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Black box analysis with linear regression on global warming

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ABSTRACT

This paper demonstrates that the conclusions drawn from datasets on global temperature anomaly and atmospheric CO2 from NOAA can vary depending on the range of investigated periods. By examining the data from both macroscopic and microscopic perspectives, the study reveals that different levels of analysis can produce different outcomes from the same datasets based on statistics.

Introduction

Black box machine learning models are used for high stakes decision-making, causing problems in healthcare, criminal justice. Instead of explaining these models, it's better to design inherently interpretable models (Rudin, 2019). Rudin highlighted the difference between explaining black boxes and using interpretable models, reasons to avoid explainable black boxes in high-stakes decisions, challenges to interpretable machine learning, and examples where interpretable models could replace black box models (Rudin, 2019).

Aggarwal et al. discussed correlation analysis, which determines the strength of the relationship between two continuous variables (Aggarwal and Ranganathan, 2017). They also examined linear regression analysis, which predicts the value of one continuous variable based on another. Additionally, they explored the assumptions and potential pitfalls associated with this type of analysis.

Porter et al. reported a literature search to define problems with the use of correlation coefficient and bivariate linear regression in medical publications (Porter, 1999). A screening of papers and letters published in the British Medical Journal, The Lancet, and the New England Journal of Medicine during 1997 identified fifteen categories of errors, eight of which were important or common. They included failure to define the relevant sample number, display of misleading scatterplots, unwarranted importance attached to significance levels, and omission of confidence intervals for correlation coefficients and around regression lines.

Bewick et al.'s review presented methods for analyzing the relationship between two quantitative variables, including the calculation and interpretation of the sample product moment correlation coefficient and the linear regression equation (Bewick et al., 2003). The review discussed common misuses of these techniques, as well as tests and confidence intervals for population parameters. Additionally, they highlighted potential failures of the underlying assumptions.

This paper illustrates that the same model and datasets can yield different results depending on the range of periods investigated. In other words, macroscopic and microscopic perspectives can lead to different conclusions. This paper discusses contradicting conclusions with two datasets from NOAA on the global temperature anomaly associated with CO2.

In a black box model, the internal workings of the model are not known to the user. The model takes in inputs and produces outputs as shown in Fig. 1, but the relationship between the inputs and outputs is not transparent. Linear regression is a type of black box model that can be used to predict a continuous output variable based on one or more input variables.

One way to determine if the current input is not enough to predict the output using a black box model with linear regression is to assess the model's performance. If the model's predictions are not accurate, it may indicate that the current input is not sufficient to predict the output. Both macroscopic and microscopic views are necessary when verifying a model, and it is important to vary the range of investigated periods to ensure the model's accuracy.

Solomon et al. presented evidence for global warming due to CO2 emissions (Solomon et al., 2009). However, Hansen et al. proposed an alternative scenario (Hansen et al., 2000). This paper investigates the validity of the CO2 hypothesis using statistical analysis of two monthly datasets. The National Oceanic and Atmospheric Administration (NOAA) began measuring CO2 levels in March 1958, limiting the available data. Despite this limitation, this paper presents two opposing conclusions based on statistics, demonstrating both a positive and negative association between global CO2 levels and temperature anomalies.

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Fig. 1. Black box model with input and output.

In the realm of climate science, the National Oceanic and Atmospheric Administration (NOAA) is widely recognized as a highly reliable source of data. Its global temperature dataset, NOAAGlobalT, is particularly esteemed for its comprehensive coverage and rigorous methodology. While there are several other notable datasets used in the Intergovernmental Panel on Climate Change's Sixth Assessment Report (IPCC AR6), such as GISS and BE from the United States, HADCRUT from the United Kingdom, and CMST from China, NOAA stands out for its consistent accuracy and reliability. Each of these datasets has its strengths and contributes valuable insights to our understanding of global climate patterns. However, NOAA's long-standing commitment to scientific integrity, its use of advanced technology in data collection, and its rigorous quality control processes have earned it a reputation as one of the most trusted sources in the field. It's important to note that the choice of dataset can depend on the specific research question being addressed, and using multiple datasets can provide a more robust understanding of climate trends. Nevertheless, when it comes to reliability and trust, NOAA is often the preferred choice among climate scientists. In this study, we have utilized the global temperature and CO2 datasets from the National Oceanic and Atmospheric Administration (NOAA). NOAA's datasets are highly regarded in the field of climate science due to their comprehensive coverage, rigorous methodology, and consistent accuracy. The use of these trusted datasets strengthens the reliability of our findings and conclusions.

The P-value is a statistical measure that helps us determine if the observed enough data could have occurred under the null hypothesis. It does not, in itself, provide evidence for or against the alternative hypothesis.

The observation about the potential impact of volcanic eruptions on the discrepancy between overall and local trends is insightful. We have conducted a thorough analysis to investigate this possibility. While we found evidence of temperature decreases during periods of volcanic activity, the impact on the overall trend appears to be minimal. However, we acknowledge that further research is needed to fully understand the complex interplay between volcanic eruptions and temperature anomalies. To address this, we need to conduct a sensitivity analysis to assess the robustness of our results under different scenarios. To this end, a sensitivity analysis is required to evaluate the resilience of our findings under varying scenarios. It's worth noting that the proposed black-box scenarios were constrained by a limited number of variables within the datasets.

To calculate the p-value for comparing two sets of data, we typically use a statistical test such as the *t*-test. The formula for the t-statistic is:

$$t = \frac{\overline{X}_A - \overline{X}_B}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}}$$

where:

- $\overline{X}_A$ and $\overline{X}_B$ are the sample means of Set A and Set B, respectively.
- s_A^2 and s_B^2 are the sample variances of Set A and Set B, respectively.
- n_A and n_B are the sample sizes of Set A and Set B, respectively.

The p-value is then calculated by comparing the absolute value of this t-statistic to a t-distribution with degrees of freedom equal to $n_A + n_B - 2$. The p-value represents the probability of observing a t-statistic as extreme as, or more extreme than, the observed value under the null hypothesis.

In a linear regression model, three key components play crucial roles in interpreting the results: R-squared, p-value, and the slope. R-squared, also known as the coefficient of determination, is a statistical measure that quantifies the proportion of the variance for a dependent variable explained by an independent variable or variables. It serves as a gauge of how well the regression predictions mirror the actual data points. An R-squared of 100 % signifies that changes in the dependent variable are entirely accounted for by changes in the independent variable(s). However, a low R-squared isn't necessarily indicative of a poor model, as it could simply reflect inherent variability in the data.

The p-value in the context of linear regression is used to ascertain the statistical significance of each coefficient in the model. The null hypothesis posits that the variable has no correlation with the dependent variable. If the p-value falls below a chosen significance level (usually 0.05), we reject the null hypothesis and conclude that there is evidence that the coefficient differs from zero. In other words, the predictor is meaningful and should be retained in the model.

The slope in a linear regression model quantifies the steepness of the line and is also referred to as the impact coefficient of the variable. It denotes the change in the dependent variable given a one-unit change in the independent variable, with all other independent variables held constant. The slope of the regression line, or the regression coefficient, represents the rate at which Y changes for each unit change in X.

In summary, R-squared measures the goodness of fit of the model, the p-value tests the significance of each predictor, and the slope quantifies the effect of each predictor. These components are all crucial in interpreting the results of a linear regression analysis.

Methods

The first-order linear regression can be expressed as CO2 = aX + b and temperature = cX + d, where X is a year-month variable, and a (slope), b (intercept), c (slope), and d (intercept) are coefficients. If a and c have opposite signs, there may be a negative association between CO2 and temperature. If a and c have the same sign, there may be a positive relationship between CO2 and temperature. R-squared is a statistical measure to assess the goodness of fit between observed data and predicted values. A p-value <0.05 indicates that there is sufficient evidence to suggest that the difference between the groups from which the samples were taken is statistically significant, and that the null hypothesis can be rejected (Dahiru, 2008; Di Leo and Sardanelli, 2020; O'Brien et al., 2015). This means that it is unlikely that the observed difference between the groups occurred by chance alone.

A new application called gtempco2 has been developed and made available on the Python Package Index (PyPI) to facilitate reproducibility and validation of the claims proposed in this paper (GitHub). If Python is installed on the system, users can easily install and run the application. The application allows users to interactively enter a start date and end date to visualize data on global temperature anomalies and CO2 levels. gtempco2 is to plot a graph for a user-specified time period with two lines representing global temperature and global CO2 levels. The graph includes first-order regression lines with coefficients, p-value and R-squared values.

The P-value is a statistical measure that helps us determine if the observed enough data could have occurred under the null hypothesis. It does not, in itself, provide evidence for or against the alternative hypothesis. The p-value in the context of linear regression is used to ascertain the statistical significance of each coefficient in the model. The null hypothesis posits that the variable has no correlation with the dependent variable. If the p-value falls below a chosen significance level (usually 0.05), we reject the null hypothesis and conclude that there is evidence that the coefficient differs from zero. In other words, the predictor is meaningful and should be retained in the model.

Results

Fig. 2 presents the results of an analysis of data from March 1958 to June 2023. The R-squared values for CO_2 and Temperature anomaly (T anomaly) are 0.976 and 0.831, respectively, indicating a strong positive linear relationship between these variables and the independent variable. Additionally, the p-value for Temperature anomaly is 0.000, suggesting that the relationship between Temperature anomaly and the independent variable is statistically significant. These results provide evidence that global temperature anomaly may be strongly associated with CO_2 levels, as both variables have positive slopes.

Fig. 3 illustrates the relationship between global CO_2 and temperature anomaly during the period from March 1990 to March 1994. Fig. 3 shows that the slopes of the two variables have opposite signs, indicating a negative association between them. Additionally, the p-value for temperature anomaly is 0.000 and that for CO_2 is 0.00877, suggesting that the relationship between temperature anomaly and the independent variable is statistically significant. These results provide evidence of a negative association between global CO_2 levels and temperature anomaly during this specific time period.

Discussion

The author attributes the declining temperature trend depicted in Fig. 3 primarily to the eruption of the Pinatubo volcano in the Philippines in June 1991, as suggested by Parker et al. (Parker et al., 1996). A similar downward trend in temperature was observed around 1982, believed to be a consequence of the El Chichón volcanic eruption in Mexico (Dutton and Christy, 1992). Both instances are thought to result from a decrease in the amount of direct solar radiation reaching the Earth's surface due to the retention of volcanic ash in the atmosphere.

Schmidt and Rahmstorf's research illustrated that an 8-year moving average unveils a downward trend in temperature, partially due to volcanic eruptions and El Niño and La Niña events (Schmidt and Rahmstorf, 2008). However, when considering a 15-year moving average, the temperature trend consistently showed an increase. For example, the unusually high temperatures linked to the 1998 El Niño event were followed by a period of seeming temperature decline, which can be ascribed to natural variability. Their study underscored the importance of choosing suitable data intervals when discussing climatology. They cautioned that overlooking factors such as natural variability, volcanic eruptions, and other temporary events can lead to misinterpretations when drawing conclusions about climatological temperature changes (Schmidt and Rahmstorf, 2008).

Based on the short-term investigation, the cooling phenomena were observed due to El Niño/La Niña events and volcanic eruptions. It's important to note that while these cooling events are natural, they can be influenced by human activities. Our research seeks to explore this complex interplay between natural climate phenomena and human-induced changes, thereby contributing to a more nuanced understanding of our climate system.

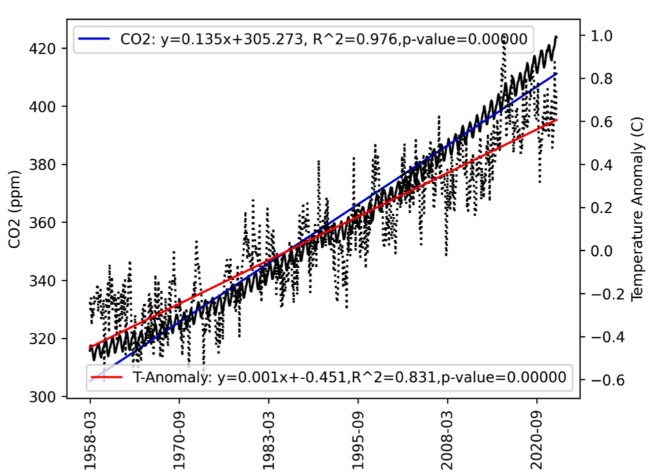

Fig. 2. Global CO_2 and temperature anomaly from March 1958 to June 2023.

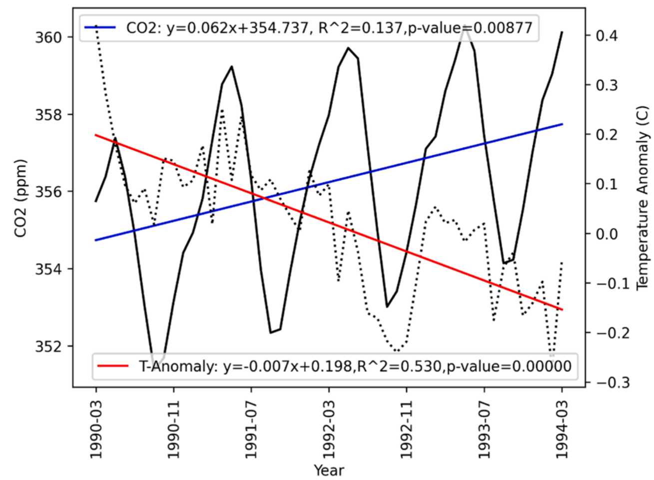

Fig. 3. Global CO_2 and temperature anomaly from March 1990 to March 1994.

Indeed, it's a significant point to emphasize that natural cooling phenomena could potentially be realized through man-made technology. This concept, often referred to as climate engineering or geoengineering, involves deliberate and large-scale intervention in the Earth's climate system with the aim of mitigating climate change or its impacts.

While this is a complex and controversial field with many ethical, political, and environmental considerations, it's an area of active research and holds potential for future climate strategies. However, it's crucial to remember that such interventions should not be seen as a substitute for reducing greenhouse gas emissions and pursuing sustainable practices. They could, at best, be part of a broader climate strategy. As always, any technological solutions must be approached with caution, rigorous scientific testing, and comprehensive understanding of potential risks and benefits. We believe that this approach will strengthen our study and provide valuable insights into the multifaceted nature of climate change.

Conclusion and implication

Based on the given information, it appears that the relationship between global CO_2 levels and temperature anomaly may vary over time. While the long-term data from March 1958 to June 2023 suggests a strong positive association between the two variables, the short-term data from March 1990 to March 1994 shows a negative association. This evidence could be used to challenge the hypothesis that there is a consistent positive relationship between global CO_2 levels and temperature anomaly. With the proposed tool, discovered short-term cooling phenomena was due to El Niño/La Niña events and volcanic eruptions

The implications of these findings are that further research may be necessary to fully understand the relationship between global CO_2 levels and temperature anomaly. It may be important to consider other factors that could influence this relationship, such as changes in climate patterns such as total solar irradianceor (TSI) and human activities. Additionally, these results highlight the importance of considering both long-term and short-term data when evaluating the relationship between these two variables. Ultimately, a more nuanced understanding of the relationship between global CO_2 levels and temperature anomaly could help inform efforts to address climate change and its impacts. The short-term negative association can be used in climate-engineering for mitigating the global warming.

CRediT authorship contribution statement

Yoshiyasu Takefuji: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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