Applied Economics and Finance; Vol. 9, No. 3; 2022
ISSN 2332-7294 E-ISSN 2332-7308
Published by Redfame Publishing

A Review of the Anthropogenic Global Warming Consensus: An Econometric Forecast Based on the ARIMA Model of Paleoclimate Series

Gilmar Veriato Fluzer Santos[1], Lucas Gamalel Cordeiro[1], Claudio Antonio Rojo[1], & Edison Luiz Leismann[1]

[1] PPGAdm, Universidade do Oeste do Paraná, Cascavel, Brasil

Correspondence: Gilmar Veriato Fluzer Santos, PPGAdm, Universidade do Oeste do Paraná, Cascavel, Brasil.

Received: July 19, 2022 Accepted: August 26, 2022 Available online: September 2, 2022

doi:10.11114/aef.v9i3.5703 URL: https://doi.org/10.11114/aef.v9i3.5703

Abstract

This paper projects a climate change scenario using a stochastic paleotemperature time series model and compares it to the prevailing consensus using Autoregressive Integrated Moving Average Process Model (ARIMA). The parameter estimates of the model were below that established by the anthropogenic experts and governmental organs, such as the IPCC (UN) over a 100-year scenario. Results from the ARIMA model suggest a current period of temperature reduction and a probable cooling. The results from this study add a statistical element of paleoclimate to the debate that contradicts the current scientific consensus.

Keywords: global warming, Paleoclimatology, time series, Arima model, climate scenarios, forecasting

1. Introduction

Controversies regarding global warming and its effects on the economy and the environment are the subject of global discussion and debate. These controversies also partially determine how governments and companies develop their policies and conduct their business.

Human action has been responsible for climate change and global warming (greenhouse effect) according to the followers of anthropogeny and other international bodies such as the IPCC (Intergovernmental Panel on Climate Change - UN); as echoed by most scientific publications (more than 90% of research studies) that show that global warming is anthropogenic. This explanation has been established as the "official version" by IPCC advocates (Salzer, Neske & Rojo, 2019; Cook et al. 2013; Bray, 2010; Anderegg et al., 2010; Oreskes, 2004). The IPCC Working Group Chair, Jim Skea, stated: "Limiting warming to 1.5 ℃ is possible within the laws of chemistry and physics but doing so requires unprecedented changes" (IPCC Special Report, 2019).

Nevertheless, assessing the state of scientific contestations on certain issues when the scientific community considers a proposition a fact is essential as posited by Shwed and Bearman (2010). The authors also explain how internal dissent in the face of consensus diminishes.

The defenders of the naturalistic cause present arguments that challenge published research studies by claiming that anthropogenic global warming is theoretically fragile with calculated misinformation, and its historical sample of only 150 years is insufficient to establish a consensus often supported by agnotology and metric uncertainties (Molion, 2008; Legates *et al*. 2015; Legates, Soon & Briggs, 2013; Reinsinger *et al.* 2010).

Notably, the more research explores the past, the more the anthropogenic thesis is weakened. Davis (2017) and Harde (2019) found that changes in the atmospheric CO2 concentration did not cause changes in ancient climate temperature. They also found that climate change was not related to the carbon cycle but to native impacts. Easterbrook (2016), in his evidence-based book opposed CO2 emissions as the primary source of global warming; however, this thesis has been captured by politics and dubious computer modeling.

Furthermore, other anthropogenic studies either ignore the paleoclimatology factor in research or factor it in as an element of uncertainty, such as the research by Haustein *et al*. (2017), Cook e*t al*. (2013), Mitchell *et al*. (2017), Medhaug e*t al*. (2017), similar to studies at the genesis of the IPCC studies (Solomon *et al*. 2007). However, scientists such as Easterbrook (2016) and the arguments present in Koonin's book (2021), are increasingly pointing to data which suggests that climate changes result from natural cycles that have been occurring for thousands of years,.

Thus, there is a gap in this debate which is the absence of a broader time horizon and statistical predictability to climate change. This study, set out to establish a climate prediction scenario for the next 100 years based on a 12,000-year paleotemperature series (Holocene Period) and the uncertainties within that the data were used to make this prediction. We adopted the Autoregressive Integrated Moving Average (ARIMA) model, also known as Box-Jenkins. Box-Jenkins ARIMA model's objective is to provide a valid basis for forecasting, after all tests, parameters, and diagnostics have been performed. We obtained the ARIMA database from the article by Kaufman et al. (2020), who applied five statistical methods of thermal reconstruction to verify global mean surface temperature (GMST) to the present day.

Our results indicated the fragility of the anthropogenic thesis by showing significant divergence from the latest scenario projected by the IPCC that predicted an increase of more than 1.5 ℃ in the planet's temperature by 2050 (IPCC, 2019).

Therefore, we established an additional variable for the global warming debate to stimulate critical discussion about the consensus that prevails today.

2. Data, Method, and Its Justification

The data used in this research were obtained from Kaufmann et al., (2020) unprecedented multi-method reconstruction research of mean land surface temperature (GMST) during the Holocene era (12,000 years) to the present day, "whose database is the most comprehensive global compilation of previously available published Holocene proxy temperature time series" (Kaufman et al., 2020, p. 01).

Primary data from the current study is available as individual CSV files and merged as a netCDF file at figshare 35 and at NOAA Palaeoclimatology 36 (https://www.ncdc.noaa.gov/paleo/study/29712). A CSV file with the multi-method joint median and 5th and 95th percentiles is also available in both data repositories. All were used as **input data** to compose the 12k time series of paleotemperatures in the two variables (the median and the uncertainty set) and fed into IBM SPSS-Statistics software (v. 22). The data generated for the development of this research are available in supplementary file.

The Arima model is an established predictive tool, as demonstrated in the works of Babu & Reddy (2014), Valipour (2015) and Katimon, Shahid & Mohsenipour (2018).

In this study, our methodology was based on the use of this model for long-term forecasting in time series, both in economic and stochastic variables, such as temperatures for example suggested in the book by Gujarati & Porter (ch. 21-22, 2011).

To respond to our research question, the data were represented graphically and fed into the software IBM - SPSS Statistics, v. 22, for ARIMA - Box Jenkins methodology. Figure 1 shows the evolution of the 12k median of the data set extracted from Kaufmann *et al*. (2020) on a 100-year scale, with milestone "0" being the year 2019 (p. 8) calculated from the different reconstruction methods.

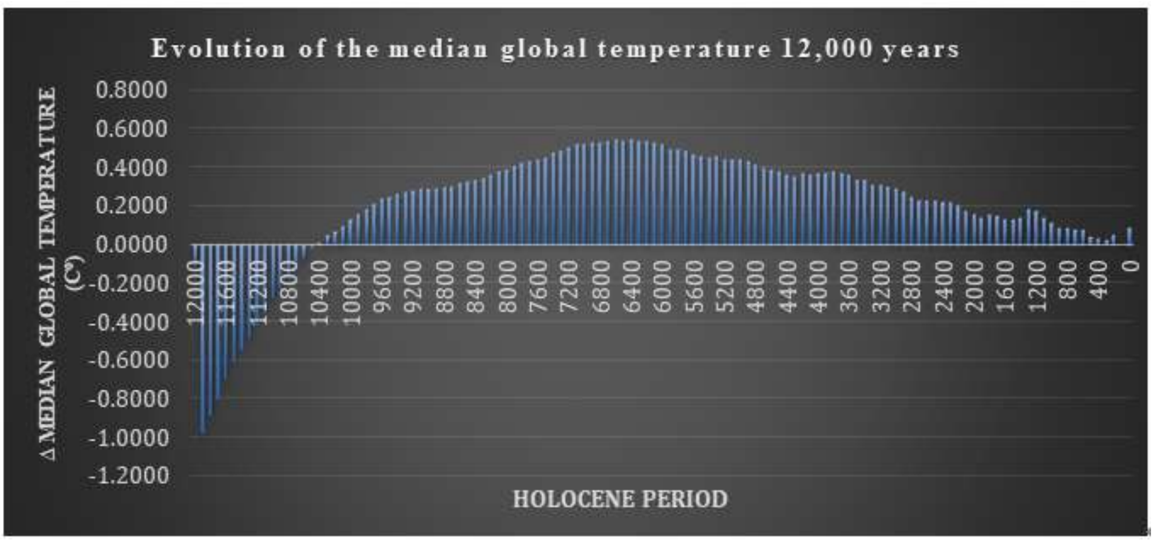

Figure 1. Evolution of the Global Median 12k years temperature

Source: Author elaboration (adapted from Kaufman et al. (2020 p. 06) from CSV file data at https://www.ncdc.noaa.gov/paleo/study/29712).

Figure 2 depicts the 5th and 95th percentile range of the set that takes into consideration various sources of uncertainty, including proxy temperature, chronology, and methodological choices, as per Kaufman et al. (2020 p. 03).

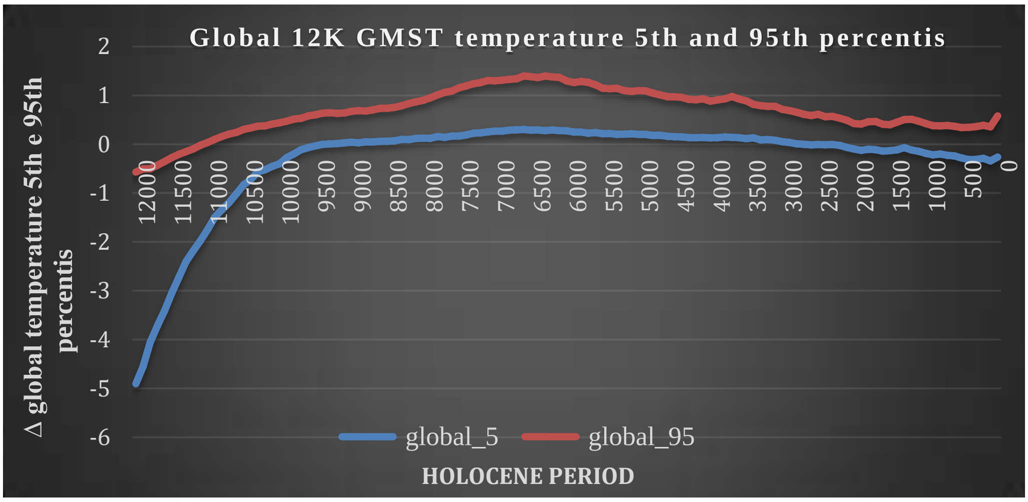

Figure 2. Evolution of the parameters 5th and 95th global percentiles (uncertainties)

Source: Author elaboration (adapted from CSV file data - temp 12K all methods percentiles at https://www.ncdc.noaa.gov/paleo/study/29712).

The average temperature of the 1800-1900 period for each composite was used as the pre-industrial reference period that was defined by the authors as an anomaly of 0 °C; an average which served as the reference for the IPCC (1850-1900). Hence, this period was removed from each member of the ensemble to avoid issuing individual records and different reconstructions (Kindly refer to page 04 of Kaufmann et al. (2020). The forecasts of the two-time series, median and uncertainties, were generated in the IBM - SPSS Statistics software, version 22, in a specific session for ARIMA modeling.

2.1 Stochastic Processes and the Stationarity Test

To introduce the forecast, we graphically and mathematically presented the results that the SPSS software generated for the two variables of this study, the median and the uncertainty set. We presented the graphs in this section, the mathematical formulation of their results and the structuring of the uncertainty set (same pattern) in a supplementary file.

Firstly, we applied two tests to verify the **stationarity** of the time series: **(1) graphical analysis** and **(2) the correlogram test;** condition for using the ARIMA (BJ) model.

An important condition for model reliability is the residuals of the ACF (Autocorrelation Function) and PACF (The partial autocorrelation function) correlations, ***the white noise***. For the model to be validated as the most adequate model, ACF and PACF should be concentrated around the mean, and the degree of significance should be absolute (0 or close) as represented in figure 3. (*Note: Retardo means Lag; "de resíduo" means of waste*)

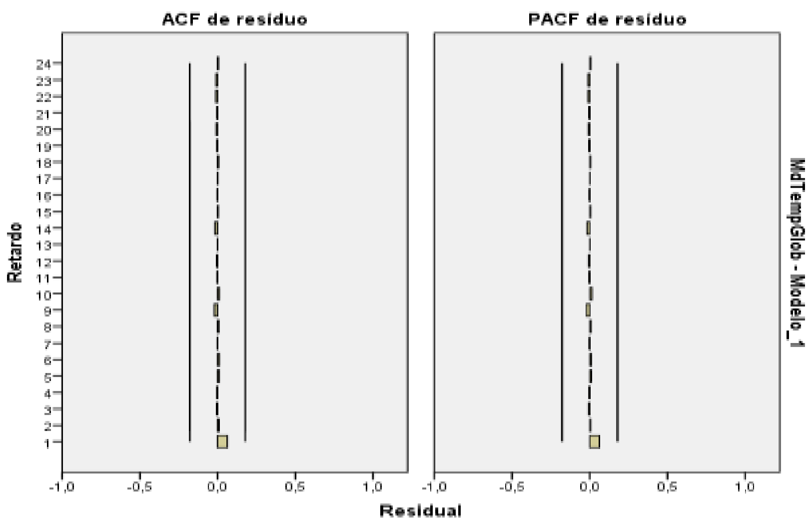

Figure 3. Residuals of the ACF and PACF correlograms (White noise)

Source: prepared by the author (SPSS - Statistics v. 22)

Thus, once stationarity was achieved (see p. 7-9), we could model it with an autoregressive process (AR), which we represented by Y_t the Median (Md) at period t (Holocene) as:

$$(Y_t - \delta) = \alpha^1(Y_t - \delta) + u_t \quad (1)$$

where δ is the mean of Y and ut is an uncorrelated random error with zero mean and constant variance α^2 (this is white noise); thus Yt follows a first-order stochastic autoregressive or AR process (1).

The AR process we have just discussed is not just a mechanism that may have generated Y. In this case, Y may evolve into a first order moving average process, or an MA (1). If we model Y in as shown below:

$$Y_t = \mu + ß_0\, u_t + ß_1 u_t - {}_1 \quad (2)$$

where μ is a constant and u, as before, is a white noise stochastic error term. Here Y at period t is equal to a constant plus a moving average of the current and past error terms. More generally, we can represent it like this

$$Y_t = \mu + ß_0 u_t + ß_1 u_{t-1} + ß_2 u_{t-2} + \cdots + ßq u_t - q \qquad (3)$$

which is an MA(q) process. Briefly, a moving average process is a linear combination of white noise error terms. Therefore Y, most likely has characteristics of both AR and MA and is therefore ARMA. Then Yt follows an ARMA (1,1) process, and can be written as

$$Y_t = \Theta + \alpha_1 Y_{t-1} + ß_0 u_t + ß_1 u_{t-1} \qquad (4)$$

because there is an autoregressive term and a moving average term. In the Equation, ɵ represents a constant term. In general, in an ARMA (p, q) process, there will be p autoregressive terms and q moving average terms.

In the fit chart, shown in figure 4, the two lines coincide and almost overlap indicating that this is the best of the models tested. The outliers present between 1 and 5 dates were retain to ensure the series is robust and to guarantee its impartiality and uncertainty for future events (Stockinger & Dutter, 1987). *Note: observado means observed; ajuste means adjust; UCL: the upper control limit; LCL: the lower control limit.*

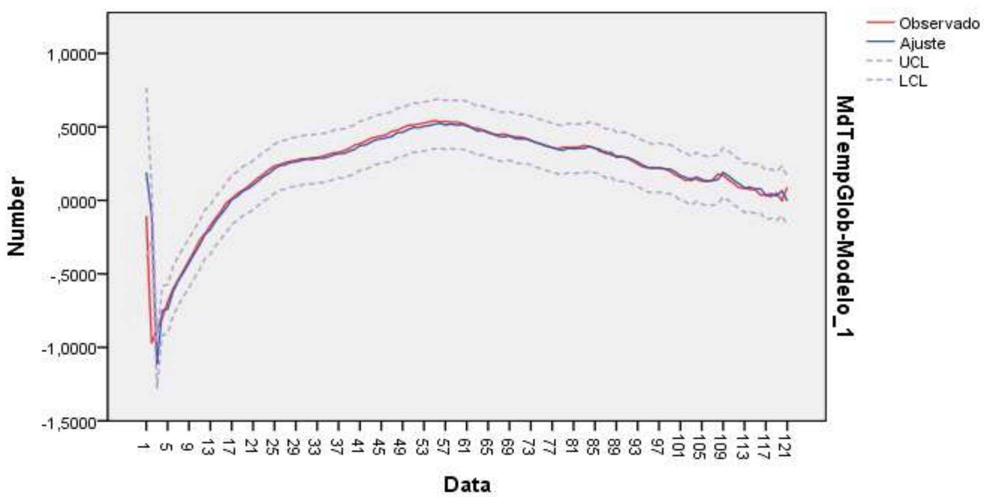

Figure 4. Graph of the adjusted 12k median series

Source: elaborated by the author (SPSS- Statistics)

Froom Figures 1, 2 and 4, the series **are not stationary;** the data do not circulate it and express a trend around a mean line for the 12K global temperature median series (Figure 5) . *Note: número de sequência means sequence number.*

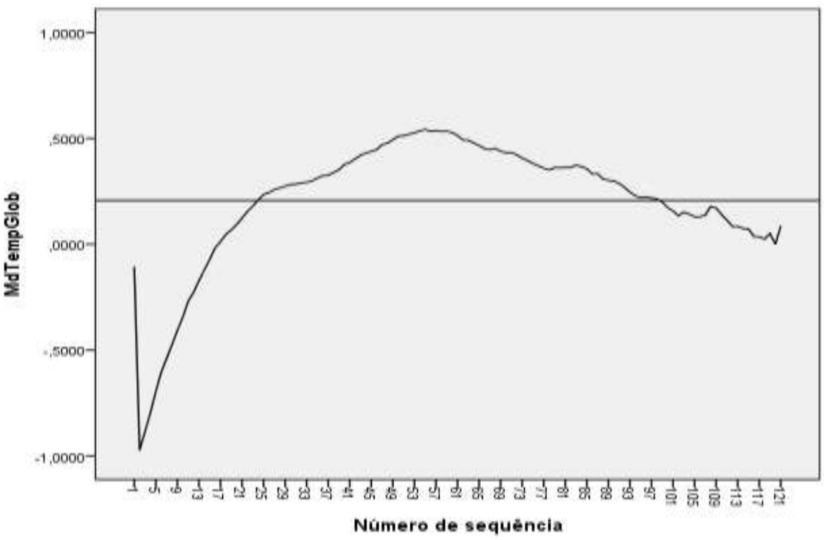

Figure 5. Graphical test for stationarity

Next, we applied correlation tests, also known as "F" correlation function: ACF (automatic) and PACF (partial) to make the series stationary, as shown in figures 6 and 7, and Table 1. *Note: coeficiente means coefficient. Número de retardo means Lag numbers.*

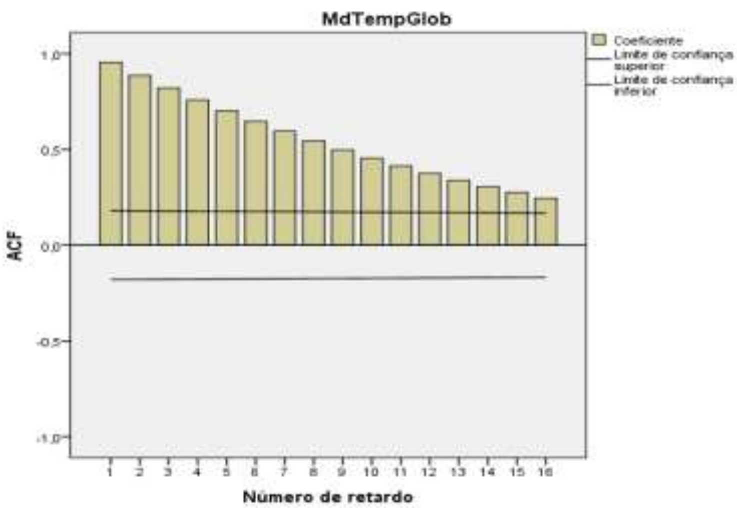

Figure 6. Graphical test of autocorrelation (automatic)

Table 1. LJung Box statistical report (Ho and H_1 hypotheses)

Automatic correlations					
Series: MdTempGlob					
Lag	Autocorrelation	Standard Error[a]	Box-Ljung Statistics		
			Value	df	Sig.[b]
1	,956	,090	113,376	1	,000
2	,887	,089	211,775	2	,000
3	,821	,089	296,777	3	,000
4	,759	,089	370,121	4	,000
5	,702	,088	433,357	5	,000
-	-	-	-	-	-
-	-	-	-	-	-
16	,246	0,84	723,810	16	,000

a. The underlying process considered is independence (white noise).

b. Based on the asymptotic chi-square approximation.

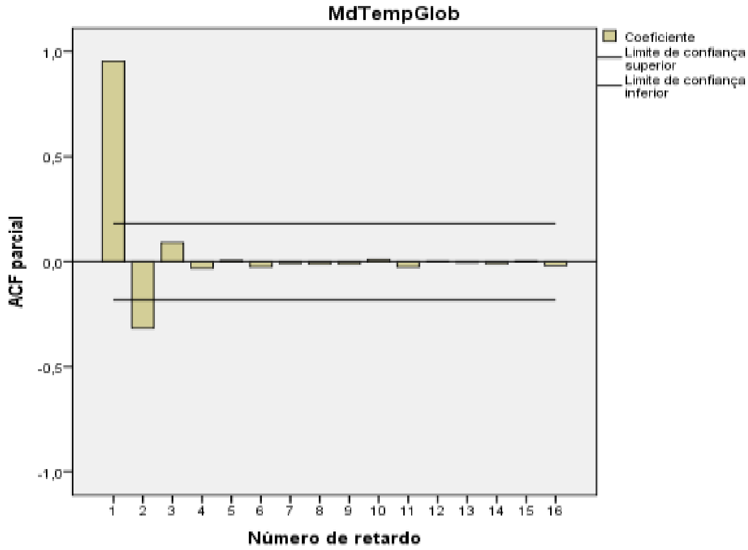

Figure 7. Graphical test of partial autocorrelation – PACF

Graphical and correlation analysis indicated that we had to normalize the series to make it stationary**.** The process occured with the choice of the first lag (lag), which exceeded the confidence interval in both tests and whose degree of graphical significance was higher, i.e., it had the highest correlation and the lowest value according to the Ljung-Box statistic. The lag that met these criteria, therefore, was number 1, highlighted in Table 1.

From these results, we graphically represented (Figure 8) the **stationarity** adjusted, as a function of the first differentiation (lag 1):

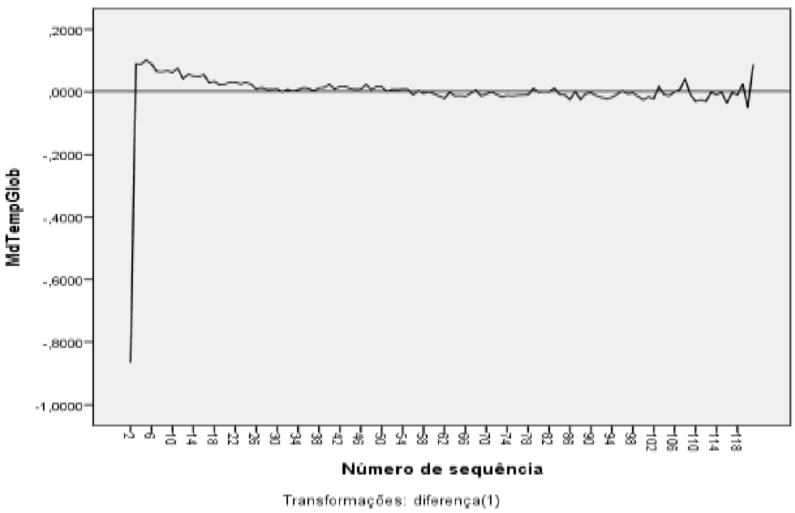

Figure 8. Adjusted stationarity as a function of lag 1

We then replicated this modeling for the probabilistic analysis of the uncertainties, represented by the 5th and 95th percentiles, at a 90% confidence level, since it assumed the same stationarity criteria and tests (graph and correlogram) of the median. The graphical representation of the uncertainty set is described in the supplementary file.

2.2 Applying the Box- Jenkins Model

Box-Jenkins's method aims (Figure 9) is to estimate a statistical model and interpret it according to the sample data. If this estimated model is used for forecasting, we should assume that its characteristics are constant over the period and particularly in future periods. Any model that is inferred based on stationary data can be interpreted as stationary or stable and therefore provides a valid basis for prediction (Pokorny, 1987, Gujarati and Porter, 2011).

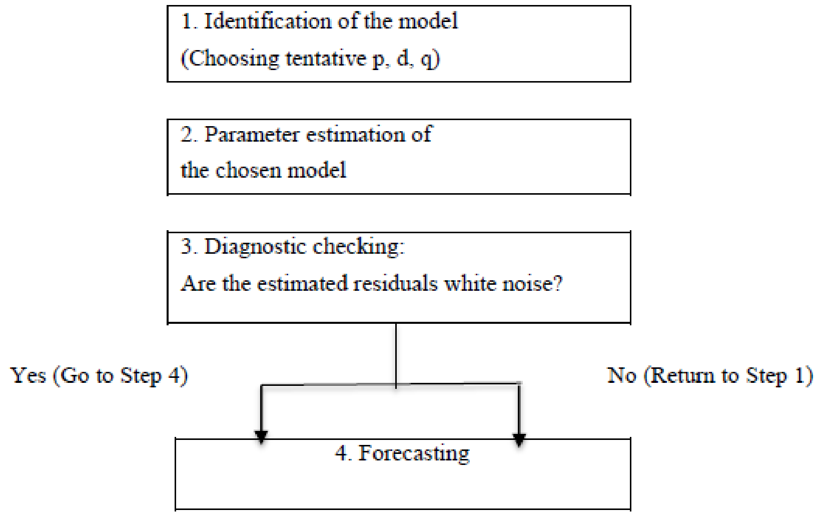

Figure 9. The Box–Jenkins methodology

Step 1: Identification. We concluded this step by finding the appropriate values of p, d and q. We also showed how the correlogram and the partial correlogram facilitated this task.

Step 2: Estimation. We identified the appropriate p and q values and estimated the parameters of the autoregressive and moving average terms included in the model.

Step 3: Diagnostic check. Having chosen a particular ARIMA model and estimated its parameters, the chosen model fitted the data perfectly as attested by the white noise of the residuals.

Step 4, Forecasting: One of the reasons why ARIMA modeling is popular is due to its success in forecasting. In many cases, ARIMA forecasts for both long- and short-term variables,are more reliable than those obtained from traditional econometric modeling (Gujarati and Porter, 2011, p. 762;778).

We concluded that the MedTempGlobal (as described in the data/figures) time series model was not stationary and we had to normalize it, making it stationary with constant mean and variance and its covariance invariant over time. Therefore, it is an integrated time series, i.e., it combines the two autoregressive processes (AR and MA) in the same set.

An important point to note is that when using the Box- Jenkins methodology, we must have both a stationary time series and a time series that is stationary after one or more differentiations (Gujarati and Porter, 2011).

Then, we can state that if a time series is integrated of order **1**, therefore, it is **I (1)**, after differentiating it becomes **I (0)**, that is, stationary. In general, if a time series is **I *(d)***, after differentiating it *d* times, we get an **I (0)** series.

If one has to differentiate a time series *d* times to make it stationary and apply the ARMA (p, q) model to it, one will say that the original time series is **ARIMA (*p, d, q*)**, that is, it is a moving average **integrated autoregressive time series**, where p denotes the numbers of the autoregressive terms, *d* the number of times the series must be differentiated before it becomes stationary, and *q* the number of moving average terms.

We, therefore, have in this time series an ARIMA (1,0,1) model, as it was differentiated once (d = 1) before becoming stationary (of first difference), and can be modeled as an ARMA (1,1) process, as it has an AR term and an MA post stationarity.

Finally, it is important to emphasize that to optimize the results, it was necessary to run in the software SPSS - Statistics all the possible combinations of the ARIMA model *(p,d,q)* in the two parameters, to arrive at the statistically optimal model after the decomposition of the data and meeting the criteria of analysis and execution.

3. Results

The parameters used in this study were the median and the 5th and 95th percentiles representing the estimate of uncertainties with 90% confidence, as recommended by authors below:

> “Future users of this reconstruction use the full ensemble when considering the plausible Holocene GMST evolution. By representing the multi-method reconstruction as a single time series, the median of the ensemble may be best along with the 90% range of the ensemble to represent uncertainty."

(Kaufman et al., 2020, p.04).

As per the model parameters, predictions for the median were expressed as temperature estimates for the next 100 years represented by AR and MA. For statistical reliability, the degree of significance (Marôco, 2018) of the measured parameters must be extremely significant in AR and very significant in MA, as shown on the output of table 2.

Table 2. 100-year scale temperature estimates of AR and MA parameters

Arima model parameters								
					Estimate	SE	t	**Sig.**
MdTempGlob-Model_1	**MdTempGlob**	No transformation	Constant		,191	,129	1,489	,139
			AR	Lag 1	**,932**	,032	28,799	**,000**
			MA	Lag 1	**-,266**	,099	-2,695	**,008**

Source: Author elaboration with Software SPSS - Statistics v. 22.

(URL: https://www.ibm.com/support/pages/spss-statistics-220-available-download).

For the uncertainty results, the 5th and 95th percentiles, a similar to that used for the median, whose configuration is described in a supplementary file, was used. The following parameters were generated for the uncertainty results as shown in table 3:

Table 3. Output of the parameters of the 5th and 95th percentile temperatures (model uncertainty)

ARIMA model parameters								
					Estimate	SE	t	**Sig.**
GLOBAL5-Model_1	**GLOBAL5**	No transformation	Constant		-2,403	3,490	-,688	,493
			AR	Lag 1	**,999**	,003	291,464	**,000**
			MA	Lag 1	**-,700**	,069	-10,111	**,000**
GLOBAL95-Model_2	**GLOBAL95**	No transformation	Constant		,149	,684	,218	,828
			AR	Lag 1	**,996**	,006	179,006	**,000**
			MA	Lag 1	**-,382**	,106	-3,593	**,000**

Source: Author elaboration (SPSS - Statistics v. 22).

We then had a set of six different extremely significant temperature results for the estimates of the two models: **0.932°C; -0.266°C** (Tab. 2) and **0.999°C**; **-0.70°C; 0.996°C; -0.382°C** (Tab. 3). The median, extracted from the set of estimates of the two models, whose result was **0.333°C,** was the most appropriate statistical measure in this case to fulfill the objective of this study to calculate and adopt a reference standard measure. Based on our results, by the end of this millennium we will have an average global temperature below the 1.50 ℃ to 2.00 ℃ projected by the IPCC. Thus, our results indicate that, contrary to warming, the world may experience a period of decreasing temperatures over the next hundred years.

4. Discussion

Why there is so much consensus around a scenario that leaves much room for doubt? Why there is so much scientific unanimity around anthropogenic warming (97.2% according to Cook *et al*., 2013), now called "climate change"?

When comparing recent temperatures to the distribution of global maximum temperatures during the Holocene, on average there has been a 1°C increment over the pre-industrial period (1850-1900) and for most members of the ensemble. Furthermore, no 200-year interval during these series exceeded the warmth of the most recent decade (Kaufman et al., p. 5, 2000). The time horizon of the anthropogenic thesis is more recent when compared to the time of man's existence on earth (Holocene) and when the time of the anthropogenic thesis is compared to the results of this research, it lacks substantiation if analyzed in the light of statistical science.

On the other hand, Kaufman et al., (2020), who relied on the IPCC projections, admit that this century's temperatures are likely to exceed 1°C when compared to those of the pre-industrial era (1800-1900), which they considered as an anomaly of 0°C. Although the authors claim that the Holocene GMST reconstruction is comparable to the IPCC long-term projections and those seen in the last decade, the results presented here show a different and antagonistic scenario especially if one considers a hundred-year scale and the historical temporality present in the statistical series.

Furthermore, in the graphical temporal observations of the studies by Kaufman et al. (2020, p.6, fig. 3), Davis (2017, p. 6, fig. 5) and Moberg et al. (2005, p. 3, fig. 2), there is significant climate variability every 2K years casting doubt on establishing anthropogenicity as a criterion for the last 150 years. These observations are confirmed by Moberg et al. (2005) who conclude that "The resulting model reconstruction supports the case that multicentennial natural variability has been larger than is commonly thought, and that considerable natural climate variation can be expected in future." One of the villains of anthropogenic genesis, the greenhouse effect, was unveiled in 1896 by Arrhenius as a natural phenomenon beneficial to the development of biological life on the earth's surface (troposphere). Arrhenius' studies were subsequently confirmed by Miller & Spoolman (2016), who stated that, "Our climate, lives, and economies depend on the natural greenhouse effect. Greenhouse gases absorb heat radiated by the earth and the gases then emit infrared radiation that warms the atmosphere. Without the natural greenhouse effect, the earth would become cold and uninhabitable." On the contrary, other studies on the threat of the man-made greenhouse effect, such as those by Gillett & Matthews (2010) and Anderson, Hawkins & Jones (2016), are inconclusive regarding the magnitude of these effects and demonstrate uncertainty when set against the complexity of the earth's geophysical and climate systems. Therefore, reinventing this evidence as the proponents of anthropogeny orthodoxly claim, is something that does not hold up considering the historical veracity of science.

It is important to say our results do not ignore the impact that human action has brought to recent climate change which however appears insignificant in the face of the millennial variability of the climate, the size and complexity of the universe, and all the natural and astronomical phenomena that interact with the earth in the planetary system. Lastly, our predicted climate scenario cannot determine what are the true causes of recent climate change, whether natural or anthropogenic, since the two may be complementary, not divergent. Further studies on paleoclimate and its variability are needed to corroborate the estimates resulting from this research and to avail more evidence in the search for scientific truth.Therefore, reinventing this evidence as the proponents of anthropogeny orthodoxly claim, is something that does not hold up considering the historical veracity of science. However, our results do not ignore the impact that human action has brought to recent climate change which however appears insignificant in the face of the millennial variability of the climate, the size and complexity of the universe, and all the natural and astronomical phenomena that interact with the earth in the planetary system. Lastly, our predicted climate scenario cannot determine what are the true causes of recent climate change, whether natural or anthropogenic, since the two may be complementary, not divergent. Further studies on paleoclimate and its variability are needed to corroborate the estimates resulting from this research and to avail more evidence in the search for scientific truth.

5. Conclusion and Policy Recommendation

In view of our findings, it is unreasonable to subject governments and organizations to be hostages of a doubtful thesis with all its consequences in the face of scientific relativity. Subjecting government organizations and governments to the current consensus may condemn humanity to unjustifiable climate catastrophism.

All actors involved in the global climate change movement ought to be heard and their opinions taken into consideration especially when it comes to phenomena not yet proven by time and human experimentation. Every scientific consensus should not be treated as absolute truth; one of the pillars of science, which has always thrived on seeking truth through doubt.

Nevertheless, this article does not belittle the public, governmental and corporate policies in relation to the alarmism that is being given to climate change. Any public or private initiative to mitigate the impact that the planet suffers due to human action is laudable and necessary. But the future and the progress of the next generations, especially in third world countries, should be compromised by an 'official' scientific narrative that has become official; a narrative that is to the detriment of a minority that thinks and researches differently, but with foundations and arguments as important or equal to it.

Data Records

The data collected for this research were extracted from Kaufman et al., 2020, as referenced in the text. After processing, the data were fed into IBM-SPSS Statistics v. 22, at https://www.ibm.com/docs/en/spss-statistics/SaaS?topic=reference-arima, for analysis and the of results' generation. These data are avaiable in the figshare repository: https://figshare.com/articles/dataset/ArimaMedTempGlobal_spv/14429006;https://figshare.com/articles/dataset/Spreadsheet_for_entering_and_processing_paleoclimate_data_and_graphs_with_the_results_of_the_model_/14429273;https://figshare.com/articles/dataset/Mathematical_and_operational_foundations_of_the_model_mediana_and_uncertainties_/14442701.

Technical Validation

All data validation were done on the ARIMA platform of SPSS-Statistics as described in the body of the manuscript and in the data repository. For logistical reasons, only the data that satisfied the criterial for the research methodology is available in the repository.

Acknowledgements

Special thanks and recognition to professors Claudio Antonio Rojo and Edison Luiz Leismann, who provided all the support required to carry out this research. We also wish to acknowledge the legacy left behind by the authors cited in this paper, besides Kaufman et al. (2020): Routson et al. (2019), Cook et al. (2013), PAGES 2k Consortium, Marcott et al. (2013), Harde (2019), Box & Jenkins (1978), Gujarati & Porter (2011), to whom we am indebted for the knowledge acquired.

Author contributions statement

G. V. F. S. and L.G.C designed the experiment (s), C. A. R. and E. L. L. conducted the experiments, E. L. L. and C. A. R. analyzed the results. All authors reviewed the manuscript and approved the final version for publication.

Competing interests and funding sources

The authors declare no competing interests. The authors did not receive any grants from funding agencies in the public, commercial, or non-profit sectors to do this research.

Additional information

Correspondence and requests for materials should be addressed to G.V. F. S.

Author’s information

G.V.F.S: https://orcid.org/0000-0001-6216-2126

L.G.C: https://orcid.org/0000-0002-9043-7024

C. A. R: https://orcid.org/0000-0003-4484-9033

E. L. L: https://orcid.org/0000-0002-4112-8241

References

Anderegg, W. R. L., Prall, J. W., Harold, J., & Schneider, S. H. (2010). Expert Credibility in Climate Change. *Proceedings of the National Academy of Sciences Jul 2010, 107*(27), 12107-12109. https://doi.org/10.1073/pnas.1003187107

Anderson, T. R., Hawkins, E., & Jones, P. D. (2016). CO2, the greenhouse effect and global warming: from the pioneering work of Arrhenius and Callendar to today's Earth System Models. *Endeavour*, *40*(3), 178-187. https://doi.org/10.1016/j.endeavour.2016.07.002

Babu, C. N., & Reddy, B. E. (2014). A moving-average filter based hybrid ARIMA–ANN model for forecasting time series data. *Applied Soft Computing, 23*, 27-38. https://doi.org/10.1016/j.asoc.2014.05.028

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2008). *Time Series Analysis: Forecasting and Control* (4th ed). Wiley, Oxford. https://doi.org/10.1002/9781118619193

Box, G. P., & Jenkins, G. M. (1978). Time series analysis: forecasting and control. Ed. rev. holden day, são francisco: holden. Document shared on www.docsity.com

Bray, D. (2010). The scientific consensus of climate change revisited. *Ciência e política ambiental*, *13*(5), 340-350. https://doi.org/10.1016/j.envsci.2010.04.001

Cook, J. *et al* (2013). *Environ. Res. Lett.* 8 024024. https://doi.org/10.1088/1748-9326/8/2/024024

Davis, W. J. (2017). The Relationship between Atmospheric Carbon Dioxide Concentration and Global Temperature for the Last 425 Million Years. *Climate 2017*, 5, 76. https://doi.org/10.3390/cli5040076

Easterbrook, D. (Ed.). (2016). Evidence-based climate science: data opposing CO2 emissions as the primary source of global warming. Elsevier.

Gillett, N. P., & Matthews, H. D. (2010). Accounting for carbon cycle feedbacks in a comparison of the global warming effects of greenhouse gases. *Environmental Research Letters*, *5*(3), 034011. Retrieved from https://iopscience-iop.ez89.periodicos.capes.gov.br/article/10.1088/1748-9326/5/3/034011

Gujarati, D. N., & Porter, D. C. (2011). *Basic Econometrics, 5th edition*. 767-778. AMGH Editora.

Harde, H. (2019). What Humans Contribute to Atmospheric CO2: Comparison of Carbon Cycle Models with Observations. *Earth Sciences, 8*(3), 139-158. https://doi.org/10.11648/j.earth.20190803.13

Haustein, K., Allen, M. R, & Forster, P. M. *et al.* (2017). A real-time Global Warming Index. *Sci Rep, 7,* 15417. https://doi.org/10.1038/s41598-017-14828-5

IBM – SPSS Statistics v. 22. (2020). Retrieved from https://www.ibm.com/support/pages/spss-statistics-220-available-download

IPCC - Intergovernmental Panel on Climate Change. United Nations. N.Y. (2019). Retrieved from https://www.ipcc.ch/sr15/

Katimon, A., Shahid, S., & Mohsenipour, M. (2018). Modeling water quality and hydrological variables using ARIMA: a case study of Johor River, Malaysia. *Sustainable Water Resources Management*, *4*(4), 991-998. https://doi.org/10.1007/s40899-017-0202-8

Kaufman, D., McKay, N., & Routson, C. *et al.* (2020). Holocene global mean surface temperature, a multi-method reconstruction approach. *Sci Data, 7,* 201. https://doi.org/10.1038/s41597-020-0530-7

Koonin, S. E. (2021). *Unsettled: What Climate Science Tells Us, What It Doesn't, and Why It Matters*. BenBella Books.

Legates, D. R., Soon, W., & Briggs, (2013). WM Learning and Teaching Climate Science: The Perils of Consensus Knowledge Using Agnotology. *Sci & Educ, 22,* 2007-2017. https://doi.org/10.1007/s11191-013-9588-3

Legates, D. R., Soon, W., Briggs, W. M., & C. Monckton of Brenchley (2015). Consenso Climático e 'Desinformação': Uma Tréplica à Agnotologia, Consenso Científico e o Ensino e Aprendizagem das Mudanças Climáticas . Sci & Educ, *24,* 299-318. https://doi.org/10.1007/s11191-013-9647-9

Marcott, S. A., Shakun, J. D., Clark, P. U., & Mix, A. C. (2013). A reconstruction of regional and global temperature for the past 11,300 years. *Science, 339,* 1198. https://doi.org/10.1126/science.1228026

Maroco, J. (Pero Pinheiro, 2018). *Análise estatística com o SPSS Statistics* (7th ed.). 54-60.

Medhaug, I., Stolpe, M., & Fischer, E. *et al.* (2017). Reconciling controversies about the 'global warming hiatus'. *Nature, 545,* 41-47. https://doi.org/10.1038/nature22315

Miller, G. T., & Spoolman, S. E. (Cengage Learning, 2016). *Environmental Science,* 22-24.

Mitchell, D., James, R., & Forster, P. *et al.* (2016). Realizing the impacts of a 1.5 ℃ warmer world. *Nature Clim Change, 6, 7*35-737 (2016). https://doi.org/10.1038/nclimate3055

Moberg, A., Sonechkin, D., & Holmgren, K. *et al.* (2008). Highly variable Northern Hemisphere temperatures reconstructed from low- and high-resolution proxy data. *Nature, 433,* 613-617. https://doi.org/10.1038/nature03265

Molion, L. C. B. (2004). Aquecimento global: Uma visão crítica. *Revista brasileira de climatologia, 3*. Retrieved from https://revistas.ufpr.br/revistaabclima/article/view/25404

Oreskes, N. (2004). *Science.*Vol. 306, Issue 5702, p.1686. https://doi.org/10.1126/science.1103618

Pages 2k Consortium. (2019). Consistent multi-decadal variability in global temperature reconstructions and simulations over the Common Era. *Nat. Geosci., 12,* 643-649. https://doi.org/10.1038/s41561-019-0400-0

Pokorny, M. (Basil Blackwell, 1987). An introduction to econometrics. (ed. Blackwell, B.) p. 343.

Prof. Svante Arrhenius (1896) XXXI. Sobre a influência do ácido carbônico no ar sobre a temperatura do solo. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 41*(251), 237-276.

Reisinger, A., Meinshausen, M., Manning, M., & Bodeker, G. (2010). Uncertainties of global warming metrics: CO2 and CH4. *Geophys. Res. Lett. , 37* , L14707. https://doi.org/10.1029/2010GL043803.

Routson, C. C., McKay, N. P., & Kaufman, D. S. *et al.* (2019). Mid-latitude net precipitation decreased with Arctic warming during the Holocene. *Nature, 568,* 83-87. https://doi.org/10.1038/s41586-019-1060-3

Salzer, E., Neske, D. A. L., & Rojo, C. A. (2019). Global warming: bias analysis in divergent strategic scenarios. *Journal Multi-Science Research (Msr), Vitoria, 2*(2), 144-158. Retrieved from https://msrreview.multivix.edu.br/index.php/msr/article/view/43

Shwed, U., & Bearman, P. (2010). The Temporal Structure of Scientific Consensus Formation. *American Sociological Review, 75*(6), 817-840. https://doi.org/10.1177/0003122410388488

Solomon, S. *et al.* (Cambridge University Press, 2007). Climate Change 2007: *The Physical Science Basis. Working Group I Contribution to the Fourth Assessment Report of the IPCC.*

Stockinger, N., & Dutter, R. (1987). Robust time series analysis: a survey. *Kybernetika, 23*(Suppl(1)), 3-88. Retrieved from http://dml.cz/dmlcz/124955

Valipour, M. (2015). Long-term runoff study using SARIMA and ARIMA models in the United States. *Meteorological Applications*, *22*(3), 592-598. https://doi.org/10.1002/met.1491