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A Note on the Potential of Carbon Dioxide Measurements as Temperature Precursors in Numerical Weather Prediction

Frank Thomas Tveter Dr.Scient.[1*]

[1]Development Centre for Weather Forecasting, Norwegian Meteorological Institute, 0313 Oslo, Norway

Correspondence
Frank Thomas Tveter Dr.Scient., Development Centre for Weather Forecasting, Norwegian Meteorological Institute, 0313 Oslo, Norway
Email: anon@example.com

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The non-secular anomalies in carbon dioxide measurements at Mauna Loa are compared to the non-secular anomalies in the HadCRUT4 median global temperature from 1991 to 2020. A strong and significant Pearson's product-moment correlation is found between carbon dioxide anomalies and global temperature anomaly, indicating that the correlation is an actual characteristic of the atmosphere. But more important from a numerical weather prediction perspective, this result indicates that carbon dioxide anomalies can have no skills as temperature precursors on short time scales.

KEYWORDS
temperature precursors, carbon dioxide, HadCRUT4, Mauna Loa

1 | INTRODUCTION

Numerical Weather Prediction is concerned with making forecasts of the future state of the atmosphere, using any available information about the atmosphere (e.g. Lorenc (1986), Lorenc (1988), Arribas (2010)). An important element in the continuous improvement of numerical weather prediction is the handling of new types of information about the atmosphere (e.g. Lorenc (2000), Rawlins (2007), Fairbairn (2014), Gustafsson (2012), Saunders (2010), Storto (2009), Tveter (2006)). Any new precursors that can give relevant information about the atmosphere will therefore capture the attention of the numerical weather prediction community.

The strong correlation between the secular variations of global temperature and atmospheric carbon dioxide estimates on a large time scale, is well documented in the literature (e.g. Florides (2009)). The air temperature plays an important role in most processes in the atmosphere, and it is therefore a key control variable in numerical weather prediction. Carbon dioxide, on the other hand, is an inert trace gas that does not received much attention from the numerical weather prediction community. However, it has been shown using nouvelle techniques (Stips (2016)), that information on a large time scale flows from carbon dioxide to the global temperature. This begs the question if measurements of the atmospheric carbon dioxide trace gas also could be used to derive temperature precursors on shorter time scales. The correlations between the non-secular anomalies in global temperature and atmospheric carbon dioxide on short time scales, is the main focus of this note.

2 | THE DATA

This note uses in situ measurements of carbon dioxide at Mauna Lua (ML-CO2) averaged over each week provided by the NOAA Earth System Research Laboratories (ESRL). The ML-CO2 data set extends from 1975 to present day. The study also uses a HadCRUT4 median global temperature (HMGT) data set from the University of East Anglia (Morice (2012)), which extends from 1850 to present day.

The secular trends in the ML-CO2 and HMGT data sets are riddled with discontinuities. Discontinuities in the secular trends make it difficult to separate out anomalies without introducing large systematic errors. The approach in this note is to estimate the ML-CO2 secular trend over a time period where the secular trend is fairly stable.

The massive Pinatubo eruption in 1991 initiated a global cooling of the atmosphere (Kirchner (1999)). Numerical weather prediction naturally focuses on the current characteristics of the atmosphere. This note therefore uses data from the time period 1991 to 2020.

3 | METHOD AND RESULTS

The secular trend is estimated using a function that depends on as few control variables as possible, so that the anomalies are not absorbed in the estimated trend. The secular trend in the weekly measured ML-CO2 is estimated using a quadratic function in time. The resulting maximum likelihood estimate for the secular trend in ML-CO2, $\text{TREND}_{\text{ML-CO2}}$, for the period from 1991 to 2020 is given by

$$\text{TREND}_{\text{ML-CO2}}(\text{Year}) = \alpha_0 + \alpha_1 * (\text{Year} - 1991) + \alpha_2 * (\text{Year} - 1991)^2 \tag{1}$$

where α_0 is 354.106084092867ppm, α_1 is 1.47026246394882ppm/year and α_2 is 0.0186169684331077ppm/year^2. The ML-CO2 anomaly is defined as the difference between the yearly averaged ML-CO2 and the secular trend, $\text{TREND}_{\text{ML-CO2}}$. The secular trend in HMGT, $\text{TREND}_{\text{HMGT}}$, is assumed to be a linear function of the secular trend in the ML-CO2, $\text{TREND}_{\text{ML-CO2}}$. The maximum likelihood estimate gives the linear transformation

$$\text{TREND}_{\text{HMGT}}(\text{TREND}_{\text{ML-CO2}}) = \beta_0 + \beta_1 * \text{TREND}_{\text{ML-CO2}}$$

where β_0 is -2.8936969211479K and β_1 is 0.00879675801197448K/ppm. Note that this linear transformation can also be used to calculate the HMGT equivalent of the ML-CO2 yearly average. The temperature anomaly is defined as the difference between the yearly averaged HMGT and the secular trend, $\text{TREND}_{\text{HMGT}}$.

Figure 1 shows the anomalies in ML-CO2 and the one-year-delayed HMGT anomalies, where the HMGT anomalies have been linearly mapped to match the maximum ML-CO2 amplitude. The linear mapping will not affect the correlation study. Notice that the anomalies have no obvious systematic errors, indicating that the trend is well fitted. The Pearson's product-moment correlation is strong ($r(26) \sim 0.75$) and significant ($p \sim 0.000005$). Even though this result suggests that the probability that the correlation is a coincidence is about 0.0005%, some account must be

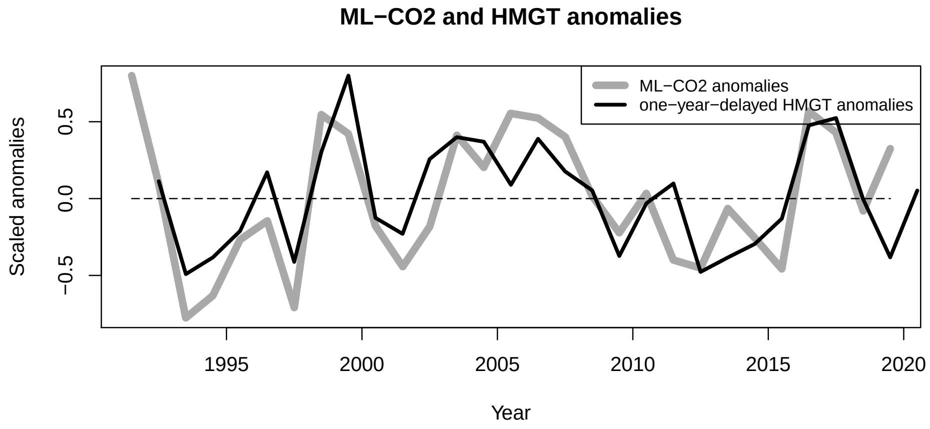

FIGURE 1 The anomalies in the annual averaged Mauna Loa measurements (ML-CO2) and one-year-delayed HadCRUT4 median global temperature (HMGT). The Pearson's product-moment correlation is strong ($r(26) \sim 0.75$) and significant ($p \sim 0.000005$), indicating that the correlation is an actual characteristic of the atmosphere.

taken for the reduction in the degrees of freedom (*df*) due to the data processing and data error correlation. But even an unjustifiably large reduction in *df*, gives a probability of more than 99.99% that the strong correlation between 1991 and 2020 was an actual characteristic of the atmosphere.

4 | CONCLUSIONS

The strong and significant correlation between the ML-CO2 anomalies and the delayed HMGT anomalies from 1991 to 2020, indicates that the correlation is an actual characteristic of the atmosphere. However, the delay in carbon dioxide measurement anomalies relative to the global temperature anomalies indicates that precursors based on carbon dioxide anomalies can have no skills in predicting global temperature anomalies.

Data sources

The ML-CO2 data is available from NOAA Earth System Research Laboratories (ESRL): `ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2_weekly_mlo.txt`. The HadCRUT4 data is available from the University of East Anglia: `https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT4-gl.dat`.

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conflict of interest

The author declares no conflict of interest.

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