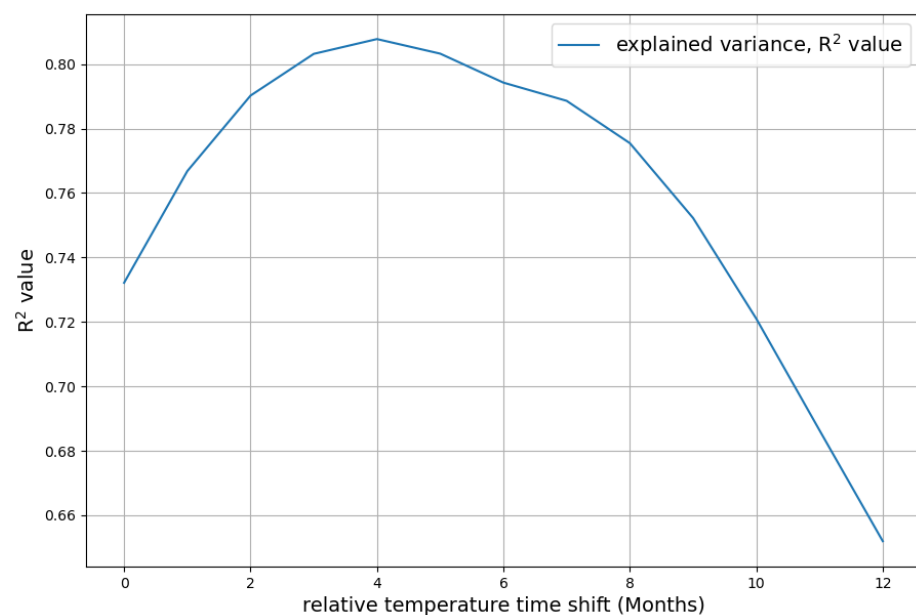


Figure 9. Explained variance of the extended model as a function of temperature shift, measured in months.

Table 2. Temperature time shift and corresponding metrics in extended sink model (R^2 , a , b , c , and $\hat{C}^0$).

Metric	Shift								
	0	1	2	3	4	5	6	7	8
R^2	0.7321	0.7668	0.7902	0.8032	0.8078	0.8033	0.7943	0.7886	0.7755
a	0.0456	0.0484	0.0497	0.0500	0.0497	0.0492	0.0485	0.0481	0.0475
b	−3.12	−3.45	−3.61	−3.66	−3.63	−3.59	−3.51	−3.49	−3.42
c	−14.20	−15.13	−15.58	−15.69	−15.57	−15.42	−15.18	−15.07	−14.85
$\hat{C}^0$	311.8	312.9	313.5	313.6	313.5	313.4	313.2	313.1	312.8

With this optimal timeshift, the final extended sink model $\hat{S}_i(C, T)$ is determined:

$$\hat{S}_i(C, T) = 0.05 \cdot \left(\sum_{k=12i}^{12i+11} \frac{1}{12} C_{k-16}^{\text{month}} - 313.5 \text{ ppm} \right) - 3.63 \frac{\text{ppm}}{^{\circ}\text{C}} \cdot \sum_{k=12i}^{12i+11} \frac{1}{12} T_{k-4}^{\text{month}} \quad (20)$$

where C_k^{month} are the measured monthly Mauna Loa CO₂ concentration data [11] and T_{k-4}^{month} are the timeshifted temperatures computed from monthly HadSST4 sea surface anomalies [12].

The CO₂ dependent absorption with 5% is significantly larger than in the simple sink model, where it was 1.8%. At first sight, it is hard to understand how this discrepancy comes about. Therefore, it is visualized with the diagram, Figure 10.

The measured sink effect from Equation (2) can be approximated directly with a linear function depending on the CO₂ concentration. This is represented by the simple sink model with the red arrow. It can also be represented by two processes: downwelling large absorption, represented by the green arrow, and upwelling natural emissions, represented by the blue arrow. The blue arrow partly compensates for the effect of the green arrow. The fact that these upwelling natural emissions are temperature-dependent makes them identifiable when including temperature in the model.

Figure 11 shows the resulting sink effect of both the simple sink model and the extended model in comparison with the measured sink data. While the simple sink model represents the trend of the data, the extended model follows the short-term deviations of 1 to 4 years very well. There is one noteworthy exception. After 1991, there was a remarkable rise in the sink rate, which has no correspondence with the model variability caused by temperature. The reason has been described by Roy Spencer [7], who writes, “Significant model departures from observations occurred for three years after the 1991 eruption of Mt. Pinatubo” and explains it as a consequence of increased photosynthesis due to more diffuse solar radiation.

¹⁴C Absorption vs. Sink effect

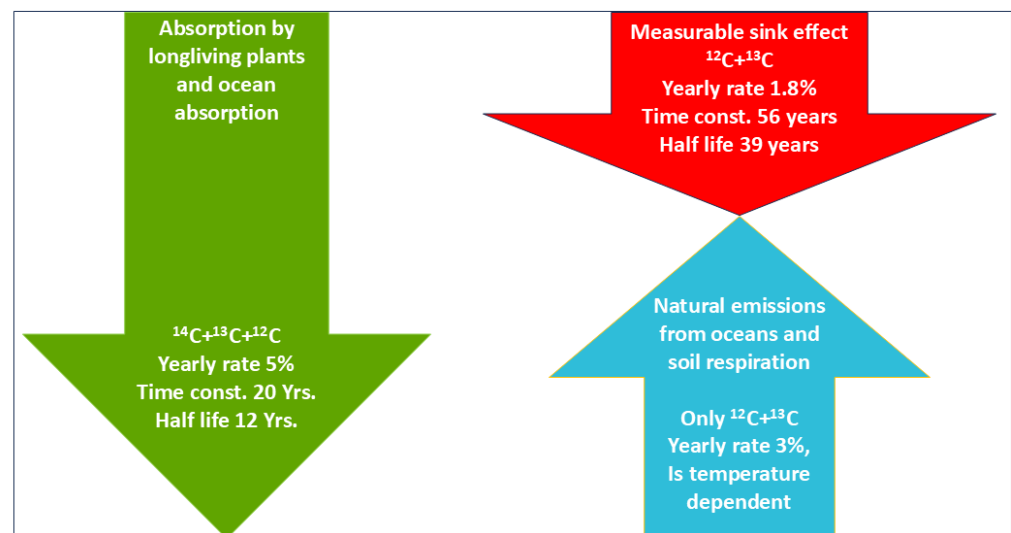


Figure 10. Composition of the measured sink effect (red) by absorptions (green) and natural emissions (blue).

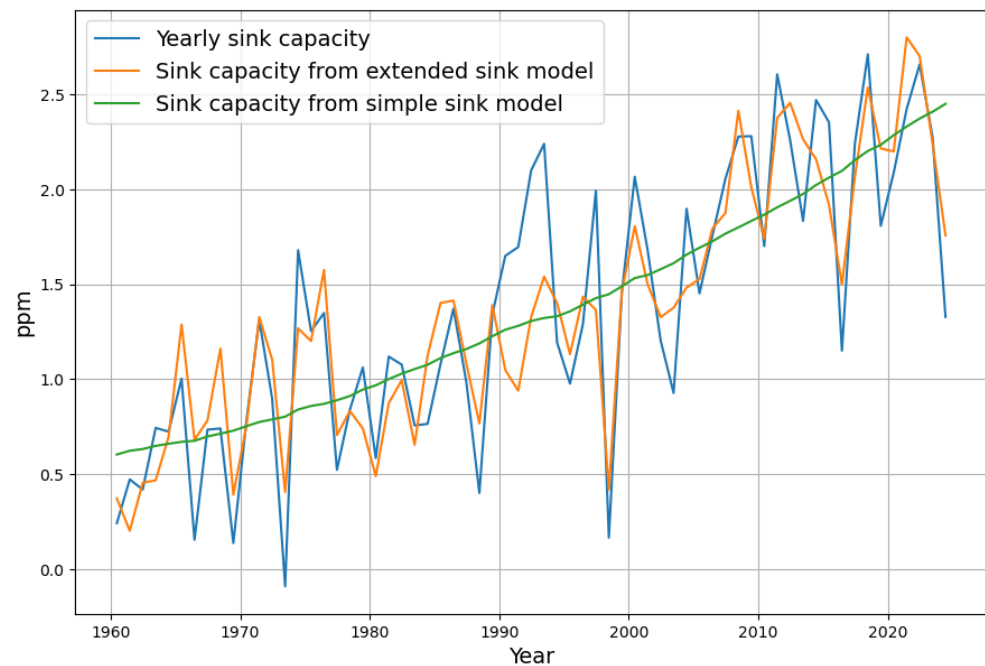


Figure 11. Sink effect of averaged monthly data (blue): results of simple sink model (green) and extended sink model (orange).

3.3. Comparing the Absorption Rate of the Extended Sink Model with the Decay Rate of the Bomb Test Data

According to Equation (20), the extended sink model has the result that the yearly absorptions are rather large, approximately 5% of the CO_2 concentration beyond the equilibrium concentration, which is partly compensated by a significantly large effect of temperature dependence on natural emissions, approximately $3.6 \text{ ppm}/^\circ\text{C}$ ($7.7 \text{ GtC}/^\circ\text{C}$) per year. The 95% confidence interval of the absorption rate is [0.042, 0.058].

The decay rate of bomb test data with the Suess effect correction is 5.1% per annum. This rate matches very closely the determined absorption rate by the extended sink model within the statistical error boundaries. This supports the ability of the extended sink model to separate natural absorptions from natural emissions instead of mixing them as in the simple sink model. The absorption rate is, therefore, only controlled by the CO_2 concentration, while natural emissions are controlled by sea surface temperature.

3.4. Comparing the Temperature Coefficient of the Extended Model with the Empirical Natural Emissions

The possible range of natural emissions temperature dependency was determined in Section 2.2.2 to be in the range of between $6.7 \text{ GtC}/^\circ\text{C}$ per year and $10.5 \text{ GtC}/^\circ\text{C}$ per year. With the temperature coefficient of the extended model, the value $3.6 \text{ ppm}/^\circ\text{C} = 7.7 \text{ GtC}/^\circ\text{C}$ with the 95% confidence interval [5.9, 9.5] $\text{GtC}/^\circ\text{C}$ can be considered as a very good match.

Therefore, the empirically determined rates of temperature dependency are a good confirmation for the extended sink model.

3.5. Reconstruction of the Concentration Growth from Both Sink Models

The calculations show clearly that the concentration-dependent absorptions of oceans and land plants have not changed at all, but that the natural emissions have increased due to temperature increases.

How is this reflected in the model-based reconstruction of the concentration growth? Figure 12 shows what the inclusion of temperature means for modeling the yearly concentration growth.

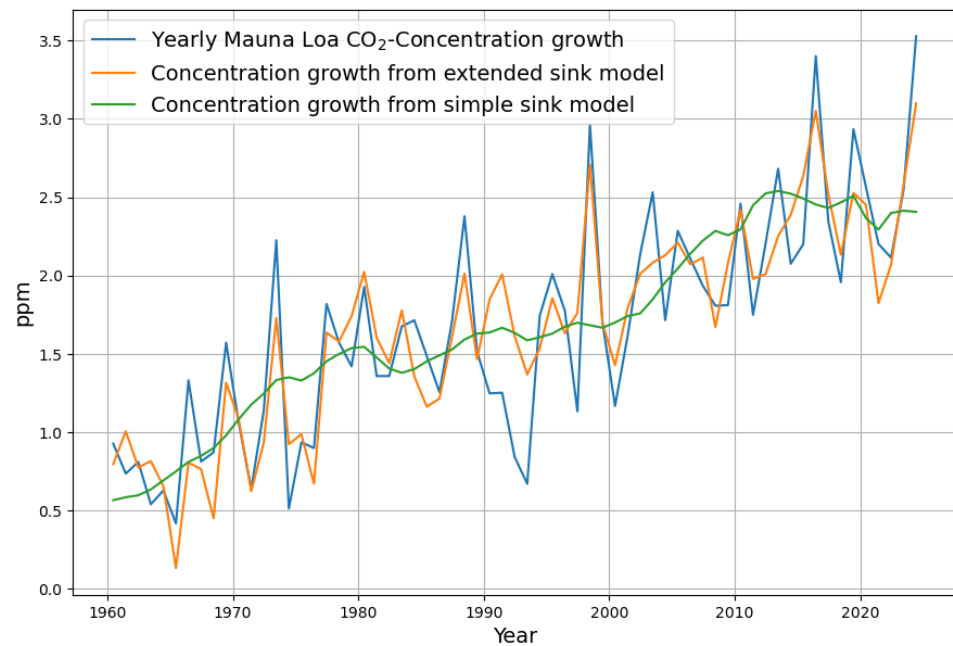


Figure 12. Concentration growth of averaged monthly data (blue) and its modeling with the simple sink model (green) and temperature-dependent extended sink model (orange).

While the green curve represents the widely known concentration-based simple sink model, the orange curve also takes into account the dependence on temperature, as described. It turns out that the current large increase in concentration growth is a natural consequence of the underlying rise in temperature. While the green curve of the concentration-dependent model predicts a decrease in concentration growth for 2023 and 2024, the extended sink model follows nicely the actual rising concentration growth values.

The monthly concentration growth is also reconstructed by the two models as shown in Figure 13. Also in the monthly resolution, the temperature model matches very well the variability of the measured data.

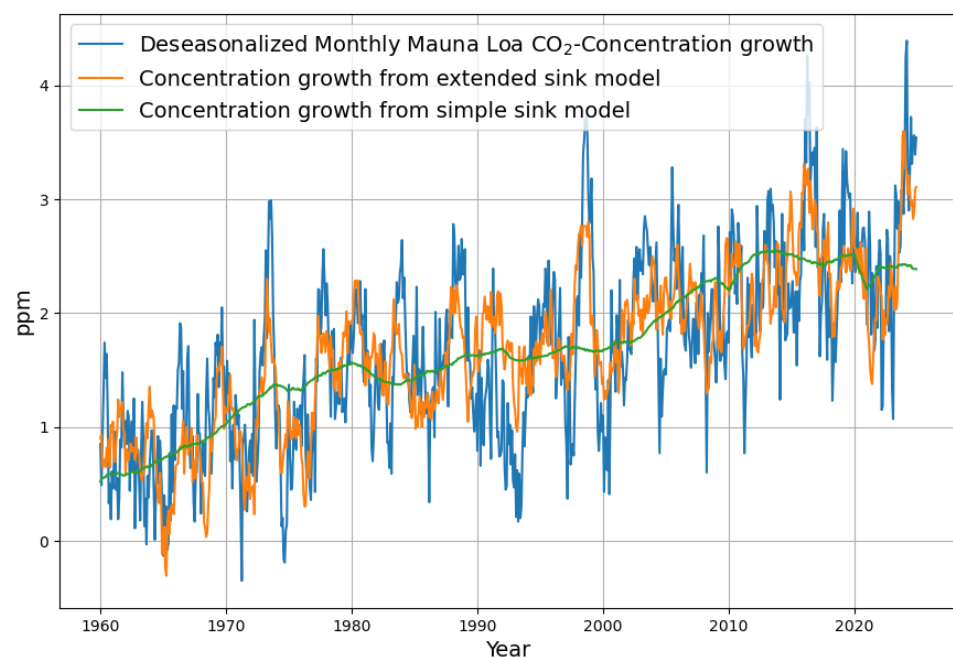


Figure 13. Monthly concentration growth (blue) and its modeling with simple sink model (green) and temperature-dependent extended sink model (orange).

4. Conclusions

The continuity equation, together with the observed consistent decrease in the ^{14}C concentration in the atmosphere after 1963 and the observation of temperature-dependent natural emissions, are powerful tools for evaluating observations.

One purpose of this article is to explain the recent rise in concentration growth as a consequence of rising sea surface temperatures instead of a hypothetical unobserved decline in absorption by oceans or plants. While the rise in concentration growth is real, the cause is not a failure of sinks but a larger rise in temperature beyond the trend that corresponded to CO_2 level rise.

It should, therefore, not be off-limits to consider temperature as a “normal” cause of CO_2 concentration changes in the public debate, as an influencing factor instead of speculating about the absence of sinks without evidence.

This does not exclude a causality in the other direction; the greenhouse effect, the rather large temperature coefficient on natural CO_2 emissions, certainly limits the possible climate sensitivity.

Regarding causality, the first climate-relevant test of the temperature-dependent model was made on the VOSTOK ice-core data [10], where there were no anthropogenic emissions and the CO_2 concentration of the last 400,000 years was modeled from preceding temperature data.

The temperature-dependent model makes it possible to separate better between the actual anthropogenic origin of CO_2 changes and the natural causes, among which temperature is a very important one. Many people were confused when, in 2020, no effect of the anthropogenic emission reduction could be seen in the concentration growth. When the temperature effect is removed, as is the case in the simple model, then the effect of the lockdown-caused emission reduction can be seen, e.g., the green curve in Figure 12.

The most important contribution is that it became possible to separate downwelling absorptions from upwelling natural emissions. Through the evaluation of the bomb test ^{14}C time series and by the Suess effect correction, we have a reliable estimate of the yearly absorption rate as 5% of the CO_2 concentration. Together with the precise CO_2 concentration measurements on Mauna Loa and the accepted measurements of anthropogenic emissions from the International Energy Agency (IEA), the continuity Equation (1) constrains the yearly net natural emissions. Together with the extended model, we also have an understanding of their temperature dependency.

Some misunderstandings and misconceptions are challenged by the discussed concepts.

- The most obvious is the argument of some climate skeptics that anthropogenic emissions have no effect because they are apparently “drowned” in the huge natural carbon cycle. The fact is that anthropogenic emissions are a direct cause of concentration growth. Nature behaves as a strict net sink. This is obvious from Figure 7. Both models ended up with a significant, consistent net sink effect for the last 70 years when reliable data were available. Therefore, anthropogenic emissions must have significantly contributed to the total concentration growth. The extended model can hypothetically switch off the variability of natural emissions by setting the parameter for the temperature to 0. Alternatively, the anthropogenic emissions can be set to an arbitrary constant value so that only the temperature-controlled natural emissions control the CO_2 concentration growth.
- Natural emissions by gardens, animals, and even agriculture, in general, are increasingly becoming a political target. As discussed, increasing natural emissions from biota are almost always a secondary consequence of a previous increase in photosynthesis and, therefore, NPP. But they are only a fraction of NPP. Therefore, extreme care has to be taken not to create more harm than good by carbon-related political inter-

ference with biota or agriculture. Mechanical agriculture and chemical contributions to agriculture are already accounted for by the measured anthropogenic emissions. It is, therefore, not legitimate to count them twice by attaching their effect to the biological product.

- The necessary time shift, where temperature change precedes changes in concentration change, is a clear statement of causality that, to a certain degree, CO₂ concentration change follows temperature. Climate models should include this causality and honestly face the consequences. The most dramatic is that it leads in a natural way to a much higher absorption rate of the sink system than the currently accepted value.

Of course, questions for further research remain. Due to the fact that the continuity equation must hold at all time scales, we expect new insights about the carbon cycle from systematically investigating multiple timescales and the behavior of model parameters.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All evaluations are based on publicly available data and software: sea surface temperature data (yearly): <https://www.metoffice.gov.uk/hadobs/hadsst4/data/download.html>, CO₂ concentration Mauna Loa: <https://gml.noaa.gov/ccgg/trends/data.html>, CO₂ emissions, concentration, concentration growth, land use change: <https://www.globalcarbonproject.org/carbonbudget/>, <https://www.icos-cp.eu/science-and-impact/global-carbon-budget/2022>, Software: <https://www.anaconda.com/products/distribution> (all accessed on 15 June 2025), Python modules matplotlib, statsmodels.

Acknowledgments: Ferdinand Engelbeen has given helpful critical comments on an early version of the manuscript, and pointed to the study of Takahashi et al. about temperature dependence of ocean emissions. Reflecting on the issues he raised helped a lot to deepen the understanding and clarify some formulations. I want to thank Fritz Vahrenholt for the intensive discussions about the relevance of the temperature term. Rolf Dübal gave valuable formal hints that helped to improve the quality of the manuscript.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviation

The following abbreviation is used in this manuscript:

NPP Net Primary Production

Appendix A. Computation Details of Deseasonalization

Deseasonalization has the goal of removing all seasonal information from a signal with a nonlinear trend. The seasonal component is assumed to be identical and cyclical every year.

Following [38], the measured information samples y_i at month i are split into 3 components, the nonlinear trend model component $\hat{y}_i^{trend}$, the yearly periodic model component $\hat{y}_i^{periodic}$, and an unknown residual $y_i^{residual}$:

$$y_i = \hat{y}_i^{trend} + \hat{y}_i^{periodic} + y_i^{residual} \quad (A1)$$

The trend model is a polynomial model, here of order 3:

$$\hat{y}_i^{trend} = a_0 + a_1 \cdot i + a_2 \cdot i^2 + a_3 \cdot i^3 \quad (A2)$$

and the yearly periodic model for monthly data is

$$\hat{y}_i^{periodic} = a_4 \cdot \sin\left(\frac{i \cdot \pi}{6}\right) + a_5 \cdot \cos\left(\frac{i \cdot \pi}{6}\right) + a_6 \cdot \sin\left(2 \cdot \frac{i \cdot \pi}{6}\right) + a_7 \cdot \cos\left(2 \cdot \frac{i \cdot \pi}{6}\right) \quad (A3)$$

First, the parameters of the trend model are estimated by ordinary least squares minimization over all n data points:

$$\min_{a_0, a_1, a_2, a_3} \sum_{i=0}^{n-1} \left(y_i - (a_0 + a_1 i + a_2 i^2 + a_3 i^3) \right)^2$$

The difference between the original data and the polynomially approximated data are the detrended data

$$y_i^{detrend} = y_i - \hat{y}_i^{trend} \quad (A4)$$

They are displayed as the blue graph in Figure A1. The detrended data are modeled with the periodic model by an ordinary least squares minimization:

$$\min_{a_4, a_5, a_6, a_7} \sum_{i=0}^{n-1} (y_i^{detrend} - \hat{y}_i^{periodic})^2$$

These optimization problems are solved with the class OLS from Python Statsmodels [19].

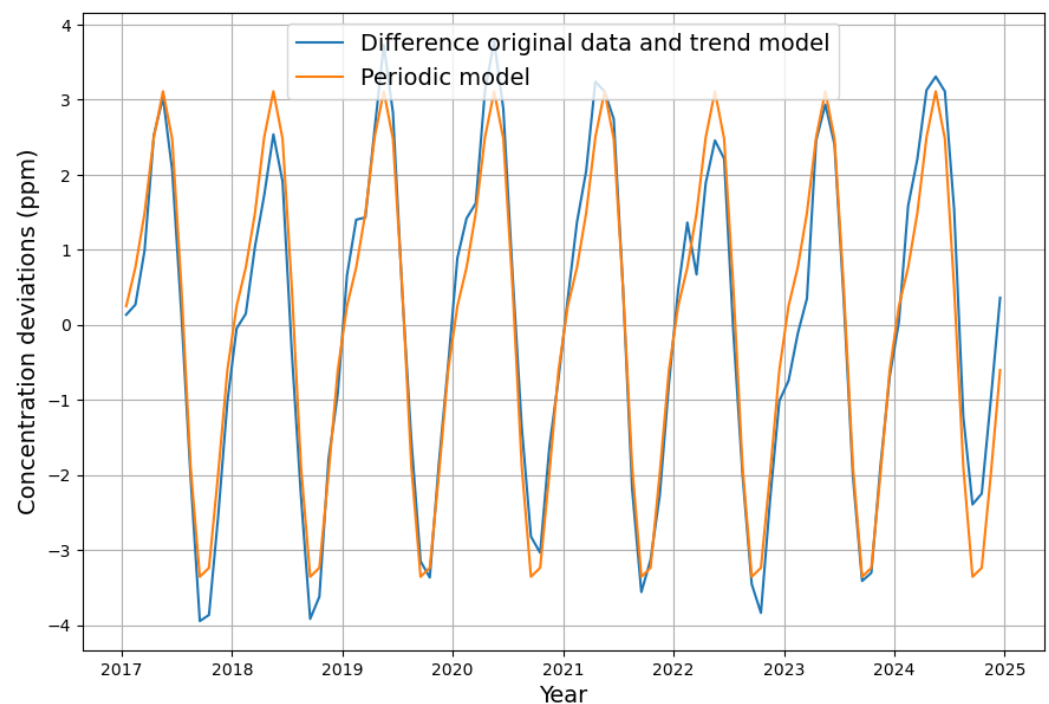


Figure A1. Difference of CO₂ concentration data and polynomial trend model (blue); periodic model of this difference (orange).

The orange graph of Figure A1 shows the approximation of the detrended and zero mean data by the periodic model of sine- and cosine-functions up to degree 2.

The goal of the process, the deseasonalized data, are the difference of the original data and the periodic model. Figure A2 shows the original CO₂ concentration data, the trend model, the sum of trend model and periodic model, and the deseasonalized CO₂ concentration data.

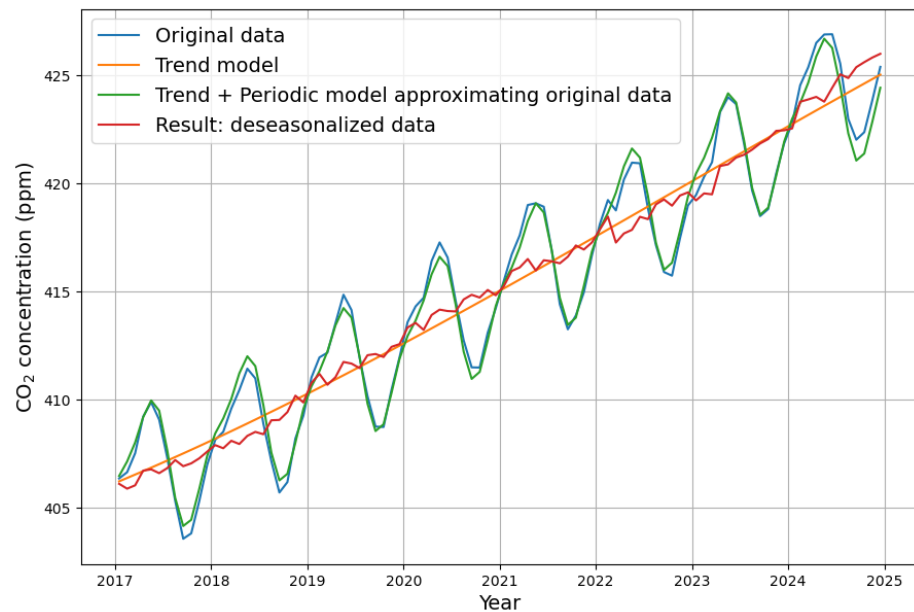


Figure A2. Deseasonalization process: original data (blue), trend model (orange), trend model + periodic model (green), resulting deseasonalized data (red).

Appendix B. Deseasonalization of Concentration Growth

The continuity equation according to Equation (1) includes concentration growth

$$G_i = C_i - C_{i-1}$$

This makes deseasonalization particularly simple, when the time unit i is a month. Instead of taking the difference of immediate neighbors, the difference to the data from exactly 1 year before is taken, and the result is scaled:

$$G_i = \frac{C_i - C_{i-12}}{12}$$

When applied on the last 8 years of the Mauna Loa data set, the result looks like this.

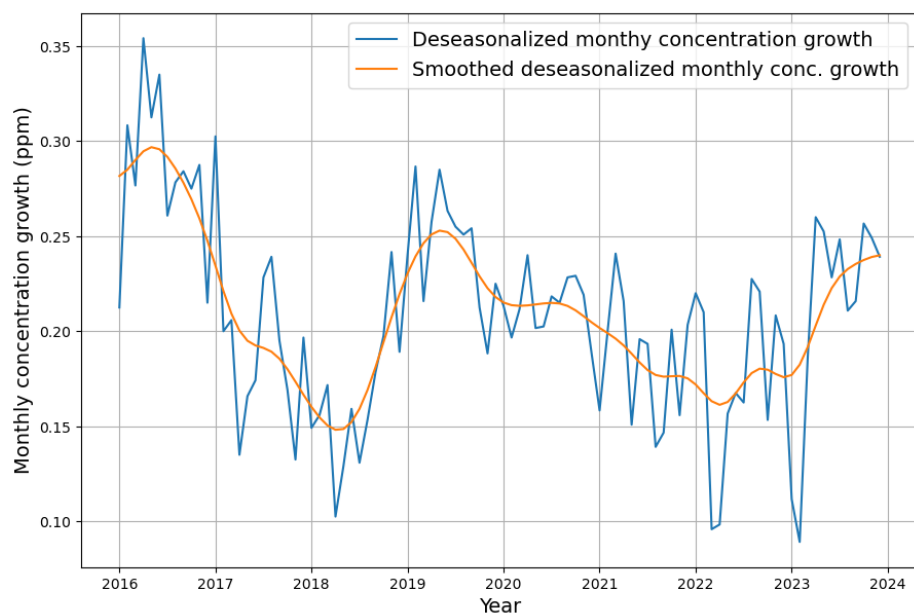


Figure A3. Deseasonalized growth of CO₂ concentration between 2016 and 2024.

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