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Global Temperature and Carbon Dioxide Nexus: Evidence from a Maximum Entropy Approach

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Abstract: The connection between Earth's global temperature and carbon dioxide (CO_2) emissions is one of the highest challenges in climate change science since there is some controversy about the real impact of CO_2 emissions on the increase of global temperature. This work contributes to the existing literature by analyzing the relationship between CO_2 emissions and the Earth's global temperature for 61 years, providing a recent review of the emerging literature as well. Through a statistical approach based on maximum entropy, this study supports the results of other techniques that identify a positive impact of CO_2 in the increase of the Earth's global temperature. Given the well-known difficulties in the measurement of global temperature and CO_2 emissions with high precision, this statistical approach is particularly appealing around climate change science, as it allows the replication of the original time series with the subsequent construction of confidence intervals for the model parameters. To prevent future risks, besides the present urgent decrease of greenhouse gas emissions, it is necessary to stop using the planet and nature as if resources were infinite.

Keywords: global temperature; carbon dioxide (CO_2) emissions; maximum entropy; climate change

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1. Introduction

Global warming is still widely debated due to divergent opinions. Some believe that it results from human actions, others look at it as a natural cause, while some even see it as a non-relevant problem, thinking it does not exist at all [1–3]. Many theories have emerged around the inexistent consensus. One of the claims is that global warming exists due to the sun's effects. Another claim attributes global warming to human action, which rises greenhouse gases (GHGs) like carbon dioxide [1,4,5]. Others ignore global warming and pretend that the problem does not exist at all. As evidenced by Letcher [6], the root cause of our present changing climate is the build-up of greenhouse gases, the most important of these gases being carbon dioxide, mainly caused by the burning of fossil fuels [7].

The quick economic expansion of some economies has been done at the expense of more environmental pollution, but greenhouse gas effects are only reflected in the long run [8]. This is because a substantial amount of CO_2 emissions enters the atmosphere, remaining there for centuries, and its effects on climate change are only reflected over decades or even millennia [9–13]. If that point is reached, we cannot reverse it thereafter by just stopping emissions, and these effects should be valued today by decision-makers. Although other GHGs like CH_4 and N_2O (methane, nitrous oxides) have a stronger ability to absorb the radiation, their contribution to global warming is insignificant, since they have a lower concentration in the atmosphere as compared with CO_2. The scientific community claims that, on the one hand, CO_2 doubling in the atmosphere will increase the average surface temperature of the Earth by +3.8 °C, while on the other hand, its halving will decrease the global temperature by −3.6 °C [4]. These pointed amounts depend, as well, on the change in the humidity of the air, which in turn depends on the air's temperature.

Thus, exploring the contribution of CO_2 emissions, maybe the strongest greenhouse gas, to global warming and temperature is needed to develop cost-effective interventions. Limiting this warming is essential. The latest carbon dioxide emissions reported affirm the belief that the global warming compliance goal of "below 1.5 °C or 2 °C" will be achieved shortly [14,15]. With the Paris Agreement in December 2015, the debate on whether limiting warming to 1.5 °C is compatible with the current emissions level was opened. The Paris Agreement participants agreed to restrict the global average temperature increase to less than 2 °C and to limit global warming to 1.5 °C, and the latter was found by Millar et al. [16] to not be a geophysical impossibility. The Intergovernmental Panel on Climate Change (IPCC) scenarios (to produce negative emissions) highlight pathways to reduced climate change impacts [17,18]. Indeed, "Holding the increase in the global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change" (e.g., United Nations [19], p. Art 2.1 (a)).

Still, it should be noted that the global warming goal of 1.5 °C asserts that carbon dioxide emissions due to human activity must reach "net zero" by 2050 to ensure the average rise in global temperature at 1.5 °C above preindustrial levels. This has to be achieved to reduce the catastrophic climate change risk over populations and the Earth. The IPCC report highlights that "temperature extremes on land are projected to warm more than the global mean surface temperature (high confidence); extreme hot days in mid-latitudes warm by up to about 5 °C at global warming of 1.5 °C and about 4 °C at 2 °C, and extremely cold nights in high latitudes warm by up to about 4.5 °C at 1.5 °C and about 6 °C at 2 °C (high confidence). The number of hot days is projected to increase in most land regions, with the highest increases in the tropics (high confidence)" [17]. Thus, the adoption of the mitigation and adaptation strategies is simultaneously the most effective economic and technical solution for the global warming issue [4,20,21].

From the above, it may be argued that there is a strong, direct, and positive correspondence between carbon dioxide concentration and temperature, turning climate change into one of the strongest challenges faced by humankind [22,23]. To understand the true impact of climate change on nature's vital processes and how to mitigate these, we first need to understand patterns and magnitudes of the relationship between global temperature and emissions. The increased launching of anthropogenic greenhouse gases in the atmosphere, in particular CO_2 emissions, moves average global temperatures upwards. Urgency is now posed to the need to prevent global warming, which is leading to extreme weather and related catastrophes [5,24]. The rising temperature worldwide is reflected in ocean warming, ice melting, rising sea levels, and reduced snow cover [3]. Air pollution leads to environmental degradation and is mainly responsible for Earth's warming (powered by the greenhouse gas effect) [17].

It has been highlighted by [25], while exploring the probability of achieving CO_2 emission targets set by the Paris Agreement of the top ten emitters during 1991–2015, that the volume of CO_2 emissions is expected to raise in 2030 by 26.5–36.5% as compared to the 2005 levels. Rau et al. [26] explored the global potential for converting renewable electricity to negative CO_2 emissions hydrogen, pointing out that combinations can be done by increasing energy generation and CO_2 removal by more than 50 times at equivalent or lower costs. Kalra et al. [1] also modeled the relationship between global temperatures and atmospheric concentrations of CO_2, CH_4, and N_2O over a dataset of 65 years. However, the authors used linear regression, decision tree regression, random forest regression, and artificial neural networks, concluding that the latter performs better. They proved that the contribution of carbon dioxide in the increase of global temperatures is the maximum of the considered greenhouse gases. As such, the current analysis only concentrates on CO_2 greenhouse gas emissions by making use of a maximum entropy methodology to explore its relationship with global temperature.

Recent studies also explored the relationship between CO_2 emissions and global temperature. The IPCC [27] report highlights the total net anthropogenic GHG emissions rise during 2010–2019, and the continuous cumulative growth of CO_2 emissions since 1850. However, growth rates were stronger in 2000–2009 when compared to those of 2010–2019, evidencing environmental improvements. Additionally, evidenced are regional disparities reflecting different development stages and income-dependent variations. Cost reductions and global adoptions of low-emissions technologies are mainly attributed to innovation policies pursued [27]. Nationally determined contributions announced before COP26 indicated that it was likely that warming will exceed 1.5 °C during the 21st century, and recent contributions in the literature also discuss and put these problems at the forefront [2,3,7,8,24,28,29]. In [2] it was concluded that the number of deaths increased significantly with the repetition of extreme weather events. Using a methodology based on long memory and fractional integration, [28] concluded that emissions present heterogeneous behavior in terms of persistence in pandemics, even if temperatures are more homogeneous, evidencing mean reverting behaviors. In 2020, [3], also using fractional integration and cointegration methodologies, concluded that CO_2 emissions and temperatures are not cointegrated. However, assuming that emissions are weakly exogenous concerning the temperatures, the results pointed to a positive relationship with a long memory pattern.

Accounting for the last 425 million years, [8] points to a pressing need for research on the relationship between CO_2, biodiversity extinction, and related carbon policies, concluding that changes in emissions did not cause a temperature change in the ancient climate. Additionally, [24] looks at both cause and causality relating to the "hen-or-egg" effect. Results support the hypothesis that the dominant direction is from temperature to CO_2 emissions (1980–2019). For China, [29] calculated the pathway in global emissions and its contribution to global warming up to 2050 (since 2005). They called attention to the fact that the larger differences in emission pathways of different atmospheric pollutant emissions. Proposing a forecast error variance decomposition, [7] contradicts [30] findings of causality from various forcings to global temperature. Therefore, and in the presence of multiple and contradicting results, the present article tries to contribute to this stream of research.

The anthropogenic CO_2 emissions are mostly due to transportation, working machines, and consumption [31], reduced recently with the COVID-19 confinement all over the world [32]. Strict measures to limit the virus spreading were placed in the recent COVID-19 outbreak. These included grounded airlines, factories, businesses that were shut and closed down, and people confined in their homes. Thus, a drastic reduction was registered in anthropogenic carbon dioxide emissions, and [32] argues that this is the ideal time to test if CO_2 emissions are the overwhelming contributor to CO_2 concentrations and global warming, or even to check if these have a limited effect on CO_2 concentrations that are driven by the temperature. Moreover, it would be possible to explore the effect of the prolonged and unprecedented cut in carbon dioxide emissions of the CO_2 concentration.

As such, there is some evidence that CO_2 is the most relevant greenhouse gas in the increase of global warming (e.g., [30,33]). Thus, this study aims to contribute to this discussion, through a powerful methodology in the analysis of time series, namely, the maximum entropy bootstrap, which, as far as we are aware, has not been used previously to explore this relationship, probably due to its novelty. Furthermore, [34] argued that the response to anthropogenic emission scenarios often requires a simple model linking emissions of carbon dioxide to global temperature changes, given that future climate changes will largely be determined by future cumulative CO_2 emissions (e.g., [30,33,35]), leaving room to the need to explore the link existent between global temperature and CO_2 emissions.

Besides this introduction with the framework included, the rest of the article develops as follows. Section 2 exposes the data and the methodology employed in this work to evidence its novelty and usefulness in the study of the relationship between CO_2 emissions and global temperature. Afterward, Section 3 presents all the results and discusses them, while Section 4 concludes by pointing out directions for decision-makers.

2. Data and Methodology

The data for global temperature and CO_2 were collected on 1 October 2020 from (1) NASA Global Climate Change: Vital Signs of the Planet; (2) National Centers for Environmental Information, National Oceanic and Atmospheric Administration; and (3) Jet Propulsion Laboratory, California Institute of Technology, Education Section (These were considered reliable sources to collect all the information needed for this work: https://climate.nasa.gov/vital-signs/carbon-dioxide; https://www.ncdc.noaa.gov/cag/global/time-series/globe/land_ocean/1/12/1880-2016; https://www.jpl.nasa.gov/edu/teach/activity/graphing-global-temperature-trends). The monthly average data for CO_2 (in PPP; parts per million) were transformed to annual values and the information for global temperature (annual global land and ocean temperature anomalies in °C) was converted to actual temperature (annual absolute values).

Monthly data for CO_2 only exists from 1958 (incomplete year and includes missing values). In 1964 there is a lack of information for three months and in 1975 there is a lack of information for one month, and in 1984. In these three years, the annual average of CO_2 is calculated with the existing information, and it was not considered necessary to apply imputation techniques for missing values.

The maximum entropy bootstrap for time series proposed by H. D. Vinod ([36,37]) is a powerful technique that allows for statistical formulations free of restrictive and unnecessary assumptions usually adopted in time series analysis. The technique creates a large number of replicates for inference purposes that satisfy the ergodic theorem and the central limit theorem. Those generated elements of the ensemble retain the shape of the original time series, as well as the time-dependence structure of the autocorrelation and the partial autocorrelation functions. As an illustration, Figure 1 presents the original series of the annual average of CO_2, between 1959 and 2019, and five resamples provided by the maximum entropy bootstrap.

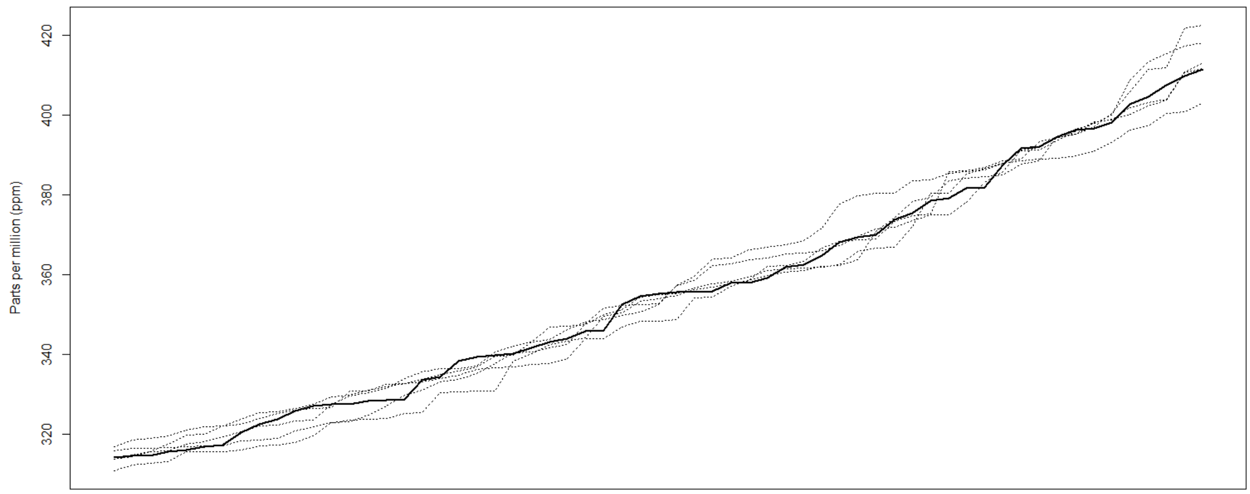

Figure 1. The annual average of CO_2 between 1959 and 2019 (solid), and five resamples (dotted).

A general description of the maximum entropy bootstrap algorithm ([36,37]) for a random replicate of a time series is provided next: (1) the original data are sorted to create order statistics, and the order index vector is stored; (2) the middle points from the order statistics are computed; (3) the trimmed mean of deviations among all consecutive observations, the lower limit for the left tail and the upper limit for the right tail are computed; (4) the mean of the maximum entropy density [38] within each interval is computed; (5) pseudorandom numbers from a [0, 1] uniform interval are generated and the sample quantiles of the maximum entropy density at those points are computed and sorted; (6) the sorted sample quantiles are reordered using the index vector stored in (1). Then, steps (2) to (6) were repeated a large number of times (1000 replications in this study).

As noted by [36,37], the technique avoids all structural changes and unit root type testing, and all the usual shape-destroying transformations like detrending or differencing to achieve stationarity. See [36,37,39] for additional details of the algorithm and the advantages of the technique, including the ones over the traditional bootstrap. For a review of maximum entropy, see [38].

Furthermore, and in addition to the advantages mentioned above, the maximum entropy bootstrap is particularly appealing in this area of climate change, given the difficulties in the measurement of global temperature and CO_2 emissions with high precision, widely discussed in the literature. Thus, the maximum entropy bootstrap, by not imposing parametric restrictions, allows for greater freedom in statistical modeling and inference through the replications of the original time series and the subsequent construction of confidence intervals for the model parameters. A recent proposal to improve the estimation of parameters is discussed in [40]. Moreover, since the inference is based on the analysis of confidence intervals, the use and possible misinterpretations of p-values are avoided, following recent recommendations from the statistical community (e.g., [41]).

Although other models were tested (These models and corresponding results are available upon request to the authors. The Schwarz criterion was used to select the possible best lag combinations among several experiments.), given the objective of this study, two realistic models to evaluate the relationship between global temperature and CO_2 were defined as

$$TEMP_t = b_1 + b_2 CO2_{t-m} + e_t, \tag{1}$$

and

$$TEMP_t = b_1 + b_2 TEMP_{t-1} + b_3 CO2_{t-m} + e_t, \tag{2}$$

for $m = 0,\ 1,\ 2,\ 3$, where $TEMP$ represents global temperature (in °C), $CO2$ represents carbon dioxide (CO_2; in parts per million), e represents the noise component, and t represents the period (year). For clarity and the reader's convenience, the eight particular models are described in Table 1.

Table 1. Models under study.

Model 1	$TEMP_t = b_1 + b_2 CO2_t + e_t$
Model 2	$TEMP_t = b_1 + b_2 CO2_{t-1} + e_t$
Model 3	$TEMP_t = b_1 + b_2 CO2_{t-2} + e_t$
Model 4	$TEMP_t = b_1 + b_2 CO2_{t-3} + e_t$
Model 5	$TEMP_t = b_1 + b_2 TEMP_{t-1} + b_3 CO2_t + e_t$
Model 6	$TEMP_t = b_1 + b_2 TEMP_{t-1} + b_3 CO2_{t-1} + e_t$
Model 7	$TEMP_t = b_1 + b_2 TEMP_{t-1} + b_3 CO2_{t-2} + e_t$
Model 8	$TEMP_t = b_1 + b_2 TEMP_{t-1} + b_3 CO2_{t-3} + e_t$

Three time periods were considered: 1959 to 2019 (the entire data available on the sources; more complete data for CO_2 only exist from 1959), 1959 to 1989, and 1990 to 2019.

3. Results and Discussion

Tables 2–7 present the results provided by the maximum entropy bootstrap, considering 1000 replications of the original series. The highest density regions (HDR) were adopted here to compute the confidence intervals [42]. (The R packages meboot ([36]) and hdrcde ([43]) were used in this work.) For all tables, the column Estimate represents the median of the estimates obtained from the 1000 models. Additionally, at the bottom of all the tables, the adjusted R^2 values are presented. The hypothesis test for the parameters of interest in (1) and (2) is defined by

$$H_0 : \ b_i = 0 \text{ vs. } H_1 : \ b_i \neq 0, \tag{3}$$

for $i = 2$ (for Model 1 to Model 4) and $i = 3$ (for Model 5 to Model 8). If the null hypothesis, H_0, is rejected (zero does not belong to a specified confidence interval), then the corresponding variable ($CO2_{t-m}$) is considered relevant to explain the response variable ($TEMP_t$) at the corresponding significance level, assuming the statistical model and the sample used in the study.

Table 2. Results for Model 1 to Model 4 (data from 1959 to 1989).

		Estimate	Highest Density Regions		
			CI 90%	CI 95%	CI 99%
Model 1	b_1 ***	10.8514	(10.3647, 11.3193)	(10.2646, 11.3988)	(9.9705, 11.6188)
	b_2 ***	0.0096	(0.0082, 0.0111)	(0.0080, 0.0114)	(0.0077, 0.0123)
Model 2	b_1 ***	10.5906	(10.0564, 11.0974)	(9.9559, 11.1907)	(9.7232, 11.4025)
	b_2 ***	0.0104	(0.0089, 0.0120)	(0.0086, 0.0123)	(0.0080, 0.0130)
Model 3	b_1 ***	10.3552	(9.7862, 10.9002)	(9.6450, 11.0284)	(9.3398, 11.2920)
	b_2 ***	0.0111	(0.0095, 0.0129)	(0.0091, 0.0133)	(0.0086, 0.0143)
Model 4	b_1 ***	10.0218	(9.3833, 10.6493)	(9.2229, 10.7935)	(8.7793, 11.1610)
	b_2 ***	0.0122	(0.0103, 0.0141)	(0.0099, 0.0147)	(0.0092, 0.0161)

Note 1: Adjusted R^2 values lie, approximately, between 0.55 and 0.58 for Model 1 to Model 4. Note 2: *** means that the null hypothesis $H_0 : b_i = 0$ $(i = 1, 2)$ is rejected at 1% significance level. This note is valid for Tables 2–4. Note 3: (1) Estimate represents the median of the estimates from the 1000 replications; (2) CI represents Confidence Intervals; (3) all the values are rounded to four decimals. This note is valid for Tables 2–7.

Table 3. Results for Model 1 to Model 4 (data from 1990 to 2019).

		Estimate	Highest Density Regions		
			CI 90%	CI 95%	CI 99%
Model 1	b_1 ***	10.7968	(10.2239, 11.2865)	(10.0709, 11.3605)	(9.7997, 11.5144)
	b_2 ***	0.0098	(0.0087, 0.0114)	(0.0085, 0.0117)	(0.0081, 0.0125)
Model 2	b_1 ***	10.5704	(9.9635, 11.0832)	(9.7829, 11.1805)	(9.4867, 11.3637)
	b_2 ***	0.0104	(0.0092, 0.0121)	(0.0088, 0.0126)	(0.0085, 0.0134)
Model 3	b_1 ***	10.4452	(9.7737, 11.0476)	(9.5662, 11.1694)	(9.2934, 11.3482)
	b_2 ***	0.0108	(0.0093, 0.0127)	(0.0091, 0.0134)	(0.0084, 0.0138)
Model 4	b_1 ***	10.5971	(9.8105, 11.3096)	(9.6304, 11.4214)	(9.3000, 11.6257)
	b_2 ***	0.0105	(0.0087, 0.0126)	(0.0084, 0.0135)	(0.0078, 0.0140)

Note: Adjusted R^2 values lie, approximately, between 0.77 and 0.80 for Model 1 to Model 4.

Table 4. Results for Model 1 to Model 4 (data from 1959 to 2019).

		Estimate	Highest Density Regions		
			CI 90%	CI 95%	CI 99%
Model 1	b_1 ***	10.7702	(10.4785, 11.0369)	(10.3841, 11.0907)	(10.2669, 11.1820)
	b_2 ***	0.0098	(0.0092, 0.0106)	(0.0091, 0.0109)	(0.0087, 0.0112)
Model 2	b_1 ***	10.6825	(10.3883, 10.9703)	(10.2887, 11.0451)	(10.1637, 11.1452)
	b_2 ***	0.0101	(0.0094, 0.0111)	(0.0090, 0.0113)	(0.0087, 0.0117)
Model 3	b_1 ***	10.6056	(10.2914, 10.9179)	(10.2122, 10.9922)	(10.0784, 11.1155)
	b_2 ***	0.0104	(0.0095, 0.0112)	(0.0093, 0.0115)	(0.0090, 0.0119)
Model 4	b_1 ***	10.5136	(10.1717, 10.8562)	(10.0890, 10.9368)	(9.9576, 11.0637)
	b_2 ***	0.0107	(0.0097, 0.0116)	(0.0095, 0.0119)	(0.0092, 0.0122)

Note: Adjusted R^2 values are, approximately, 0.90 for all the models.

Table 5. Results for Model 5 to Model 8 (data from 1959 to 1989).

		Estimate	Highest Density Regions		
			CI 90%	**CI 95%**	**CI 99%**
Model 5	b_1 ***	8.0595	(6.6394, 9.4517)	(6.3287, 9.7472)	(5.9504, 10.1514)
	b_2 ***	0.2364	(0.1081, 0.3680)	(0.0880, 0.3900)	(0.0513, 0.4300)
	b_3 ***	0.0078	(0.0061, 0.0096)	(0.0059, 0.0100)	(0.0053, 0.0105)
Model 6	b_1 ***	7.9913	(6.6003, 9.3576)	(6.3089, 9.6422)	(5.9299, 10.0183)
	b_2 ***	0.2367	(0.1108, 0.3657)	(0.0883, 0.3899)	(0.0547, 0.4260)
	b_3 ***	0.0081	(0.0062, 0.0100)	(0.0060, 0.0104)	(0.0055, 0.0108)
Model 7	b_1 ***	8.0505	(6.6420, 9.4314)	(6.4061, 9.6673)	(5.9973, 10.0762)
	b_2 ***	0.2189	(0.0891, 0.3452)	(0.0676, 0.3671)	(0.0193, 0.4164)
	b_3 ***	0.0088	(0.0069, 0.0109)	(0.0064, 0.0114)	(0.0058, 0.0122)
Model 8	b_1 ***	8.0624	(6.6410, 9.4922)	(6.2816, 9.8576)	(5.8244, 10.3240)
	b_2 **	0.1880	(0.0555, 0.3198)	(0.0277, 0.3474)	(−0.0160, 0.3906)
	b_3 ***	0.0100	(0.0080, 0.0124)	(0.0075, 0.0129)	(0.0068, 0.0143)

Note 1: Adjusted R^2 values lie, approximately, between 0.55 and 0.58 for Model 5 to Model 8. Note 2: *, **, and *** means that the null hypothesis $H_0 : b_i = 0$ $(i = 1, 2, 3)$ is rejected, respectively, at 10%, 5%, and 1% significance levels. This note is valid for Tables 5–7.

Table 6. Results for Model 5 to Model 8 (data from 1990 to 2019).

		Estimate	Highest Density Regions		
			CI 90%	**CI 95%**	**CI 99%**
Model 5	b_1 ***	8.2304	(6.1863, 10.2813)	(5.7369, 10.7287)	(4.9466, 11.5143)
	b_2 *	0.2146	(0.0216, 0.4079)	(−0.0173, 0.4474)	(−0.0865, 0.5183)
	b_3 ***	0.0082	(0.0059, 0.0106)	(0.0054, 0.0111)	(0.0045, 0.0123)
Model 6	b_1 ***	8.1764	(6.1097, 10.1755)	(5.6693, 10.5740)	(4.8516, 11.3057)
	b_2 *	0.2168	(0.0286, 0.4085)	(−0.0051, 0.4447)	(−0.0831, 0.5299)
	b_3 ***	0.0084	(0.0060, 0.0107)	(0.0056, 0.0112)	(0.0049, 0.0119)
Model 7	b_1 ***	8.1411	(5.8628, 10.3898)	(5.4782, 10.7756)	(4.7647, 11.4932)
	b_2 *	0.2156	(0.0051, 0.4227)	(−0.0337, 0.4615)	(−0.1170, 0.5458)
	b_3 ***	0.0086	(0.0061, 0.0115)	(0.0055, 0.0118)	(0.0047, 0.0131)
Model 8	b_1 ***	7.9782	(5.7322, 10.2690)	(5.3466, 10.6520)	(4.6333, 11.3643)
	b_2 *	0.2431	(0.0307, 0.4539)	(−0.0133, 0.4978)	(−0.0769, 0.5612)
	b_3 ***	0.0078	(0.0052, 0.0108)	(0.0047, 0.0116)	(0.0039, 0.0129)

Note: Adjusted R^2 values lie, approximately, between 0.79 and 0.81 for Model 5 to Model 8.

The first and very important result is that the null hypothesis $H_0 : b_i = 0$ $(i = 2, 3)$ is rejected at a low significance level, whatever the model or the period considered, where b_i is the parameter associated with CO_2 (i.e., b_2 for Model 1 to Model 4; and b_3 for Model 5 to Model 8). Since both limits of the corresponding confidence intervals are positive, this means that an increase in the annual average of CO_2 corresponds to an increase in global temperature. Without loss of generality, considering, for example, Model 1 in Table 4, using this sample with data from 1959 to 2019, and considering the statistical model described by Model 1, it is estimated that, on average, a unit increase on the annual average of CO_2 implies an increase between 0.0087 °C and 0.0112 °C on global temperature, with a confidence level of 99%.

Figures 2–4 present the highest density regions (HDR) for the b_2 estimates, considering Model 1 to Model 4 under the three time periods in the study. (All the other HDR graphics are available upon request to the authors. They are omitted here for the sake of simplicity. Additionally, the percentile method was computed for comparison purposes, but the interpretation was qualitatively the same.) The HDR reported is the graphical representation of the corresponding results in Tables 2–4 (CI 90% in blue; CI 95% in green; CI 99% in red). The graphics reveal the shift of the HDR to the right of the zero value (revealing the positive impact of CO_2), with the zero value not being included in any of the HDR considered.

Table 7. Results for Model 5 to Model 8 (data from 1959 to 2019).

		Estimate	Highest Density Regions		
			CI 90%	**CI 95%**	**CI 99%**
Model 5	b_1 ***	7.6958	(5.9925, 9.3377)	(5.6427, 9.6643)	(5.0849, 10.1839)
	b_2 ***	0.2779	(0.1260, 0.4388)	(0.0973, 0.4708)	(0.0361, 0.5386)
	b_3 ***	0.0073	(0.0056, 0.0088)	(0.0052, 0.0091)	(0.0044, 0.0100)
Model 6	b_1 ***	7.6392	(5.9650, 9.2738)	(5.6486, 9.5633)	(4.9699, 10.1846)
	b_2 ***	0.2784	(0.1279, 0.4409)	(0.1025, 0.4702)	(0.0422, 0.5390)
	b_3 ***	0.0074	(0.0057, 0.0090)	(0.0053, 0.0092)	(0.0044, 0.0103)
Model 7	b_1 ***	7.6838	(6.0082, 9.2874)	(5.6970, 9.5721)	(5.0672, 10.1429)
	b_2 ***	0.2703	(0.1194, 0.4321)	(0.0928, 0.4631)	(0.0363, 0.5294)
	b_3 ***	0.0076	(0.0058, 0.0093)	(0.0054, 0.0097)	(0.0045, 0.0104)
Model 8	b_1 ***	7.6759	(6.0352, 9.2988)	(5.7103, 9.5465)	(5.0206, 10.0625)
	b_2 ***	0.2622	(0.1117, 0.4191)	(0.0828, 0.4553)	(0.0291, 0.5247)
	b_3 ***	0.0079	(0.0061, 0.0097)	(0.0057, 0.0101)	(0.0048, 0.0107)

Note: Adjusted R^2 values lie, approximately, between 0.90 and 0.91 for Model 5 to Model 8.

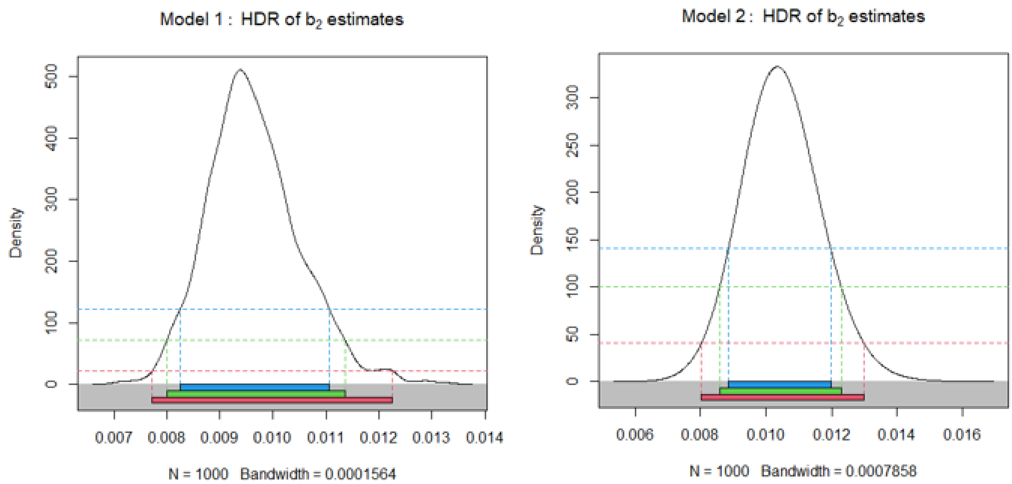

Figure 2. *Cont.*

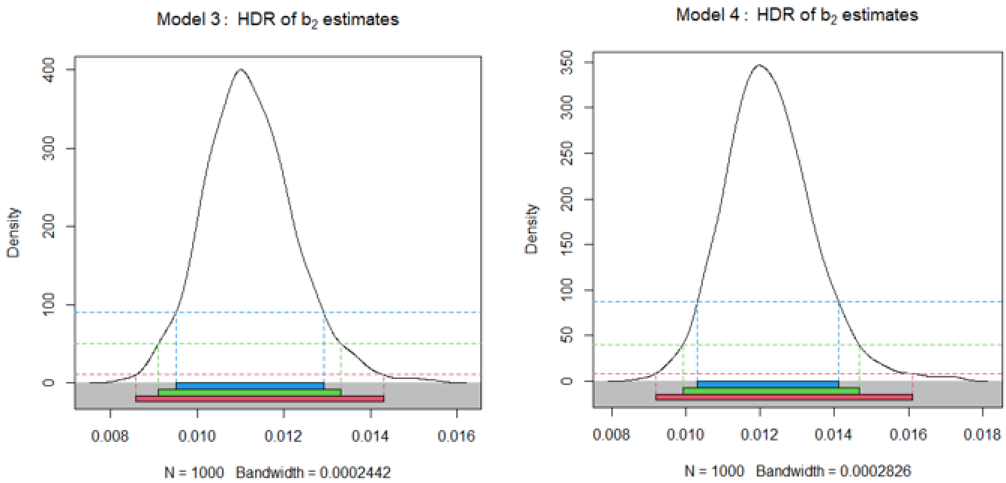

Figure 2. HDR of b_2 estimates. Model 1 to Model 4 (data from 1959 to 1989).

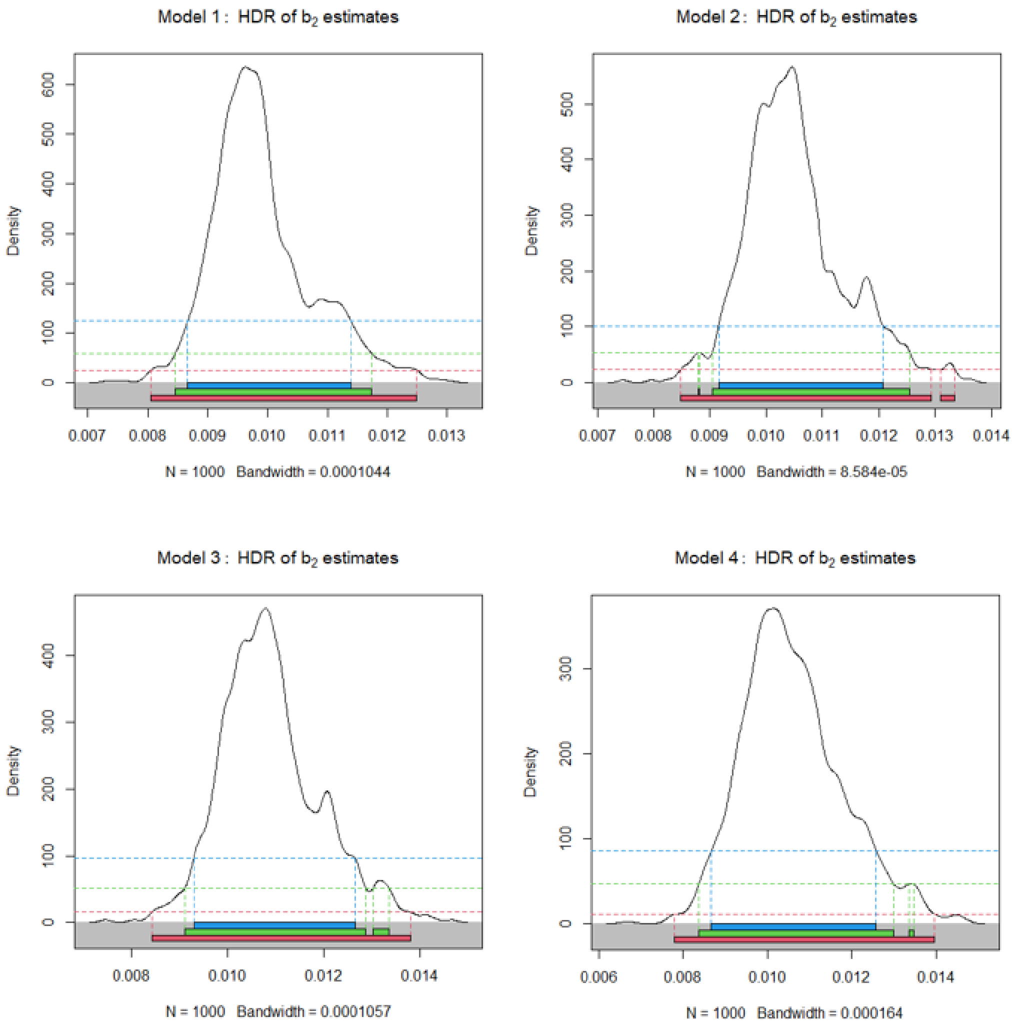

Figure 3. HDR of b_2 estimates. Model 1 to Model 4 (data from 1990 to 2019).

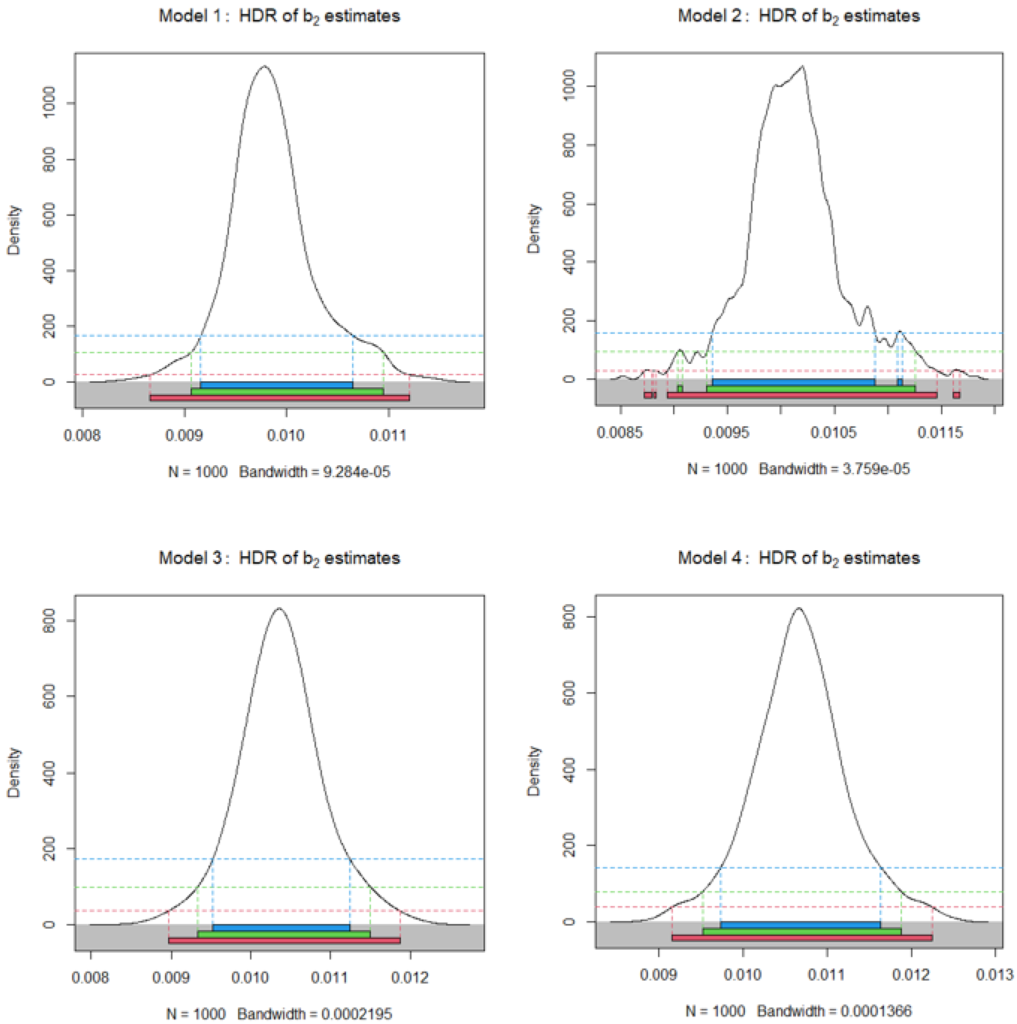

Figure 4. HDR of b_2 estimates. Model 1 to Model 4 (data from 1959 to 2019).

From the analysis undertaken, we can infer that there is a positive impact of CO_2 in the increase of the Earth's global temperature, supporting similar results obtained with other statistical techniques available in the literature. This is an important finding because it is obtained with a methodology (not usually used in climate change science, as far as we know) that allows the replication of the original time series with the subsequent construction of confidence intervals for the model parameters, which represents an important advantage. The choice of the methodology for the construction of confidence intervals and the estimation method used, although it does not compromise the results of this work, could be seen as possible limitations of this approach in other theoretical scenarios.

As evidenced by [5], joint forces worldwide are needed to fight global warming and climate change. Sometimes, governmental institutions' unresponsiveness leads to hampered effects, but the general population should be accountable. Moreover, poverty and the lack of appropriate infrastructure pave the way to the negative worldwide dissemination of these effects ([5]). Thus, air pollution needs to be mitigated, and we advocate the need to quickly reduce global warming through our results, such as to protect human life and health, and to ensure a sustainable future for the entire Earth planet. For that to be true, future human actions should be rethought as to the overuse of fossil fuels as energy resources, and drivers of greenhouse gases, with the latter driving the increase in the average surface temperature of the Earth ([4]).

4. Conclusions

This work explores through a recent technique the relationship between carbon dioxide emissions and global temperature on Earth. This methodology, in addition to its statistical advantages, is particularly appealing in the area of climate change, given the difficulties in the measurement of global temperature and CO_2 emissions with high precision (usually reported in the literature and perhaps one of the reasons for some to discredit scientific studies), as it allows for the replication of the original time series with the subsequent construction of confidence intervals for the model parameters. However, under different technical premises, it is estimated that an increase in the annual average of CO_2 will always drive an increase in global temperature, regardless of the time series model considered.

Urgently, decision-makers should be aware that at the current rate of increase in CO_2 emissions, it would hardly be possible for countries to fulfill the Paris Agreement. For that, measures against pollution increases, stricter CO_2 abatement policies, a strict reduction of fossil fuel energy consumption and production, the promotion of renewable energy sources, and others, should be promoted and mandatory. Provided that the release of CO_2 emissions is only reflected in the long-run global temperature effects, the recent COVID-19 pandemic will, fortunately, lead us to reflect on the need for changing life habits, given that the reduction in CO_2 emissions will only be strongly noticed in the next decades and centuries. Still, it remains to be seen if the stricter restrictions and confinements would be enough to save the planet and allow us to enjoy a green and breathable planet Earth, with a positive impact on human, plant, and animal health in the medium to long future.

Only CO_2 emissions are considered here as a factor contributing to global temperature rises, and, therefore, to global warming. Other greenhouse gases should be considered, along with other factors which able to explain the global temperature rise (excessive use of fossil fuels, land exploration, forest harvesting, population growth, urbanization, demanding and unsustainable harming lifestyles, technology misuses, quick industrialization, and excessive use of resources, among many others). In other words, to prevent the future rise of global temperature, we need to decrease carbon emissions, but mainly need to stop using nature as a raw material for exploration.

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