Theoretical and Applied Climatology (2021) 146:713–721
https://doi.org/10.1007/s00704-021-03764-0

ORIGINAL PAPER

Anthropogenic climate change: the impact of the global carbon budget

Margarete Redlin[1] · Thomas Gries[1]

Received: 19 September 2019 / Accepted: 20 August 2021 / Published online: 31 August 2021

Abstract
Using time series data for the period 1959–2015, our empirical analysis examines the simultaneous effects of the individual components of the global carbon budget on temperature. Specifically, we explore the possible effects of carbon emissions caused by fossil fuel combustion, cement production, land-use change emissions, and carbon sinks (here in terms of land sink and ocean sink) on climate change. The simultaneous inclusion of carbon emissions and carbon sinks allows us to look at the coexistent and opposing effects of the individual components of the carbon budget and thus provides a holistic perspective from which to explore the relationship between the global carbon budget and global warming. The results reveal a significant positive effect of carbon emissions on temperature for both fossil fuels emissions and emissions from land-use change, confirming previous results concerning carbon dioxide and temperature. Further, while ocean sink does not seem to have a significant effect, we identify a temperature-decreasing effect for land sink.

1 Introduction

Climate change is one of the biggest challenges humanity currently faces. The planet is heating up, with both land and oceans getting warmer. A recent report of the Intergovernmental Panel on Climate Change (IPCC) records global warming of 1.5 °C above pre-industrial levels (IPCC 2018). It is well known that human influence in the shape of greenhouse gas emissions plays an important role in natural greenhouse warming. However, the extent to which the increasing greenhouse gas concentration may enhance the increase in the planet's surface temperature has been a controversial scientific and political issue in recent years.

Human activities increase atmospheric carbon dioxide levels primarily through the burning of coal, oil, or natural gas in industry, heating, electrical power generation, and cement production. Further, land use and land-use change impact the global carbon budget through deforestation and land clearing (IPCC 2000). Deforestation and the slow warming of the oceans, in turn, impact the capacity to absorb carbon dioxide and decrease the land and sea carbon sink. The natural carbon sinks are not able to bind or convert all the carbon dioxide that is additionally released into the atmosphere. As a result, the carbon dioxide concentration in the atmosphere increases. The IPCC (2018) reports a 45% increase in carbon dioxide concentration over pre-industrial levels. This increasing carbon dioxide concentration absorbs the infrared radiation emitted by the planet's surface and traps the solar heat radiating from Earth toward space. As a consequence, the Earth's climate heats up, melting both polar ice caps as well as mountain glaciers, which raises the oceans' water level and increases sea and river temperatures. Climate change is also likely to promote extreme weather phenomena such as extreme summers and colder-than-normal winters, along with heatwaves, drought, hurricanes, blizzards, and rainstorms.

Consequently, anthropogenic forcing has become a central topic in environmental science. The effect of carbon dioxide levels on the climate has been studied for decades using various methodological approaches. The human impact on climate has been primarily analyzed using climate models, with considerable efforts made to develop process-based carbon cycle models including emissions, sinks, and climate feedbacks to gain a better understanding of the global carbon budget and its effect on the climate both

✉ Margarete Redlin
margarete.redlin@notes.upb.de

Thomas Gries
thomas.gries@notes.upb.de

[1] University of Paderborn, Warburger Str. 100, 33098 Paderborn, Germany

at regional and global scale.[1] These models are also used to simulate and quantify the climate's response to human activities and other external forces. However, the downside is that these models are very complex and not fully able to display the aggregate climate and carbon cycle with all its processes, interactions, and feedbacks. Therefore, model errors can affect the validity of model projections.

Hence, a more data-driven literature strand has applied econometric techniques to examine causality patterns between radiative forcing and climate. Using standard Granger causality methods and time series analysis typically applied in empirical macroeconomics, the researchers examine the causal effect of anthropogenic activities on changes in temperature. Kaufmann and Stern (1997), Sun and Wang (1996), and Tol and de Vos (1993, 1998) provide evidence that radiative forcing has played a role in historical temperature records. However, this strand of research has been criticized. For instance, Triacca (2001) argues that the indirect approach applied by Kaufmann and Stern (1997) allows also for other conclusions. More importantly, Triacca (2005) shows that standard Granger causality methods are not appropriate for the non-stationary nature of the data. Therefore, more recent studies test for a direct relationship between individual forcing and temperature, overcoming the methodological weakness by applying the causality method suggested by Toda and Yamamoto (1995). This method allows for causality testing between variables irrespective of their stationarity and cointegration patterns (Kodra et al. 2011; Attanasio 2012; Attanasio et al. 2013; Triacca et al. 2013; Stern and Kaufmann 2014).

That being said, these studies are limited in their validity because of their bivariate focus. With the exception of Triacca et al. (2013) and Stern and Kaufmann (2014), who extend their examinations to a trivariate setting controlling for other relevant determinants of changes in global temperature, these studies test for a causal relationship between emissions and temperature without considering the complexity of the global carbon budget and controlling for other relevant elements.

When investigating the effect of carbon dioxide on the climate, it is necessary to consider the global carbon cycle as a complex system including trends in anthropogenic emissions; their redistribution among the atmosphere, ocean, and terrestrial biosphere; and the response of natural sinks. The Global Carbon Project (GCP) provides estimates that quantify these individual components of the global carbon cycle in their global carbon budget report (GCP 2018). It quantifies the growth rate of atmospheric carbon dioxide concentration as the difference between the input and uptake of carbon dioxide. The input into the atmosphere is measured by emissions from fossil fuel combustion, oxidation, and cement production and emissions resulting from deliberate human activities on land, including those leading to land-use change. The uptake of carbon dioxide is estimated as ocean sink and land sink and the response of the storage capacities of land and ocean to climate and other anthropogenic and natural changes (GCP 2018).

The Global Carbon Project (2018) reports emission estimates of 9.4 GtC y^{-1} (gigatons of carbon per year) for emissions from fossil fuels and 1.3 GtC y^{-1} for emissions from land-use change for the period between 2007 and 2017. At the same time, the uptake in this period is estimated as 2.4 GtC yr^{-1} of carbon dioxide uptake in the ocean and 3.0 GtC y^{-1} carbon dioxide uptake on land. The estimates indicate that more than a half of the emitted carbon has been taken up, with less than half remaining in the atmosphere and potentially impacting the climate. Thus, global warming depends on both anthropogenic carbon dioxide emissions and natural carbon dioxide sinks. Since the individual emissions and sinks show different trends, a consideration of selected emissions on temperature or an accumulation of emissions and sinks – as is mostly conducted in empirical carbon dioxide-temperature research – can limit the significance of results. Therefore, we expand the current econometric literature on this topic by examining the simultaneous effect of all individual components of the complex global carbon budget on temperature.

Assuming that all past carbon emissions and sinks may potentially lead to permanent atmospheric change, we analyze the effect of cumulated values of emissions for fossil fuel burning and land-use change as well as natural land and ocean sinks on various temperature series for the period 1959–2015.

The paper is structured as follows. The next chapter presents the econometric framework including the data and the trends of the individual series, the model, and the methodology. Chapter 3 shows the estimation results, and Chapter 4 concludes.

2 Econometric framework

The econometric framework aims at exploring whether the individual elements of the global carbon budget – carbon dioxide emissions from fossil fuel and industry, and land-use change, as well as the ocean and terrestrial carbon dioxide sinks – have an impact on temperature.

2.1 Data

Our empirical analysis examines the effect of the components of the global carbon budget on temperature using

[1] See Randall et al. (2007) and Piao et al. (2013) for an overview and the evolution of carbon cycle models.

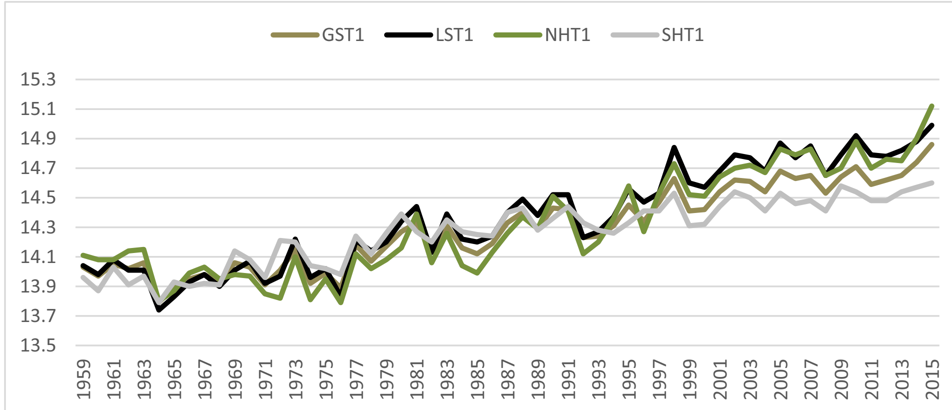

Fig. 1 NASA GISS temperatures 1959–2015 (in °C). Source: NASA Goddard Institute for Space Studies

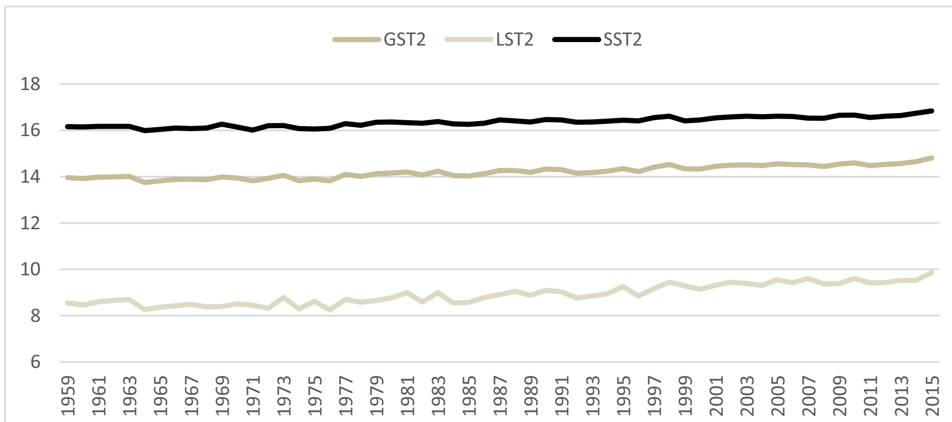

Fig. 2 NCDC NOAA temperatures 1959–2015 (in °C). Source: National Climatic Data Center of NOAA

time series analysis for the period 1959–2015. To verify result robustness, we use alternative temperature measures and data sources as dependent variables while distinguishing between northern and southern hemisphere, land and sea surface, and global surface temperature anomalies. The global carbon budget is represented by net carbon flux from fossil fuel combustion and cement production and land-use change as well as ocean and land sink.

2.1.1 Temperature

We use temperature values measured in degrees Celsius expressed as anomalies from the average of the base years from three different sources. This serves as a sensitivity analysis and safeguards against inaccuracies in the data and biased results.

First, we use annual global surface (gst1), northern hemisphere (nht1), southern hemisphere (sht1), and global land surface temperature (lst2) for the reference period 1951–1980 from the NASA Goddard Institute for Space Studies (GISS) in the USA.

Second, we use global surface temperature (gst2) and its components – global land surface temperature (lst2) and sea surface temperature (sst2) – derived from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA) in the USA. The reference period for these anomalies is 1902–2000.

Finally, we use annual global surface (gst3), northern hemisphere (nht3), and southern hemisphere (sht3) temperatures derived from the Carbon Dioxide Information Analysis Center (CDIAC) and developed by the Climatic Research Unit of the University of East Anglia, UK, in conjunction with the UK Met Office's Hadley Centre for Climate Prediction. The anomalies are computed relatively to the reference period 1961–1990.

All temperature records are presented in Figs. 1, 2 and 3. Although all series refer to different long-term averages and display rhythmic annual variations, they vary in close concert to each other and show an overall increase over the observation period.

2.1.2 The global carbon budget

With reference to the global carbon budget report (GCP 2018), the global carbon model is defined as:

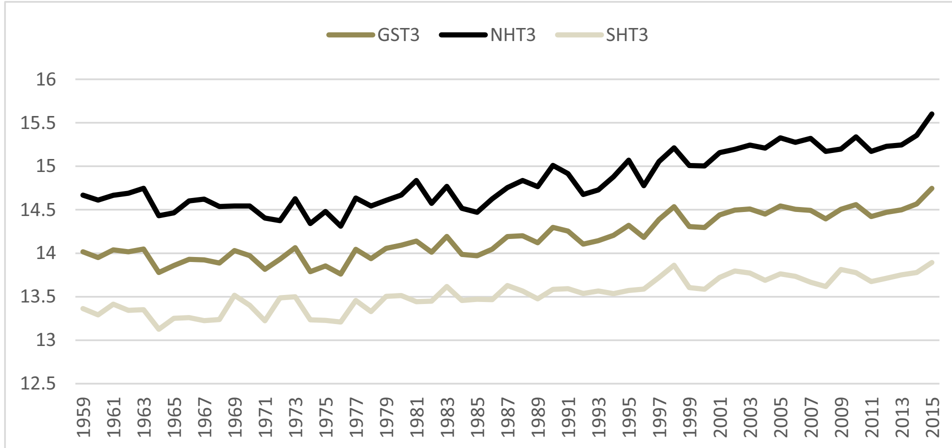

Fig. 3 CDIAC temperatures 1959–2015 (in °C). Source: Carbon Dioxide Information Analysis Center

$$\text{EFF} + \text{ELUC} = \text{GATM} + \text{SOCEAN} + \text{SLAND} + \text{BIM}$$

where EFF is carbon dioxide emissions from fossil fuel and industry, ELUC represents emissions from land-use change, GATM is the growth rate of global atmospheric carbon dioxide concentration, SOCEAN and SLAND represent the ocean and terrestrial carbon dioxide sinks, and BIM is a mismatch measure. CDIAC provides separate estimates for the individual components for the period 1959–2017.[2]

Carbon dioxide emissions from fossil fuel include the combustion of fossil fuels through a wide range of anthropogenic activities (e.g., transport, heating and cooling, industry, fossil industry's own use, and gas flaring), cement production, and other process emissions (e.g., chemical and fertilizer production) (GCP 2018). The estimates rely primarily on historical energy consumption data (Boden et al. 2017).

Net carbon emissions from land use, land-use change, and forestry include carbon flux from deforestation, afforestation, logging, and forest degradation, shifting cultivation and forest regrowth following timber harvest or abandonment of arable land. While some of these activities lead to carbon emissions, others lead to sinks; therefore, the estimates represent the net sum of the anthropogenic emissions and the uptake caused by land-use change (GCP 2018). The estimates rely on two bookkeeping models of Houghton and Nassikas (2017) and Hansis et al. (2015).

The ocean sink includes the carbon dioxide uptake in the ocean including coasts and territorial seas. It is estimated from the average of several global ocean biogeochemistry models that reproduce the observed mean ocean sink of the 1990s (GCP 2018).

The terrestrial sink accounts for the uptake of carbon dioxide on land including inland waters and estuaries. It comprises the combined effects of fertilization as well as the effects of climate change. The estimates do not include land sink resulting directly from land-use change, since this is already captured in the net emissions from land-use change. Land sink is estimated as the multi-model mean from several dynamic global vegetation models that reproduce the observed mean total land uptake in the 1990s (GCP 2018). Figure 4 presents the development for the elements of the global carbon budget for the period 1959–2015.

Overall, for this period, the global carbon budget is positive, with more carbon released than absorbed, resulting in an atmospheric growth in carbon dioxide concentration. The total emissions were caused mainly by fossil carbon dioxide emissions and only to a small extent by land-use change. All components except land-use change emissions have grown since 1959. However, while fossil fuel emissions and ocean sink show a smooth increase with some decadal variability, land sink shows a pronounced inter-annual cyclic variation.

2.2 Estimation model

Since in our empirical analysis we want to examine whether past carbon dioxide emissions and sinks affect the present temperature, the starting point for our investigation is the concept of Granger non-causality (Granger 1969) based on the model:

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + u_t,$$

where a variable x is said to Granger cause a variable y if it can be shown that past values of x provide statistically

[2] The method used to estimate the global carbon budget differs from the estimation of historical fluxes. For example, the historical estimates of atmospheric growth and ocean sink do not account for year-on-year variability (GCP 2018). Hence, although the usage of the global carbon budget estimates limits the time period in comparison to historical estimates, we rely on the more differentiated and qualitatively better estimates of the global carbon budget.

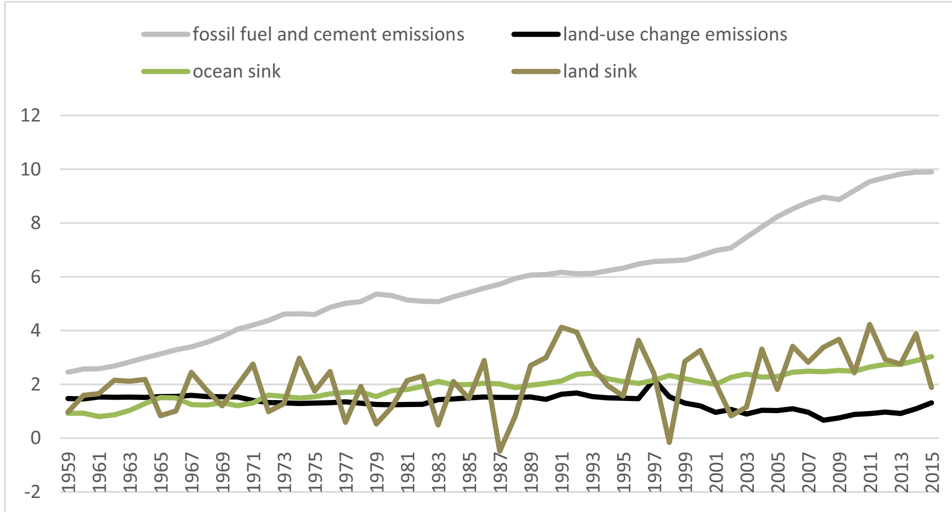

Fig. 4 Carbon dioxide emissions 1959–2015 (in 10^{15} g). Source: Carbon Dioxide Information Analysis Center

significant information on values of y taking into consideration also past values of y. In other words, if the prediction using past terms of x and y is better than the prediction using only past terms of y, then the past of x contains a useful information for forecasting y that is not in the past of y. The application of this concept based on our variable selection for carbon emission and sink leads to the following model:

$$temp_t = \mu + \sum_{i=1}^{p} \alpha_i temp_{t-i} + \sum_{i=1}^{p} \beta_{1,i} ff_{t-i} + \sum_{i=1}^{p} \beta_{2,i} luc_{t-i} + \sum_{i=1}^{p} \beta_{2,i} os_{t-i} + \sum_{i=1}^{p} \beta_{k,i} ls_{t-i} + u_t,$$

where t refers to the time period, $temp_t$ represents the temperature series, ff_t is carbon dioxide emissions from fossil fuel and industry, luc_t represents emissions from land-use change, os_t and ls_t represent the ocean and terrestrial carbon dioxide sinks, and p is the optimal lag length.[3]

To model the variable in a manner that captures the inherent characteristics of its time series, we use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to determine the optimal lag structure of the series. The information criteria point at a long lag length, which is plausible given the theoretical reasoning that a possible effect on temperature is not an immediate effect of current or recent emissions and sinks, but rather a long-run effect of cumulated values. Table 1 shows the development of the information criteria of a VAR model where global surface temperature is regressed on carbon emissions from fossil fuel and land-use change and land and ocean sink.

As we can see, the highest number of lags shows the best AIC and BIC results. Including more than nine lags is not possible since some of the lags are omitted because of collinearity problems. Thus, it is not possible to test for a higher number, even though these lags may be very helpful in explaining the variations in temperature. Further, an increasing number of lags lead to a decrease in observations and thus also in a decrease in the degrees of freedom, raising concern over how meaningful the results would be. Since carbon emissions and sinks lead to permanent atmospheric change, all past values may potentially impact current temperatures. Therefore, we exploit all available information using all lags to explain temperature anomalies by including

Table 1 AIC and BIC for the VAR model

Lags	AIC	BIC
1	−85.144	−72.992
2	−73.524	−51.443
3	−76.576	−44.753
4	−78.655	−37.279
5	−80.986	−30.254
6	−77.425	−17.538
7	−74.277	−5.444
8	−71.735	5.830
9	−194.663	−108.588

[3] The application of Granger causality assumes that the analyzed time series are stationary. We verify whether the time series under investigation contain a unit root using the Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests. The results are presented in Table 3 in the Appendix and indicate that most of the series are already stationary in levels, and some are difference stationary. Since not all variables have the same integration order, the application of the Granger non-causality methodology could lead to spurious regression problems. A convenient way of overcoming this difficulty has been suggested by Toda and Yamamoto (1995), why propose a more extensive inclusion of lags adding the maximum order of integration to the optimal lag length $$p$$. Since in our specification all lags are added up to one cumulative value, this assumption can be disregarded.

the cumulated values of carbon emissions and carbon sinks as explanatory variables, resulting in the equation:

$$temp_t = \mu + \alpha temp_{t-1} + \beta_1 \sum_{i=1}^{t} ff_i + \beta_2 \sum_{i=1}^{t} luc_i + \beta_3 \sum_{i=1}^{t} os_i + \beta_4 \sum_{i=1}^{t} ls_i + u_t$$

3 Results

Table 2 present the results for cumulative values of emissions from fossil fuel combustion and cement production, carbon emissions from land-use change, ocean sink, and land sink on temperature.[4]

First, when looking at the global fit of the regressions, all specifications show high values for the adjusted coefficients of determination with small differences in the global fit, depending on the temperature series and data source used. The explanatory variables explain up to 92 (for the gst1 temperature series) or to 79% (for the sht3 temperature series) of the variance in temperature. The results for the emission coefficients depend upon the underlying temperature series. For the temperature series provided by NASA GISS and NCDC NOAA, we can identify the expected positive effects. Specifically, we find significant results for the global temperature series provided by NASA GISS and NCDC NOAA, the land and southern hemisphere temperatures provided by NASA GISS, as well as the sea surface temperature for both variables – emissions from fossil fuel and from land-use change. The results indicate that a higher accumulation of emissions increases the underlying temperature. For example, the significant fossil fuel coefficient in specification (1) can be explained in the following way: an increase in emissions from fossil fuel combustion and cement production of 9.9 billion tons of carbon per year (GtC/y) (value for 2015) increases the global surface temperature (gst1) by 0.198 °C, holding all other explanatory variables constant. In general, the coefficients of the emissions from land-use change are higher in their magnitude; however, the pure size effect on temperature is relativized by the fact that the size of this emission variable is much smaller. If we again use the value of 2015 as an example, the coefficient can be interpreted as follows: the 2015 emissions from land-use change of 1.32 billion tons of carbon per year (GtC/yr) result in a temperature increase of 0.033°C, holding all other explanatory variables constant. The magnitude of the effects also differs with respect to the underlying temperature; while the effects are highest for the southern hemisphere temperature (sht1), sea surface temperature (sst2) has the smallest effects. We identify the clearest effect for land sink. The coefficients are negative and highly significant over all data sources and all temperature series. The effect size ranges from − 0.024 for sea surface temperature (sst2) to − 0.058 for land surface temperature (lst2). Again taking the value of 2015, which represents a sink of 1.88 billion tons of carbon per year (GtC/yr), the land sink results in a temperature decrease of 0.045 °C for sea surface temperature (sst2) and 0.109 °C for land surface temperature (lst2), holding all other explanatory variables constant. This result underlines the importance of land sink in absorbing carbon dioxide from the atmosphere and counteracting global warming. Thus, increasing land sink capacity by restoring forests may be a powerful weapon in the fight against climate change. Finally, we cannot identify an effect of ocean sink on temperature. The coefficients are insignificant throughout all but one specification.

4 Conclusion

By employing causality methods based on the Toda Yamamoto procedure, this paper examines the causal effects of carbon emissions and carbon sinks on temperature. The simultaneous implementation of emissions from fossil fuel burning, emissions from land-use change, ocean sink, and land sink enables us to perform an individual and integrated analysis of possible effects of the global carbon budget components on climate change and allows us to identify potential opposing effects of emissions and sinks. Through its holistic approach, the paper provides a significant additional contribution to existing literature on this topic and helps to explore the role of the global carbon budget in mitigating climate change.

The study reveals that carbon dioxide emissions have an important impact on the global climate. In line with current causality literature, we identify a link between carbon dioxide radiative forcing and global temperature, an effect of carbon emissions from fossil fuel on temperature, and of carbon flux from land-use change on temperature. Hence, burning coal, oil, and gas and deforestation all contribute to global warming. The dimensions of the coefficients for fossil fuel and land-use change emissions are very similar. However, given the greater magnitude of fossil fuel emissions, the latter source plays a predominant role.

Further, an important contribution of this empirical study is the negative impact of land sink on temperature. While most analyses focus explicitly on the relationship between carbon dioxide emissions and temperature, this result suggests that carbon dioxide sinks may also have a significant impact in the relationship between carbon dioxide and the

[4] The optimal lag length p for the lagged dependent variable is determined in the standard way using the Akaike and the Bayesian information criterion, where one lag shows to be optimal.

Table 2 Effects of the global carbon budget components on temperature

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	NASA GISS				NCDC NOAA			CDIAC		
	gst1	*lst1*	*nht1*	*sht1*	*gst2*	*lst2*	*sst2*	*gst3*	*nht3*	*sht3*
ff	0.020^{***} (0.007)	0.025^{**} (0.009)	0.007 (0.011)	0.036^{***} (0.008)	0.016^{**} (0.007)	0.016 (0.014)	0.014^{**} (0.007)	0.002 (0.008)	−0.003 (0.011)	0.008 (0.008)
luc	0.025^{***} (0.009)	0.034^{***} (0.012)	−0.003 (0.014)	0.059^{***} (0.010)	0.018^{*} (0.009)	0.013 (0.017)	0.017^{**} (0.008)	−0.002 (0.011)	−0.015 (0.015)	0.015 (0.011)
os	−0.028 (0.024)	−0.036 (0.031)	0.036 (0.038)	-0.106^{***} (0.025)	−0.017 (0.024)	0.018 (0.046)	−0.023 (0.021)	0.034 (0.029)	0.062 (0.039)	−0.004 (0.028)
ls	-0.040^{***} (0.008)	-0.049^{***} (0.010)	-0.043^{***} (0.012)	-0.034^{***} (0.008)	-0.034^{***} (0.008)	-0.058^{***} (0.014)	-0.024^{***} (0.007)	-0.030^{***} (0.009)	-0.034^{***} (0.011)	-0.024^{***} (0.009)
$temp_{t\text{-}i}$	−0.083 (0.124)	−0.040 (0.120)	0.069 (0.128)	−0.138 (0.129)	−0.009 (0.133)	−0.156 (0.126)	0.106 (0.142)	0.042 (0.132)	0.149 (0.129)	0.149 (0.129)
μ	15.121^{***} (1.731)	14.489^{***} (1.673)	13.142^{***} (1.801)	15.727^{***} (1.783)	14.035^{***} (1.849)	9.862^{***} (1.082)	14.400^{***} (2.292)	13.418^{***} (1.844)	12.537^{***} (1.906)	13.234^{***} (1.845)
N	56	56	56	56	56	56	56	56	56	56
adj. R^2	0.920	0.919	0.887	0.891	0.913	0.886	0.895	0.876	0.872	0.791
AIC	−121.864	−95.230	−74.951	−129.417	−121.313	−51.152	−137.580	−107.089	−76.344	−107.644
BIC	−109.712	−83.078	−62.799	−117.265	−109.161	−39.000	−125.427	−94.937	−64.192	−95.492

***, **, * Significance level of 1%, 5%, and 10%, respectively. The variables ff and luc represent net carbon flux from fossil fuel and land-use change; os and ls represent ocean sink and land sink from GCP (2018); gst1, lst1, nht1, and sht1 represent global surface, land surface, northern hemisphere, and southern hemisphere temperatures from the NASA GISS datasets; gst2, lst2, and sst2 represent the global surface, land surface, and sea surface temperatures from the NCDC NOAA dataset; and gst3, nht3, and sht3 represent global surface, northern hemisphere, and southern hemisphere temperatures from the CDIAC dataset climate. The growing storage capacity of land as a carbon sink affects temperatures and attenuates the global carbon effect on temperature.

Appendix

Table 3 Results of the unit root tests

Variable	Augmented Dickey-Fuller		Phillips-Perron	
	Levels	First diff	Levels	First diff
ff	−1.588	−5.683***	−1.235	−4.672***
luc	−2.372	−3.910**	−2.768	−8.790***
os	−3.389*	−8.664***	−3.120*	−6.272***
ls	−6.774***	−5.320***	−6.750***	−14.456***
gst1	−3.286*	−3.495**	−5.806***	−12.958***
lst1	−3.193*	−3.388*	−5.965***	−13.374***
nht1	−3.860**	−4.460***	−4.432***	−12.837***
sht1	−2.804	−4.843***	−5.839***	−13.563***
gst2	−5.098	−4.075**	−5.087***	−11.866***
lst2	−3.118	−3.606**	−6.356***	−17.619***
sst2	−4.101**	−5.793***	−4.698***	−9.470***
gst3	−3.976**	−4.198***	−4.803***	−12.612***
nht3	−2.641	−6.546***	−3.895**	−12.668***
sht3	−4.860***	−4.544***	−6.124***	−12.230***

***, **, * Significance level of 1%, 5%, and 10%, respectively. The variables ff and luc represent net carbon flux from fossil fuel and land-use change; os and ls represent ocean sink and land sink from GCP (2018); gst1, lst1, nht1, and sht1 represent global surface, land surface, northern hemisphere, and southern hemisphere temperatures from the NASA GISS datasets; gst2, lst2, and sst2 represent the global surface, land surface, and sea surface temperatures from the NCDC NOAA dataset; gst3, nht3, and sht3 represent global surface, northern hemisphere, and southern hemisphere temperatures from the CDIAC dataset. The Hannan Quinn criterion is applied to specify the lag length for the ADF test; the unit root tests are based on random walk with drift around a stochastic trend

Author contribution Both authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Margarete Redlin. The first draft of the manuscript was written by Margarete Redlin, and Thomas Gries commented on previous versions of the manuscript. Both authors read and approved the final manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability The datasets analyzed during the current study can all be obtained from publicly accessible archives.

Code availability The code generated during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval The authors paid attention to the ethical rules in the study. There is no violation of ethics.

Consent to participate This research did not involve human subjects.

Consent for publication This research did not involve personal information for which consent was to be sought.

Conflict of interest/Competing interests. The authors declare no competing interests.

References

Attanasio A (2012) Testing for linear Granger causality from natural/anthropogenic forcings to global temperature anomalies. Theoret Appl Climatol 110:281–289

Attanasio A, Pasini A, Triacca U (2013) Granger causality analyses for climatic attribution. Atmospheric and Climate Sciences 3:515–522

Boden TA, Marland G, Andres, RJ (2017) Global, regional, and national fossil-fuel CO2 emissions, oak ridge national laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A

Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74:427–431

Global Carbon Project (2018) Global carbon budget 2018. Earth System Science Data Discussions. https://doi.org/10.5194/essd-10-2141-2018. pp. 1-54, by Le Quéré C, Andrew RM, Friedlingstein P, et al.

Granger CWJ (1969) Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37:424–438

Hansis E, Davis SJ, Pongratz J (2015) Relevance of methodological choices for accounting of land use change carbon fluxes. Global Biogeochem Cycles 29:1230–1246

Houghton RA, Nassikas AA (2017) Global and regional fluxes of carbon from land use and land cover change 1850–2015. Global Biogeochem Cycles 31:456–472

IPCC (2000) Land use, land-use change, and forestry – summary for policymakers. IPCC Special Reports, [Watson, R.T.; Noble, I.R.; Bolin, B.; Ravindranath, N.H.; Verardo, D.J.; Dokken, D.J. (eds.)], Cambridge University Press, UK 6–22

IPCC (2018) Summary for policymakers. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R.

Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, Maycock, M. Tignor, and T. Waterfield (eds.)]. World Meteorological Organization, Geneva, Switzerland, 32 pp.
Kaufmann RK, Stern DI (1997) Evidence for human influence on climate from hemispheric temperature relations. Nature 338:39–44
Kodra E, Chatterjee S, Ganguly AR (2011) Exploring Granger causality between global average observed time series of carbon dioxide and temperature. Theoret Appl Climatol 104:325–335
NOAA – National Oceanic and Atmospheric Administration (2017) Global surface temperature anomalies. National Climatic Data Center, accessed 22 Dec 2017. <https://www.ncdc.noaa.gov/monitoring-references/faq/anomalies.php>
Phillips PCB, Perron P (1988) Testing for a unit root in time series regression. Biometrika 75:335–346
Stern DI, Kaufmann RK (2014) Anthropogenic and natural causes of climate change. Clim Change 122:257–269
Piao S, Sitch S, Ciais P, Friedlingstein P, Peylin P, Wang X, Ahlström A, Anav A, Canadell JG, Cong N, Huntingford C, Jung M, Levis S, Levy PE, Li J, Lin X, Lomas MR, Lu M, Luo Y, Ma Y, Myneni RB, Poulter B, Sun Z, Wang T, Viovy N, Zaehle S, Zeng N (2013) Evaluation of terrestrial carbon cycle models for their response to climate variability and to CO2 trends. Glob Change Biol 19:2117–2132
Randall DA., Wood RA, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J, Stouffer RJ, Sumi A, Taylor KE (2007) Climate models and their evaluation. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon S, Qin D, Manning M, Chen Z, Marquis M., Averyt KB, Tignor M, Miller HL (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
Sun L, Wang M (1996) Global warming and global dioxide emission: an empirical study. J Environ Manage 46:327–343
Toda HY, Yamamoto T (1995) Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics 66:225–250
Tol RSJ, de Vos AF (1993) Greenhouse statistics – time series analysis. Theoret Appl Climatol 48:63–74
Tol RSJ, de Vos AF (1998) A Bayesian statistical analysis of the enhanced greenhouse effect. Clim Change 38:87–112
Triacca U (2001) On the use of Granger causality to investigate the human influence on climate. Theoret Appl Climatol 69:137–138
Triacca U (2005) Is Granger causality analysis appropriate to investigate the relationship between atmospheric concentration of carbon dioxide and global surface air temperature? Theoret Appl Climatol 81:133–135
Triacca U, Attanasio A, Pasini A (2013) Anthropogenic global warming hypothesis: testing its robustness by Granger causality analysis. Environmetrics 24:260–268