The Relationship between Hourly CO_2 Concentrations and Hourly Temperature: Evidence from Alaska

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Key Points:

1) At NOAA's Barrow Observatory in Alaska, the annual temperature during 2015-2020 was about 3.37 ºC higher than in 1985-1990.

2) Virtually all the upward changes in annual temperature through 2015 can be attributed to higher CO_2 concentrations.

3) The model's out-of-sample hourly temperature predictions are highly accurate, but this accuracy is significantly degraded if the estimated effects of CO_2 are largely ignored.

Abstract

According to the IPCC and other leading scientific organizations, "it is extremely likely that human influence has been the dominant cause of the observed increase in global temperatures since the mid-20th century." One gap in the research underlying this assessment is that the statistical relationship between CO_2 concentrations and the hourly temperature has not been rigorously investigated. Addressing this gap in the research is challenging because the hourly temperature data are noisy, which makes it difficult to extract the CO_2 signal. Yet, this challenge needs to be resolved to advance climate science (including the emerging science of climate attribution) and public policy. The latter issue is especially important given that a significant percentage of the population does not fully embrace the scientific consensus on climate change.

This paper examines the relationship between CO_2 concentrations and hourly temperature using data from the Barrow Atmospheric Observatory in Alaska, USA. It is first noted that the average annual temperature at Barrow over the 2015-2020 period was about 3.37 ºC higher than in the 1985-1990 period. The analysis employs solar irradiance (a key driver of the weather and climate system), CO_2, and temperature data. Possible non-anthropomorphic drivers of annual temperature are also considered. The data are analyzed using an ARCH/ARMAX (Autoregressive Conditional Heteroskedasticity/ Autoregressive–Moving-Average with Exogenous Inputs) approach. This statistical method captures the data's heteroskedastic and autoregressive nature, which would otherwise "mask" CO_2's "signal" in the noisy data. The model is estimated using hourly data from 1985 through 2015. The results are consistent with the hypothesis that increases in CO_2 concentration levels have consequences for hourly temperature. The model is evaluated using data from January 1, 2016, through December 31, 2021. The model's out-of-sample hourly temperature predictions are highly accurate. However, this accuracy is significantly degraded if one accepts the claim that the effect of CO_2 on temperature is small in magnitude. The implications for selected global locations are assessed using Vector Autoregressive temperature models coupled with Granger Causality tests.

Plain Language Summary

This paper examines the relationship between CO_2 concentrations and hourly temperature using data from the Barrow Atmospheric Observatory in Alaska, USA. It is first noted that the average annual temperature at Barrow over the 2015-2020 period was about 3.37 ºC higher than in the 1985-1990 period. The analysis employs hourly solar irradiance, CO_2, and temperature data. The model controls for possible non-anthropomorphic drivers of annual temperature and other factors. The model was estimated using hourly data from 1 Jan 1985 through 31 Dec 2015. The estimated effects of CO_2 are highly statistically significant, while the non-anthropomorphic drivers, exclusive of solar irradiance, are quantitatively unimportant. The model is evaluated from 1 Jan 2016 through 31 December 2021. The model's out-of-sample hourly temperature predictions are highly accurate. However, this accuracy is significantly degraded if one accepts the claim that the effect of CO_2 on temperature is small in magnitude. The implications for the hourly temperatures at lower latitudes are assessed using an econometric model.

Index Terms
6620 Science Policy
1630 Impacts of Global Change
1616 Climate Variability
9315 Arctic Region
3270 Time series analysis
1986 Statistical methods: Inferential

Key Words:
CO_2 Concentrations, Hourly Temperature, Downward total solar irradiance, Climate Change, Arctic Region, Alaska, Granger Causality

Acronyms: AMAP, Arctic Monitoring and Assessment Program, ARCH, Autoregressive conditional heteroskedasticity; ARMA, autoregressive–moving-average; ARMAX, autoregressive–moving-average with exogenous inputs; ECMWF, European Centre for Medium-Range Weather Forecasts; ICAO, International Civil Aviation Organization; IPCC, Intergovernmental Panel on Climate Change; MFP, multivariable fractional polynomial; RMSE, root-mean-squared-error.

1. Introduction

According to the IPCC assessment of the literature on climate change, "It is extremely likely that human influence has been the dominant cause of the observed increase in global temperatures since the mid-20th century "(IPCC, 2013, p. 17). However, one gap in the research is that the statistical relationship between hourly CO_2 concentrations and the hourly temperature has not been rigorously investigated. Addressing this gap in the research is challenging because the hourly temperature data are noisy, which makes it difficult to extract the CO_2 signal. Yet, this challenge needs to be resolved to advance climate science (including the emerging science of climate attribution) and public policy. The latter issue is especially important given that a significant percentage of the population does not fully embrace the scientific consensus on climate change. For example, in Alaska, the geographic focus of this study, only about 51 % of the respondents to a 2021 survey conducted by the Yale Program on Climate Change Communication (https://climatecommunication.yale.edu/visualizations-data/ycom-us/) indicated agreement with the statement, “ Global warming is caused mostly by human activities.” While the 51% value is higher than the corresponding value of 44% in Wyoming, it underrepresents the scientific community's views, which poses challenges to implementing policies to reduce emissions.

The paper is organized as follows. Section 2 discusses the data used in the analysis. The trends in hourly temperature, downward total solar irradiance, and CO_2 concentrations at the Barrow Atmospheric Observatory are reported to provide context. The annual temperature at the nearby Barrow Airport from 1921 through 2020 is reported. The time-series nature of hourly temperature at Barrow is also discussed to facilitate the modeling discussion in the remaining sections of the paper. Section 3 discusses the spatial nature of the data. Section 4 introduces a modeling framework to examine the possible association between CO_2 concentrations and hourly temperature at the Barrow Observatory. Section 5 discusses the estimation process and also presents the results. Section 6 presents an alternative model that excludes CO2 as a covariate. It is concluded that this model specification is inferior to the specification in which CO2 is included as a covariate. Section 7 presents an out-of-sample evaluation of the model. Section 8 evaluates the implications of the results for lower latitudes. Section 9 summarizes the findings and presents a possible path for future research.

2. An Overview of the Changing Climate in Northern Alaska

The study employs temperature, solar radiation, and CO_2 data reported by the Barrow (BRW) Atmospheric Observatory. This is one of the baseline observatories of the Earth System Research Laboratory (ESRL), Global Monitoring Division (GMD), of the National Oceanic and

Atmospheric Administration (NOAA). It is located near sea level about 8 km east of Utqiaġvik (formerly Barrow), Alaska at 71.3230 degrees north and 256.6114 degrees West (Vasel et al., 2020). Continuous atmospheric measurements of CO_2 have been recorded at this observatory since July 1973 (Thoning et al., 2021). Herbert et al. (1986) discuss how the data are processed. Peterson et al. (1986) discuss operations' first ten years (1973-1982) and report the consistency of the Barrow results with the reported data from four neighboring locations. Tans and Thoning (2020) provide a general overview of the methods used to collect and process the CO_2 data at Mauna Loa, one of NOAA's other baseline observatories. Along with the hourly temperature data corresponding to BRW, the CO_2 data for BRW were downloaded using the following link: (http://www.esrl.noaa.gov/gmd/dv/data/).

Measurements of downward total solar irradiance at the Earth's surface have been reported at the BRW observatory since January 1976. Before 1998, the data were reported at three minute intervals. The data were subsequently reported at one-minute intervals. For this study, the reported values were rolled up to hourly averages. Data were dropped from the analysis if the number of valid minutes of data for an hour was less than 15.

Consideration was given to the inclusion of CH_4 data in the analysis. This action would have resulted in the loss of 26,381 hourly observations due to unavailable or invalid CH_4 measurements. (the collection of the CH_4 data commenced in 1986 but was suspended for about nine months in 2012/2013). The probable effect of this data loss on model convergence was an important consideration in excluding this variable from the analysis, model convergence being one of the major challenges of the methodology employed in this paper (STATA, 2021, p. 33). The omission of CH_4 and other variables reflecting greenhouse gas concentrations represents a shortcoming in the analysis.

The sample for this study spans from 1 Jan 1985 through 31 Dec 2015. Data before 1 Jan 1985 were not employed in this study because the reported downward total solar irradiance data largely did not meet ESRL's standards before that date. For example, only about 31% of the downward total solar irradiance values in 1984 were deemed by ESRL to be valid. The 1 Jan 2016 - 31 December 2021 time interval is reserved for out-of-sample analysis.

In thinking about meteorological issues at BRW, it is useful to begin by first noting the extremes and high variability levels in the downward total solar irradiance at this location. Regarding variability, the data from 2014 is instructive (Figure 1). Concerning the extremes, there are about 67 days of virtually total darkness each year (about 18 Nov to 22 Jan), while the sun does not completely set from about 11 May to 31 Jul.

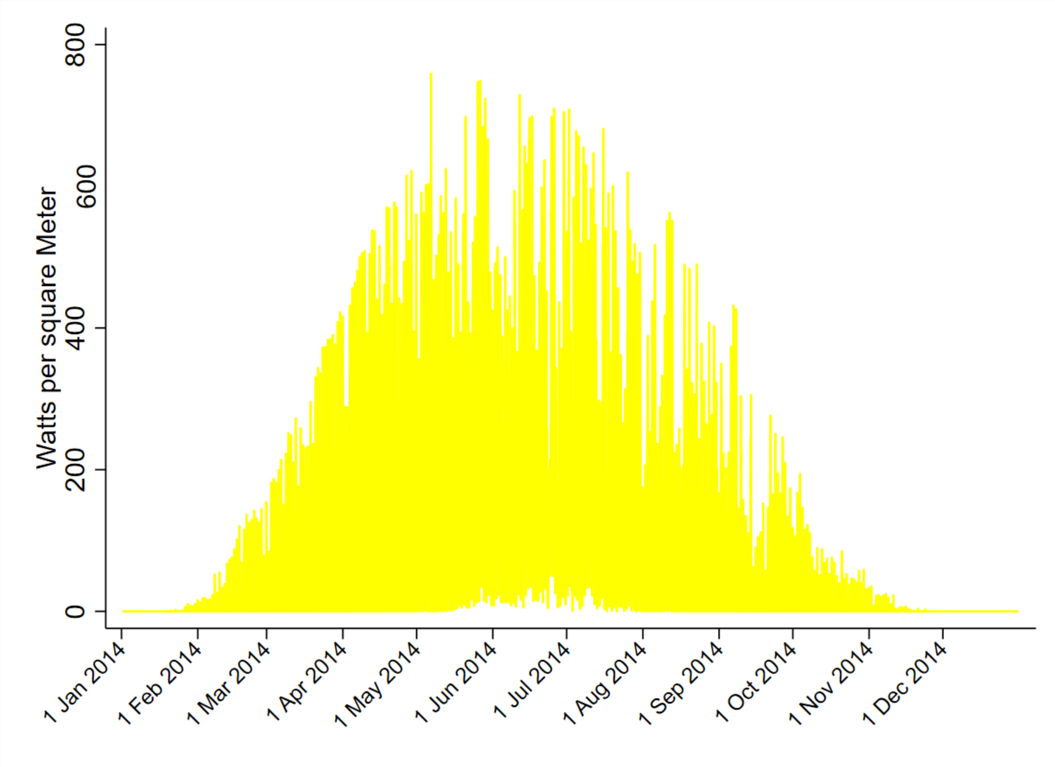

Figure 1. The level of hourly downward total solar irradiance at BRW, 1 Jan 2014 – 31 Dec 2014

The average annual temperature at BRW has increased significantly since 1985 (Figure 2). Specifically, the average annual temperature over 2015-2020 was about 3.37 ºC higher than in 1985-1990. The temperature data reported by the PABR weather station at the nearby Barrow Airport from 1985 through 2020 are consistent with the trend at BRW (Figure 3). The PABR data also indicates that the four warmest years since 1921 occurred in 2016, 2017, 2018, and 2019. In these four years, the average annual temperature was about 5.03 ºC higher than the average annual temperature from 1921 through 1939. These findings do not support the assertion by Lindzen that the recent warming is about the same as before the 1940s (2020, pp. 12-13). In terms of the magnitudes of the recent warming, the increases are consistent with Arctic amplification, as explained by Pithan & Mauritsen (2014) and Winton (2006).

The upward trend in temperature at both BRW and PABR is consistent with the temperature trend for the Arctic noted by Post et al. (2019), Markon et al. (2018, p 1190-1192), and Thoman et al. (2020, p. 4). Box et al. (2019) have reported significant changes in nine key measures of the Arctic climate system from 1971 through 2017. The qualitative story is clear: “the transformation of the Arctic to a warmer, less frozen, and biologically changed region is well underway.” (Thoman et al., 2020, p. 1).

According to AMAP, “Arctic warming can also have effects far beyond the region: for example, the recent rapid warming of the Arctic appears to have created conditions favoring a persistent pattern in the jet stream that provokes unusual extreme temperature events in the Northern Hemisphere.” (AMAP, 2019, p. 4). Taylor et al. (2017, p. 303) have indicated that it is very likely that human activities have contributed to these trends. While the literature supports this finding, it has also been suggested that the significant natural weather and climate variability in the Arctic poses an attribution challenge (Taylor et al., 2017, p. 319). Consistent with this reported variability, both downward total solar irradiance and temperature at the hourly level are highly variable (Figures 4 and 5). Concerning the hourly CO_2 concentration levels, there is a significant upward trend in the hourly CO_2 concentration levels over the sample (Figure 6). The two variables have no visually obvious relationship despite the upward trend in CO_2 concentrations and temperature (Figure 7). While some climate deniers may be tempted to claim that the data in this figure vindicates their position, the view here is that a lack of correlation between two variables does not rule out a causal relationship between the variables.

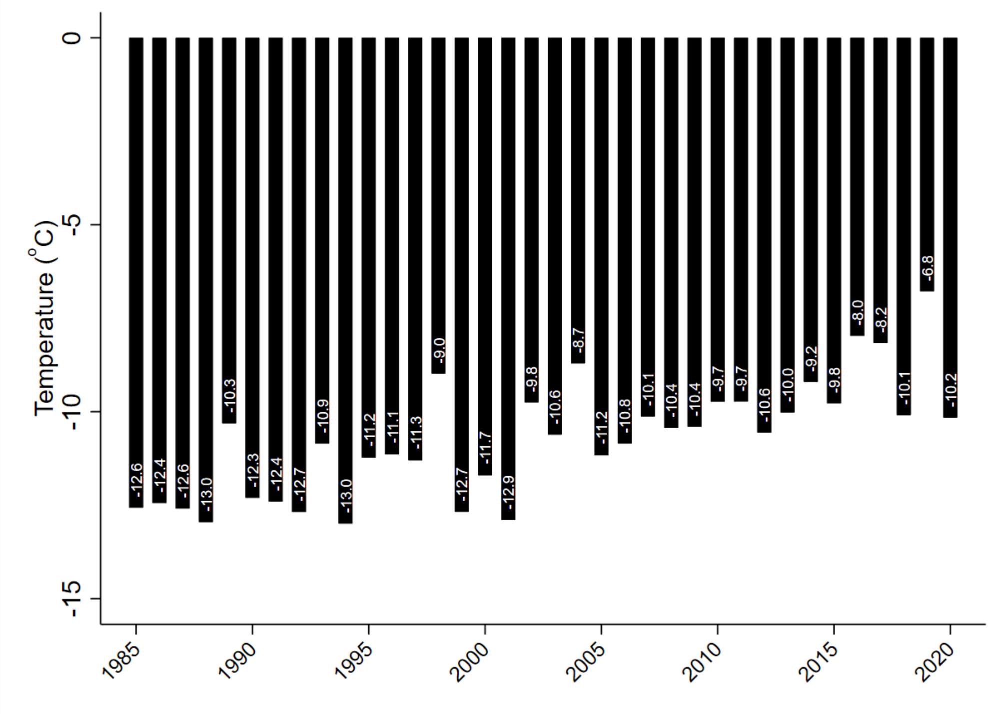

Figure 2. The average hourly temperature at the Barrow Observatory, 1985 -2020

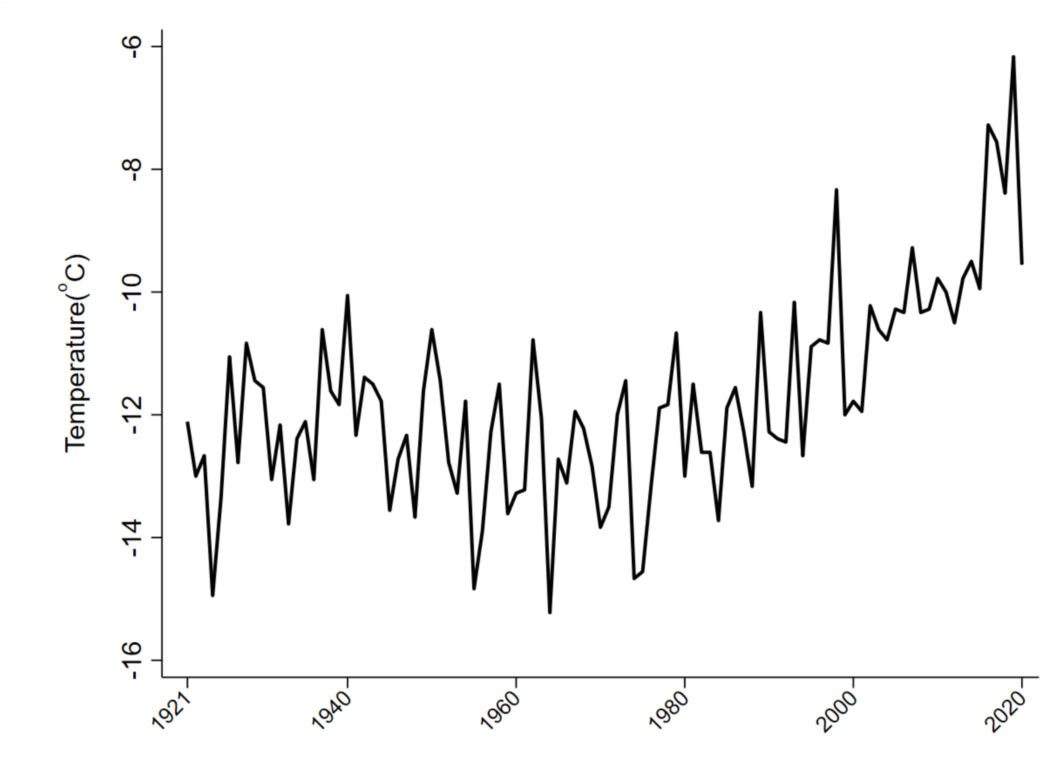

Figure 3. The average annual temperature at the PABR/Barrow Airport weather station, 1921 - 2020

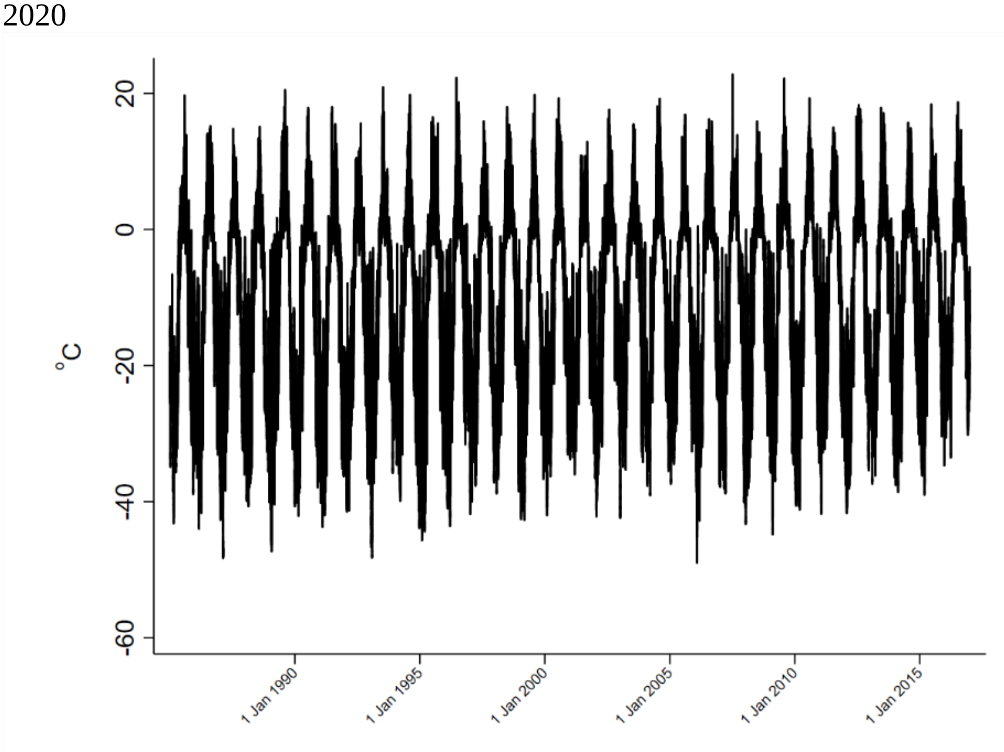

Figure 4. The hourly temperature at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

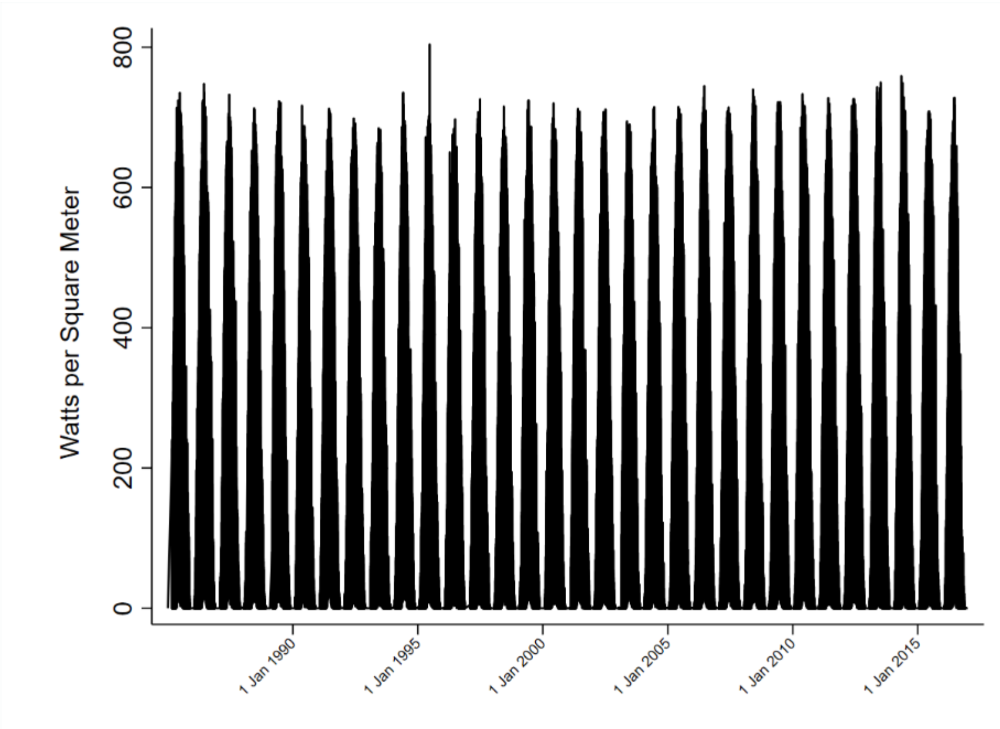

Figure 5. Hourly downward total solar irradiance levels at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

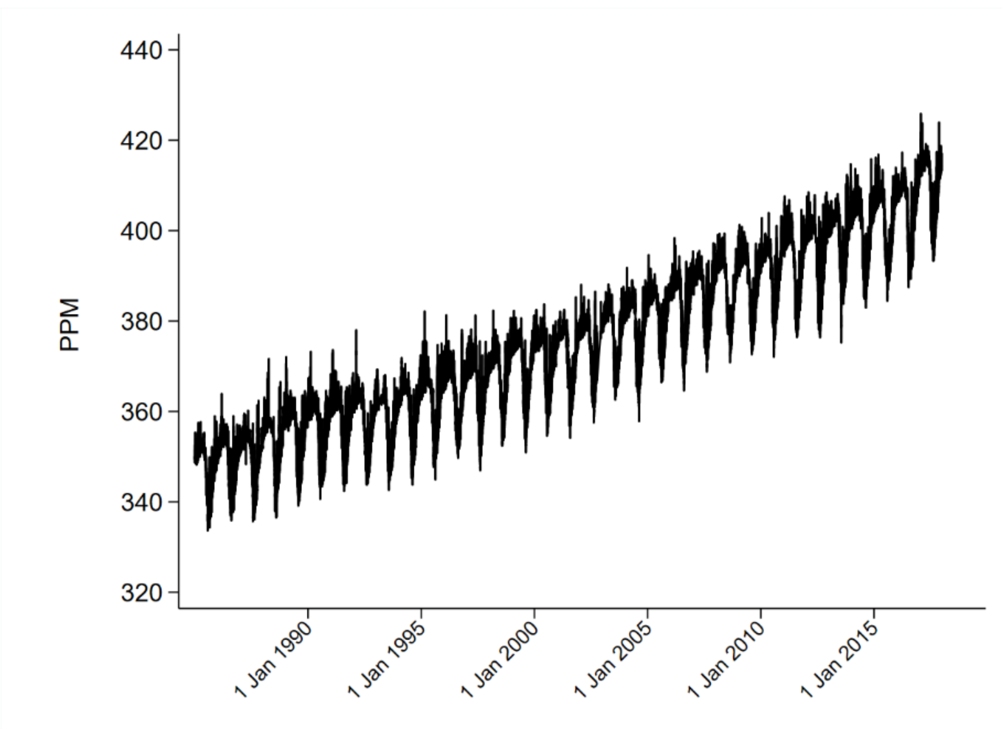

Figure 6. Hourly CO_2 concentration levels at the Barrow Observatory, 1985 -2019

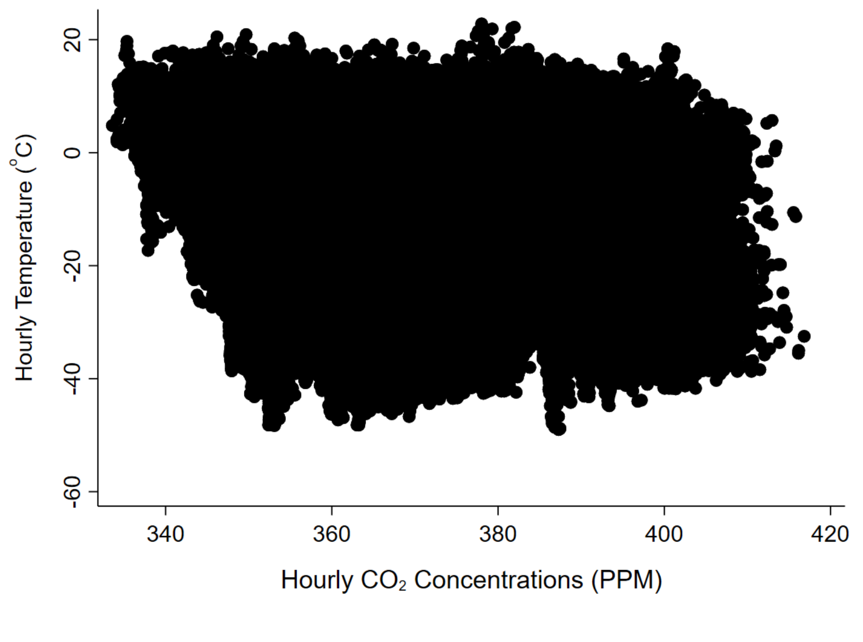

Figure 7. A scatter diagram of hourly temperature and CO_2 concentration levels at BRW, 1 Jan 1985 – 31 Dec 2015

The autocorrelative nature of hourly temperature is an important characteristic of the data (Figure 8). As the figure indicates, the autocorrelative process's magnitude and duration are significant. In terms of magnitude, the estimated one-hour autocorrelation in temperature equals 0.9970, a value that is so large that it is reasonable to wonder if there is a unit root issue. If this is indeed the case, the results of this study could be spurious for the reasons explained by Kennedy (2008, p. 301). Fortunately, an Augmented Dickey-Fuller test yields a *P*-value that is less than 0.0001 both with and without a possible trend, and thus the null hypothesis of a unit root is rejected. Consistent with this finding, the Phillips-Perron test for a unit root also yields a *P*-value less than 0.0001, both with and without a possible trend.

While the available tests do not support the null hypothesis of a unit root in the hourly temperature data, a quantitative analysis of hourly time-series temperature data needs to control for its time-series nature to effectively extract the signal from the noise in the data. The method of ordinary least squares is woefully deficient in this regard. This point is consistent with a warning by Granger and Newbold (1974, p. 117), who note the following: “In our opinion the econometrician can no longer ignore the time series properties of the variables with which he is concerned - except at his [or her] peril.” The consequences of ignoring their warning include inefficient estimates of the regression coefficients, suboptimal forecasts, and invalid tests of statistical significance. Unfortunately, an inspection of “Statistical Methods in the Atmospheric Sciences,” authored by Wilks (2019), suggests that this warning has not been fully heeded in the atmospheric sciences.

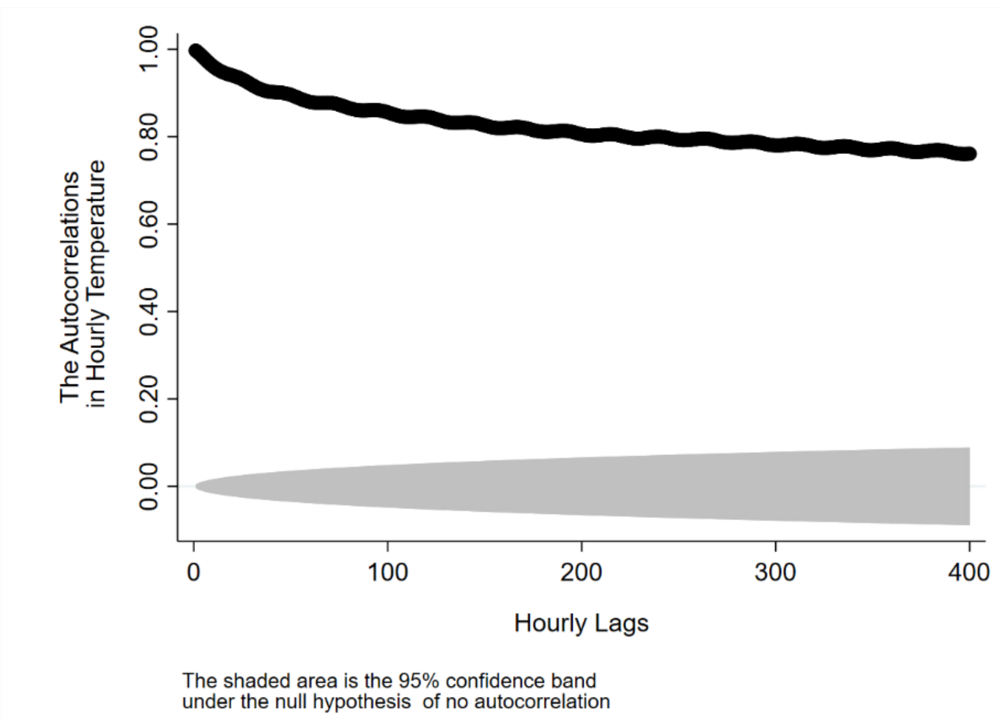

Figure 8. The autocorrelations in hourly temperature at Barrow, 1 Jan 1985 – 31 Dec 2015

3. The Spatial Properties of the Data

In this paper, the analysis focuses on a single temperature record in the Arctic, a region that many researchers believe is highly sensitive to greenhouse gases. One advantage of this approach is that it facilitates the analysis of hourly temperature, the bedrock of all the temperature records climate scientists consider, and thus is immune to the loss of information that occurs when annual averages are calculated. Some researchers may object to this approach because it may seem to ignore the temperature exchange between the Arctic and the lower latitudes. At first glance, this objection may appear reasonable. However, it misses the point that downward solar radiation at the Earth's surface, a key driver of hourly temperature, is also subject to systematic variation across latitudes, as evidenced by Granger Causality Wald tests. The tests were conducted between the incoming solar radiation at Barrow and the incoming solar radiation levels at the NOAA observatories in Hawaii and American Samoa using hourly data from 1 January 1985 through 31 December 2020. For those unfamiliar with the Granger Causality methodology, the test is based on whether the lagged values of some variable X are useful in predicting the current value of some variable Y (Granger, 1969). Because of its focus on the lagged values, the methodology does not contest the truism that correlation between two contemporaneous variables does not imply causation. Applying this methodology to the spatial values of downward solar radiation indicates that both data series exhibit two-way Granger Causality with the downward solar radiation levels at Barrow even though the spatial correlations are modest (Table 1 . It is worth noting that these results make it possible to improve the out-of-sample prediction of these short-wave radiation levels (see the far-right columns of Table 1). For example, the out-of-sample skill score associated with predicting the downward short-wave radiation level at MLO based on the lagged outcomes at BRW and MLO equals 0.750. A skill score of this magnitude is a respectable outcome given that a useless predictive method would have a skill score of zero, while a perfect method would have a score of unity (the value is calculated using a persistence forecast of the downward short-wave radiation at MLO as a reference).

In short, the evidence supports the view that the atmospheric conditions at lower latitudes (Barrow) reflect the atmospheric conditions at Barrow (lower latitudes). Concerning hourly temperature, the analysis presents evidence that the temperature at BRW exhibits two-way causality with the temperatures at MLO and SMO. These results are presented in Table 3, which also reports on this phenomenon using data from 15 other observatories.

Table 1.
Results of Granger Causality Wald Tests in terms of hourly downward solar radiation at Barrow and the outcomes at SMO and MLO, January 1, 1985 – December 31, 2015

Locations	Spatial Correlation	The null hypotheses of no two-way Granger Causality in terms of hourly temperature	Predictive Skill Score associated with an hour-ahead 2021 down radiation prediction for the non-BRW location making use of the BRW and the non-BRW lagged outcomes (a persistence prediction of the non-BRW downward radiation level is a reference)	Predictive Skill Score associated with an hour-ahead 2021 down radiation prediction for the BRW location making use of the BRW and the non-BRW lagged outcome (a persistence prediction of the BRW downward radiation level is a reference)
Barrow(BRW) and Mauna Loa (MLO)	0.602	Rejected with P values < 0.001	0.750	0.548
Barrow(BRW) and American Samoa(SMO)	0.383	Rejected with P values < 0.001	0.576	0.595
Note: The out-of-sample evaluation period makes use of about 14,000 observations between 1 Jan 2016 through 31 Aug 2017				

Interestingly, the findings of Granger Causality in the factors that affect temperature across latitudes are not limited to downward solar radiation. For example, using data from NOAA's tall towers project https://gml.noaa.gov/outreach/behind_the_scenes/towers.html), it is easily established that the null hypothesis of no two-way Granger Causality is rejected regarding the hourly CO_2 concentration levels at BRW and the levels at the WKT tower in Texas, the levels at the AMT tower in Maine, the levels at the WGC tower in California, the levels at the WBI tower in Iowa, the levels at the SNP tower in Virginia, the levels at the SCT tower in South Carolina, and the levels at the LEF tower in Wisconsin.

Given the overall Granger Causality findings, the ideal approach to estimate the effects of CO_2 on hourly temperature would be a systems approach that simultaneously estimates an equation for each location worldwide. The theoretical advantage of this approach is not the absence of bias in the estimates but the improved efficiency of the estimates since the estimated parameters in each equation reflects the information in the other equations. In the absence of the need to help model the autocorrelations presented in Figure 8, an MGARCH analysis would be an appropriate approach because it enables the analysis of multiple dependent variables (Baum and Hurn, 2021, pp. 245-251; Bauwens, et al., 2006). Unfortunately, the MGARCH procedure does not support the required MA modeling procedure to make this possible. The MGARCH procedure also does not support the ARCH-in-mean procedure that allows one to model the possible linkage between the conditional variance and the conditional hourly mean. For these reasons, the analysis will proceed by estimating an ARCH/ARMAX model in which a measure of hourly temperature at Barrow is the sole dependent variable. Based on the Granger Causality spatial findings, the ARCH/ARMAX results for BRW can be expected to have implications for locations at lower latitudes. While some may view this approach with disdain, it can yield out-of-sample findings that may be taken more seriously than the results from a global model that relies on 100 or so observations of annual data. For those concerned about potential bias, attention should be given to the accuracy of out-of-sample predictions, given that bias has adverse consequences for predictive accuracy.

4. An ARCH/ARMAX Model of Hourly Temperature

The model employed in this paper is an Autoregressive Conditional Heteroskedasticity/ Autoregressive–Moving-Average with Exogenous Inputs model of temperature (henceforth, an ARCH/ARMAX model of temperature). The ARCH terms are employed to model the conditional heteroskedasticity, a phenomenon in which the variance of the error term in the model is not constant over time but instead varies in a predictable way. ARCH models are estimated using the conditional maximum likelihood approach. Please see Baum and Hurn(2021, p. 232) for a general overview or Hamilton (1994, pp. 660-665) for a more detailed explanation of the approach. The method was devised to improve the modeling of financial and economic data but has proven invaluable in modeling any time-series variable in which there are periods of turbulence followed by a relative calm at some point. The second component of the time-series method is the autoregressive–moving-average (ARMA) method, which models the autocorrelations in the dependent variable based on autoregressive (AR) terms and moving average (MA) terms. A relatively simple example of this approach is an ARMA(1,1) process illustrated in equation (1), in which W_t is the dependent variable in time period t. Observe that W_t depends on its lag, W_{t-1}. It also depends on ϵ_t, the residual error term in period t and its lag, $\epsilon_{t-1.}$ In this equation, the coefficient φ_1 is the AR term while θ_1 is the MA term.

$$W_t = c + \varphi_1 W_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \quad (1)$$

Including the model's exogenous inputs, an ARCH/ARMAX model can be represented using two equations. In the case of hourly data, the first equation models the conditional hourly mean while the second models the conditional variance. Following Engle et al. (1987), the conditional variance or its transformation may also affect the conditional hourly mean, a phenomenon known as an ARCH-in-mean effect. A possible illustration of the overall modeling approach when the natural logarithm of y_t is the dependent variable, and there are J exogenous inputs in the conditional hourly mean equation and K exogenous inputs in the conditional variance equation is

$$\ln(y_t) = \sum_j x_{j,t}\beta_j + \sum_i \Psi_i\ g(\sigma_{t-i}^2) + \sum_P AR(p) + \sum_Q MA(q) + \epsilon_t \quad (2)$$

$$Var(\epsilon_t) = \sigma_t^2 = \sum_k Z_{k,t}\beta_j + \gamma_1 \epsilon_{t-1}^2 \quad (3)$$

where the $X_j's$ represents the exogenous inputs in the conditional hourly mean equation, the $Z's$ are the exogenous inputs in the conditional variance equation, $g(\sigma_{t-i}^2)$ is the function that reflects the conditional variance, Ψ_i represents the estimated ARCH-in-mean coefficient for period t-i (where i could be equal to 0, 1,2,3 etc.), $\sum_P AR(p)$ and $\sum_Q MA(q)$ are the sums of the autoregressive and moving average terms, with p and q being the selective lags corresponding to the AR and MA terms, respectively. These equations are only illustrative. The various components of these equations are discussed in more detail below. In particular, much of the analysis will focus on whether the linear form of the X_j 's is appropriate.

Following from Forbes and St. Cyr (2017, 2019) and Forbes and Zampelli (2019, 2020), the modeling approach employed in this paper accepts the proposition that "All models are wrong; some models are useful" (Box et al., 2005, p. 440). They are all "wrong" because they represent a simplification of reality; they can be useful if important features of that reality are captured. In the case of this research, it may be asserted that the results presented here are "wrong" because the methods rely on data from a single location. The model may be deemed "wrong" because of "specification errors," "multicollinearity," "autocorrelation," "heteroskedasticity," "overfitting," and "unit-root issues." Other readers may conclude that the model is "wrong" because it somehow "forces" the estimated relationship between CO_2 concentrations and temperature to be positive because both are rising over time (note: the correlation between temperature and CO_2 equals -0.1495). Still, others will argue that the results are "biased" because the model's dependent variable is the natural logarithm of temperature, even though there are recognized methods to remove that bias (Baum and Hurn, 2021, pp. 169-170).

Following Forbes and Zampelli (2020, p. 13), this paper accepts the proposition that the "…vulnerability of a model to be deemed as wrong even though all models are "wrong" represents a challenge to the recognition of insights provided by models that are useful." Fortunately, this challenge can be addressed by assessing a model's out-of-sample predictive accuracy. Common sense informs us that a model that yields accurate predictions is useful if the out-of-sample evaluation interval is sufficiently long. Based on this perspective, the approach in this paper proceeds by estimating a model with hourly 228,085 observations and performing an out-of-sample analysis with 33,437 hourly observations.

The proposition that "all modeling results can easily be dismissed out of hand as being wrong, even if they are useful" may have implications for climate science in general. As almost all climate scientists will attest, countless studies support the scientific consensus. Climate deniers are unfazed by this evidence because they can always point out a real or imagined flaw in these studies as evidence that the scientific consensus concerning climate change is "wrong." In this policy environment, the conclusions flowing from the standard approach taken by climate scientists will always be open to question. In Lawson's words,

> "Climate scientists "can put forward the evidence, but they cannot force their audience to agree with them. They can point to the fact that carbon dioxide is a greenhouse gas, that its levels in the atmosphere have risen by 40% since the Industrial Revolution, and that we can only account for the recent rise in global temperatures by including the enhanced greenhouse effect alongside known natural factors such as solar variability and ocean currents. They can point to the observed patterns of warming as consistent with warming due to greenhouse gases in contrast to other possible causes of warming. But in the end, the reasoning is inductive, not deductive. It is not *proof*. "(Lawson, 2014)

In short, climatologists can continue presenting unpleasant facts about climate change to decision-makers, but vocal and well-funded climate deniers can always object to the findings. Given this reality, Lawson suggests that attention be given to a null hypothesis that carbon dioxide does not significantly affect temperature. This approach, embraced in this paper, while apparently novel in climate science, is essentially the approach that statisticians employ in testing hypotheses. To be clear, some researchers, such as Stern and Kaufmann (2014), have employed this approach using annual data. However, their reliance on annual data with only 162 observations essentially made it impossible to verify the rejection of the null hypothesis using out-of-sample data.

In the model, the association between CO_2 concentrations and hourly temperature is presumed conditional on the downward total solar irradiance measured at the Earth's surface, downward total solar irradiance being the primary driver of the weather and climate system. The other drivers of the surface energy balance, such as upward and downward longwave irradiance, are not included as explanatory variables in the model because they are hypothesized to be affected by CO_2 concentrations. Upward short-wave irradiance is not hypothesized to be directly affected by CO_2 concentrations. Its inclusion as an explanatory variable is open to question, given that it is largely driven by downward solar irradiance and temperature.

In the structural component of equation (2), the CO_2 concentration level is an exogenous input. It is lagged one hour to avoid the issue of possible two-way causality between temperature and CO_2 concentrations. Other structural inputs in equation (2) include binary variables representing the solar zenith angle, the hour of the day, the day of the year, and the year. These variables are included as proxies for the drivers of the diurnal variation in temperature, the seasonal variation in temperature, and the possible non-anthropomorphic drivers of temperature unrelated to total downward solar irradiance. In terms of functional form, linearity is not presumed. Instead, the data are permitted to speak for themselves on this important issue.

The initial specification of the exogenous inputs in (2) and their possible relationship with a measure of hourly temperature is given by:

$$\begin{aligned} \ln Temp_t &= \alpha_0 + \alpha_1 ZeroSolar_t + \alpha_2 Solar_t + \alpha_3 (CO2_{t-1} * ZeroSolar_t) \\ &+ \alpha_4 (CO2_{t-1} * PosSolar_t) + \alpha_5 Solar_t * CO2_{t-1} + \sum_{h=1}^{9} \beta_h Angle_h \\ &+ \sum_{i=2}^{24} \phi_i HourofDay_i + \sum_{j=2}^{365} \gamma_j DOY_j + \sum_{k=1985}^{2014} \delta_k Year_k \end{aligned} \tag{4}$$

Where
$\ln Temp_t$ is the natural logarithm of temperature measured in Kelvin in hour t.

$ZeroSolar_t$ is a binary variable. The variable is assigned a value of one if the downward total solar irradiance level at Barrow in period t equals zero. Its value equals zero otherwise.

$Solar_t$ equals the downward total solar irradiance level at Barrow in period t.

$CO2_{t-1}$ is the atmospheric level of CO_2 concentrations at Barrow in hour t-1.

$PosSolar_t$ is a binary variable that equals one if the level of downward total solar irradiance at Barrow in period t is positive. Its value equals zero otherwise.

$Angle_h$ is a vector of nine variables representing the solar zenith angle.

$\mathrm{HourofDay}_i$ is a series of 23 variables representing the hour of the day.

DOY_j is a series of 364 binary variables representing the day of the year.

Year_k is a series of 30 binary variables representing the year of the sample.

Please note that α_1, α_2, and α_3, etc., are the coefficients corresponding to this linear specification of the exogenous inputs. From (4), the total number of structural coefficients to be estimated equals 432. Some may strongly suspect that this number of explanatory variables indicates that the model is ”overfitted.” If this claim is true, the model would be unlikely to yield accurate out-of-sample predictions even if the within-sample explanatory power is very high (Brooks, 2019, p. 271). The “rule of thumb” by Trout (2006) that overfitting is avoided when there are at least ten observations per estimated coefficient does not support this possible suspicion, given that the structural model present in this paper entails over 500 observations per estimated coefficient. Moreover, as will be seen, the model does not suffer from the consequences of overfitting in terms of out-of-sample predictive accuracy.

5. Estimation and Results

The model was estimated using hourly data over the 1 Jan 1985 - 31 Dec 2015 time interval. The analysis was conducted in two distinct stages. In the first stage, the linear specification of the exogenous inputs given by Eq. (4) is evaluated. The second estimation stage recognizes that the other components of equations (2) and (3). Concerning the ARMA components in equation (2), it is worth noting that the specifications applied in this paper are not parsimonious because the autocorrelative process in Figure 8 is not short in duration. It is recognized that this approach runs counter to the traditional time-series philosophy (Box and Jenkins, 1976, p. 17), which suspected that there was more room for prediction errors when more time-series parameters were estimated (Hamilton, 1994, p. 106). The view here is that the goal of predictive accuracy can sometimes be enhanced by including more ARMA terms. This approach makes sense given the relatively long memory property of the autocorrelations evidenced in Figure 8. The structural heteroskedasticity, i.e., the Z's in equation (3), is modeled as a function of the solar zenith angle, the hour of the day, the day of the year, the year of the sample, and the following variables: $\sqrt{CO2_{t-1}}, \sqrt{Solar_t}$. Instead of assuming that hourly temperature is independent of the conditional variance, the model permits the data to speak for itself on this issue. The ARCH-in-mean effects, i.e., the expression $\sum_i \Psi_i \; g(\sigma^2_{t-i})$ in equation (2) has the potential to capture this linkage.

The possible merits of representing the explanatory variables using a nonlinear specification are addressed using the multivariable fractional polynomial (MFP) methodology (Royston and Sauerbrei, 2008). The procedure works by cycling through a battery of nonlinear transformations of the explanatory variables until the model that best predicts the dependent variable is found. In the present case, the set of exponents that the procedure considered include 0.25, 0.3333, 0.5, 0.6666, 0.75, 1, 1.5, 2, 2.5, and 3. Recent applications of this method include Forbes and St. Cyr

(2017, 2019) and Forbes and Zampelli(2019, 2020). In the present case, the MFP results suggest the following specification:

$$\ln Temp_t = \alpha_0' + \alpha_1' \, ZeroSolar_t + \alpha_2' Solar_t^{1/4} + \alpha_3' \, (CO2_{t-1}{*}ZeroSolar_t)^3$$
$$+ \alpha_4' \, (CO2_{t-1}{*}PosSolar_t)^{1/4} + \alpha_5' \, (Solar_t {*} CO2_{t-1})^{1/4} + \sum_{h=1}^{9} \beta_h' \mathrm{Angle}_h$$
$$+ \sum_{i=2}^{24} \phi_i' \, \mathrm{HourofDay}_i + \sum_{j=2}^{365} \gamma_i' \, \mathrm{DOY}_j + \sum_{k=1985}^{2014} \delta_k' \, \mathrm{Year}_k \qquad (5)$$

Please note that α_1', α_2', and α_3' etc., are the estimated coefficients in this specification. Least squares estimation of (5) produces a seemingly respectable level of explanatory power, the R^2 being about 0.831. However, a Portmanteau test for autocorrelation (Box and Pierce, 1970; Ljung and Box, 1978) reveals that the residuals are highly autocorrelated. Consistent with Forbes and St. Cyr (2019, p.17), for lags one through 100, the *P* values are less than 0.0001. The null hypothesis of no ARCH effects is rejected with a *P*-value less than 0.0001. Consistent with these issues, the least-squares model is not useful. This finding is supported by out-of-sample predictions with an RMSE of about 5.67 ^{o} C, a value clearly indicative of a suboptimal prediction process.

ARCH/ARMAX methods can generate predictions that are much more accurate than those from a least-squares model when the dependent variable is autoregressive and heteroskedastic. In this case, the ARCH process's modeled lag lengths are 1 and 2. Consideration was given to including additional ARCH terms to model the apparent diurnal pattern of the ARCH process (e.g., 24, 48, 72, 96, etc.). Consideration was also given to employing alternative ARCH and GARCH specifications. These approaches were abandoned due to model convergence issues. The modeled lag lengths for the AR process are 1 through 12, 23, 24, 25, 26, 47, 48, 49, 71, 72, 73, 96, 97, 120, 121, 144, 145, 167, 168,169, 192, 193, 216, 240, 264, 288, 312, 335, 336, 337, 360, 384, 408, 432, 456, 480, 600, 671, 672, 673, 840, and 960. The MA modeled lag lengths are 1 through 25, 48, 49, 71, 72, 73, 96, 97, 120, 121, 144, 145, 167, 168, 169, 192, 193, 216, 240, 264, 288, 312, 335, 336, 337, 360, 384, 408, 432, 456, 480, 600, 671, 672, 673, 840, and 960. The ARCH/ARMA model, i.e., equations (2) and (3) as amended by the MFP transformation, was estimated assuming that the residual error terms correspond to the Student t distribution instead of the more typical Gaussian distribution. This approach is believed to be justified by the highly volatile nature of the weather system in the vicinity of Barrow. One shortcoming in its application here is that the "degrees of freedom" parameter is less than the minimum indicated by Harvey (2013, p. 20). Consideration was given to modeling the residual error terms using the generalized error distribution, but this approach was abandoned due to model convergence issues.

Selected estimates are reported in Table 2. It is revealed that α_2' , the coefficient corresponding to $Solar_t^{1/4}$ is positive and highly statistically significant. The CO_2-related coefficients α_3' and α_4' are also positive and highly statistically significant while α_5' is negative and highly statistically significant. These findings are consistent with the view that CO_2 concentrations have implications for hourly temperature but do not address the magnitude. Concerning the possible non-anthropomorphic drivers of temperature, it is interesting to note that 16 of the 30 variables in question are statistically significant. With 2015 being represented in the constant term, negative values for a year are consistent with higher predicted temperatures in 2015 than in the year in question. There are 13 such cases. The coefficients' median value for these cases is -0.00543, which hardly seems important.

The model's explanatory power based on the estimated structural parameters is 0.8105. The R-sq equivalence based on all the estimated parameters equals 0.9968. Those who believe that the latter level of explanatory power is somehow "too good to be true," are cheerfully invited to reinspect Figure 8 and contemplate the concept of autocorrelation and how modeling this autocorrelation can affect a model's level of explanatory power. In any event, the view here follows Hyndman and Athanasopoulos (2018, 3.4), who note that true adequacy… " can only be determined by considering how well a model performs on new data that were not used when fitting the model." It is also noted that even though a model's R^2 equivalence is a well-recognized measure of model adequacy, a good case can be made that achieving white noise in the residuals is also important (Becketti, 2013, p. 256; Kennedy, 2008, p. 315; and Granger and Newbold, 1974, p. 119). To assess whether this measure of adequacy is achieved, Portmanteau tests for autocorrelation were conducted for the hourly lags 1 through 100, 192, 284, and 672. At lag 1, the *P*-value is 0.1958. For the remaining 111 lags that were assessed, the *P*-values are less than .05, thereby rejecting the null hypothesis of a white noise error structure.

Table 2. Estimation Results

Variable	Estimated Coefficient	Absolute Value of the t-Statistic	*P*-Value
Constant term	5.465148	895.40	< 0.001
$ZeroSolar_t$	0.053421	9.25	< 0.001
$Solar_t^{1/4}$	0.01102	11.23	< 0.001
$(CO2_{t-1}*ZeroSolar_t)^3$	7.70E-11	7.57	< 0.001
$(CO2_{t-1}*PosSolar_t)^{1/4}$	0.01296	9.04	< 0.001
$(Solar_t * CO2_{t-1})^{1/4}$	-0.00232	10.42	< 0.001
$Year_{1985}$	-0.01111	9.96	< 0.001
$Year_{1986}$	-0.00371	2.36	0.018
$Year_{1987}$	-0.00983	6.91	< 0.001
$Year_{1988}$	-0.00808	6.87	< 0.001
$Year_{1989}$	-0.00498	1.76	0.079
$Year_{1990}$	-0.0033	1.47	0.141
$Year_{1991}$	-0.00285	1.82	0.068
$Year_{1992}$	-0.00664	2.21	0.027
$Year_{1993}$	-0.00265	2.52	0.012
$Year_{1994}$	-0.00339	2.47	0.014
$Year_{1995}$	-0.00384	4.43	< 0.001
$Year_{1996}$	-0.00305	1.73	0.083
$Year_{1997}$	0.001996	1.06	0.288
$Year_{1998}$	0.005733	3.48	0.001
$Year_{1999}$	-0.00766	4.34	< 0.001
$Year_{2000}$	-0.00543	4.26	< 0.001
$Year_{2001}$	-0.00359	2.97	0.003
$Year_{2002}$	0.002124	0.61	0.541
$Year_{2003}$	-0.00658	3.21	0.001
$Year_{2004}$	-0.00449	4.07	< 0.001
$Year_{2005}$	-0.00211	1.11	0.265
$Year_{2006}$	0.000883	0.33	0.743
$Year_{2007}$	0.005622	4.31	< 0.001
$Year_{2008}$	1.92E-06	0	0.999
$Year_{2009}$	0.002597	1.98	0.048
$Year_{2010}$	0.000847	0.38	0.707
$Year_{2011}$	0.001634	0.23	0.817
$Year_{2012}$	-0.00044	0.22	0.829
$Year_{2013}$	0.001147	0.46	0.643

$Year_{2014}$	0.002601	1.40	0.162
Number of Observations	228,085		
AIC	-2,278,373		
BIC	-2,268,232		
R-Square equivalence based on the full model	0.9968		
R-Square equivalence based on the model's structural component.	0.8105		

Regarding the binary variables not reported above, 336 of the 364 day-of-the-year coefficients are statistically significant, while 22 of the 23 hour-of-the-day variables are statistically significant. Only three of the nine solar angle coefficients are statistically significant.

Concerning the AR and MA terms, 44 of the 53 AR terms and 31 of the 61 MA terms are statistically different from zero. Both of the ARCH terms are statistically significant. Only one of the three ARCH-in-Mean terms is statistically significant. Regarding the variables that model the heteroskedasticity in the conditional variance, 298 of the 429 variables are statistically different from zero.

6. An alternative model that does not consider CO_2

This section considers an alternative model that does not consider CO_2 as a covariate. As before, the dependent variable is the natural logarithm of temperature. Applying the MFP procedure to ensure the best structural fit, the form of the equation is:

$$\mathrm{lnTemp}_t = \alpha'_0 + \alpha'_1\,\mathrm{ZeroSolar}_t + \alpha'_2\mathrm{Solar}_t^{1/4}$$

$$+ \sum_{h=1}^{9} \beta'_h \mathrm{Angle}_h$$

$$+ \sum_{i=2}^{24} \phi'_i\,\mathrm{HourofDay}_i + \sum_{j=2}^{365} \gamma'_i\,\mathrm{DOY}_j + \sum_{k=1985}^{2014} \delta'_k\,\mathrm{Year}_k \quad (6)$$

An ARCH/ARMAX model based on equation (6) is estimated using the same time-series specifications and input data employed in the previous section, exclusive of the CO_2-related variables. The values corresponding to the AIC (Akaike, 1974) and the BIC (Schwartz, 1978) statistics for this model specification are -2,277,736 and -2,267,626. These AIC and BIC values are higher than those reported in Table 2. Based on the AIC and BIC literature, as reported by Kennedy (2008, p. 105), this indicates that the formulation that includes the CO_2-related variables is the better specification.

7. The Model's Out-of-Sample Performance

The out-of-sample evaluation period consists of 33,437 hours over the 1 Jan 2016 to 31 December 2021 time interval. While the number of observations in this evaluation is substantial, there are significant gaps in the time series. For example, the required hourly data for 2019 are not currently available. Based on the relatively gap-free period of 2020 and 2021, there is a degree of confidence that the results presented in this section are not materially affected by the data gaps.

The out-of-sample analysis begins by noting that the dependent variable in the model is the natural logarithm of temperature measured in Kelvin. A simple retransformation might seem to yield the optimal predicted value. Unfortunately, this can result in a biased prediction (Granger and Newbold, 1976, pp. 196-197). This bias is easily resolved when the error distribution is Gaussian using a method presented by Guerrero (1993). Given the non-Gaussian error distribution in this case, the matter was resolved by following Baum and Hurn (2021, p. 170), who recommend estimating a post-processing regression without a constant term using all of the observations in the sample.. The estimated parameters from this regression was used to detransform the out-of-sample transformed predicted temperature values.

The out-of-sample temperature predictions from the ARCH/ARMAX model presented in this paper have a predictive R-square equivalence of 0.9966. Consistent with this value, there is a high degree of visual correspondence between the period-ahead ARCH/ARMAX hour-ahead predictions and the actual hourly temperature (Figure 9).

The out-of-sample predictions were compared with the ERA5T predictions for the same general location. For those unfamiliar with the ERA5T modeling results, they are produced by the Copernicus Climate Change Service at ECMWF. It represents an updated version of ERA5 modeling results which reports hourly values globally. The ERA5T hourly temperature values for the Barrow location were obtained from Meteoblue (https://content.meteoblue.com/en/specifications/data-sources/weather-simulation-data/reanalysis-datasets).

The predictions are visually more accurate than the ERA5T values for the same general location (Figure 10), although it should be noted that the ERA5T values correspond to a grid that includes land and ocean, while Barrow represents a specific land location within that grid. Nevertheless, the ERA5T values may be a useful benchmark for the ARCH/ARMAX out-of-sample predictions. Regarding the RMSEs, the ARCH/ARMAX model predictions have an RMSE equal to about 0.647 ^{o}C, while the ERA5T outcomes have an RMSE of about 1.786 ^{o}C. While some might assert that the ERA5T predictive accuracy is driven by the weather conditions of the Arctic Ocean, it may be more relevant that analysis of the ERA5T prediction errors indicates that the errors are not purely random. Specifically, the errors are conditional on the magnitude of the predicted temperature and lagged value of the CO_2 concentrations. The latter finding is consistent with the central thesis of this paper. Following Granger's discussion of prediction errors (1986, p. 91), both findings suggest a pathway to improving the accuracy of the ERA5T predictions.

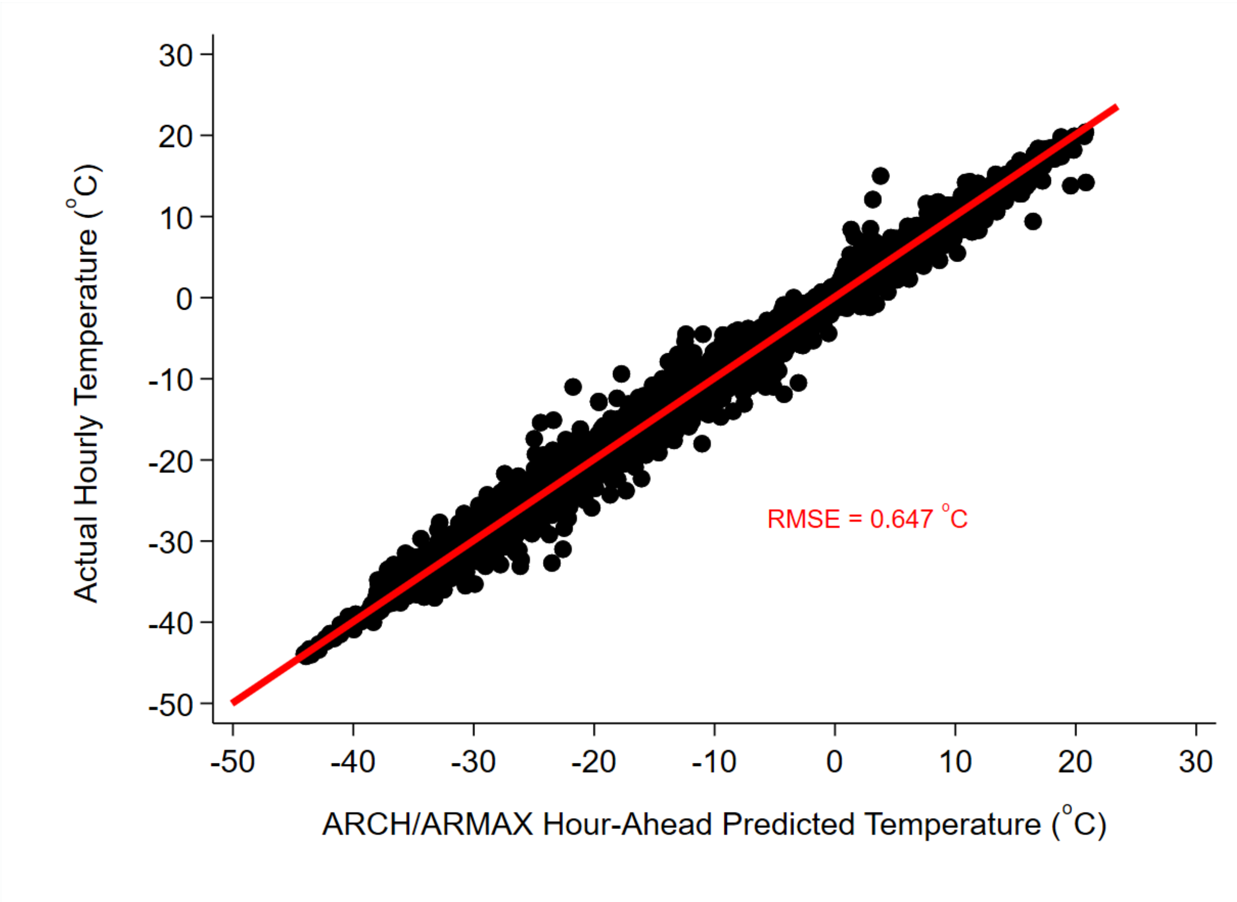

Figure 9. The out-of-sample predicted and actual hourly temperature at BRW, 1 Jan 2016 – 31 December 2021.

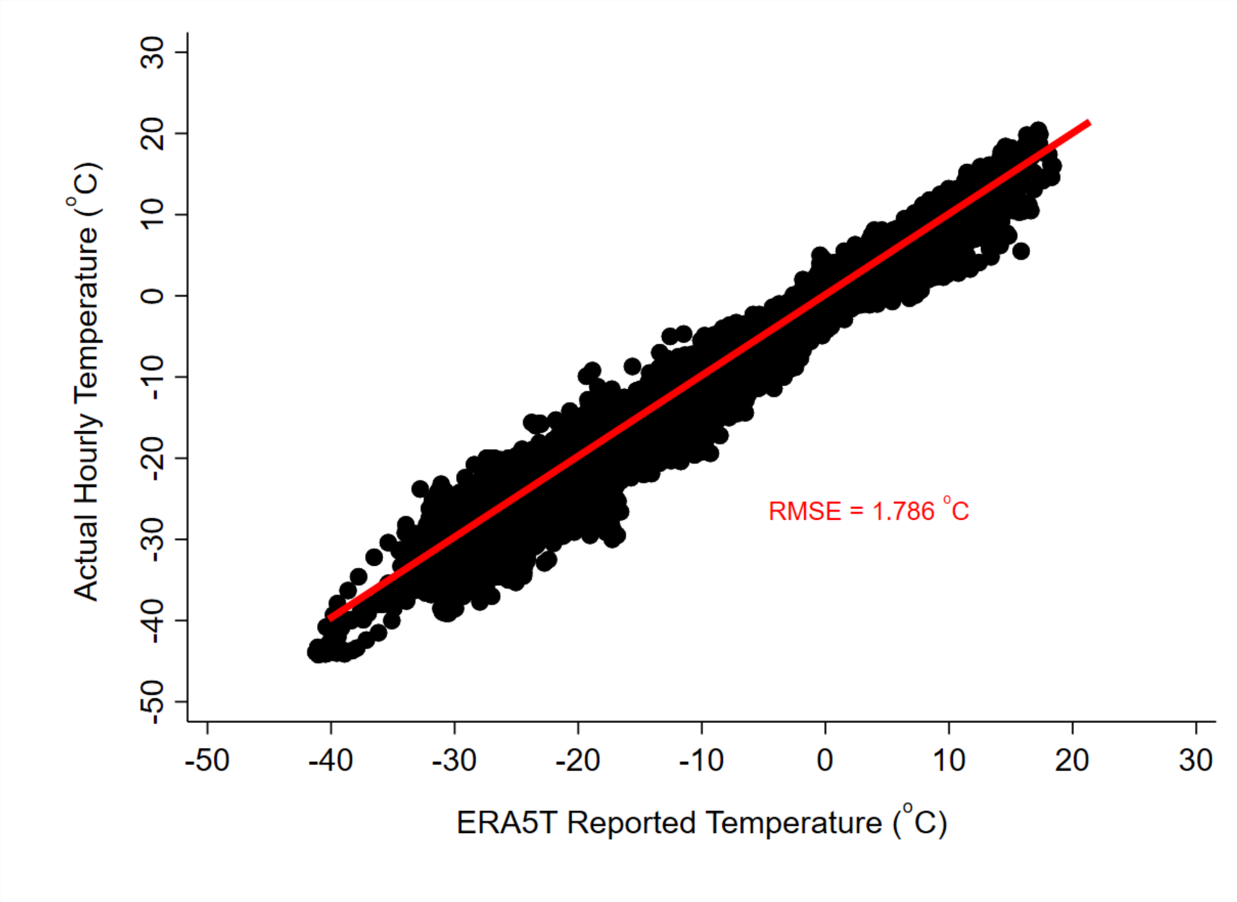

Figure 10. The ERA5T reported temperature and the actual hourly temperature at BRW, 1 Jan 2016 – 31 December 2021.

Most readers know that the estimated CO_2-related coefficients in Table 2 are point estimates. Given this reality, those who believe that the model presented here is “wrong” may contend that the CO_2-related estimates reported in Table 2 overstate the “true” effect of CO_2 on temperature. To assess the consequences of this possible claim, out-of-sample predictions were made assuming that the estimated coefficients' true value was 90 % lower. This obviously reduces the linkage between CO2 and temperature but also has consequences for predictive accuracy. Specifically, ignoring the full estimated effect of the CO_2-related coefficients results in out-of-sample predictions with an RMSE equal to 3.153 °C., which is obviously inferior to the 0.647 °C RMSE obtained when the full estimated effects are employed in making the predictions. The differential in predictive accuracy is visually apparent if one inspects the vertical distance between the scatter points and the 45^{o} line representing the relationship between predicted and actual temperature when the predictions are perfect (Figure 11). Regarding the prediction levels, the averages from the full model are not materially affected by this manipulation of the coefficients. This occurs because the time-series terms tend to keep the predictions relatively close to the lags of the actual temperature. Concerning the structural predictions, i.e., the predictions that ignore the time-series terms, disregarding the full effect of CO_2 on temperature results in predictions that are about 4.24 ^{o} C colder on average.

The finding of inaccurate predictions over the evaluation period also emerges if one assumes that CO_2 concentrations were equal to the average of their preindustrial values. According to the IPCC, this value is 287 parts per million (Ciais et al., 2013, p. 467). This value gives rise to out-of-sample predictions with an RMSE of 0.663, which is inferior to the RMSE obtained when the actual CO_2 concentration levels are used as inputs. It also gives rise to a structural prediction that is 0.756 ^{o} C colder on average. It is believed that this 0.756 ^{o} C value understates matters because the lagged temperatures, whose effects contribute to the hour-ahead predictions to some extent but are not reflected in the structural estimates, are influenced by the CO_2 levels in previous days, weeks, months, or even years. The autocorrelations in hourly temperature at BRW from January 1, 1977, through December 31, 2021, are informative in this regard (Figure 12).

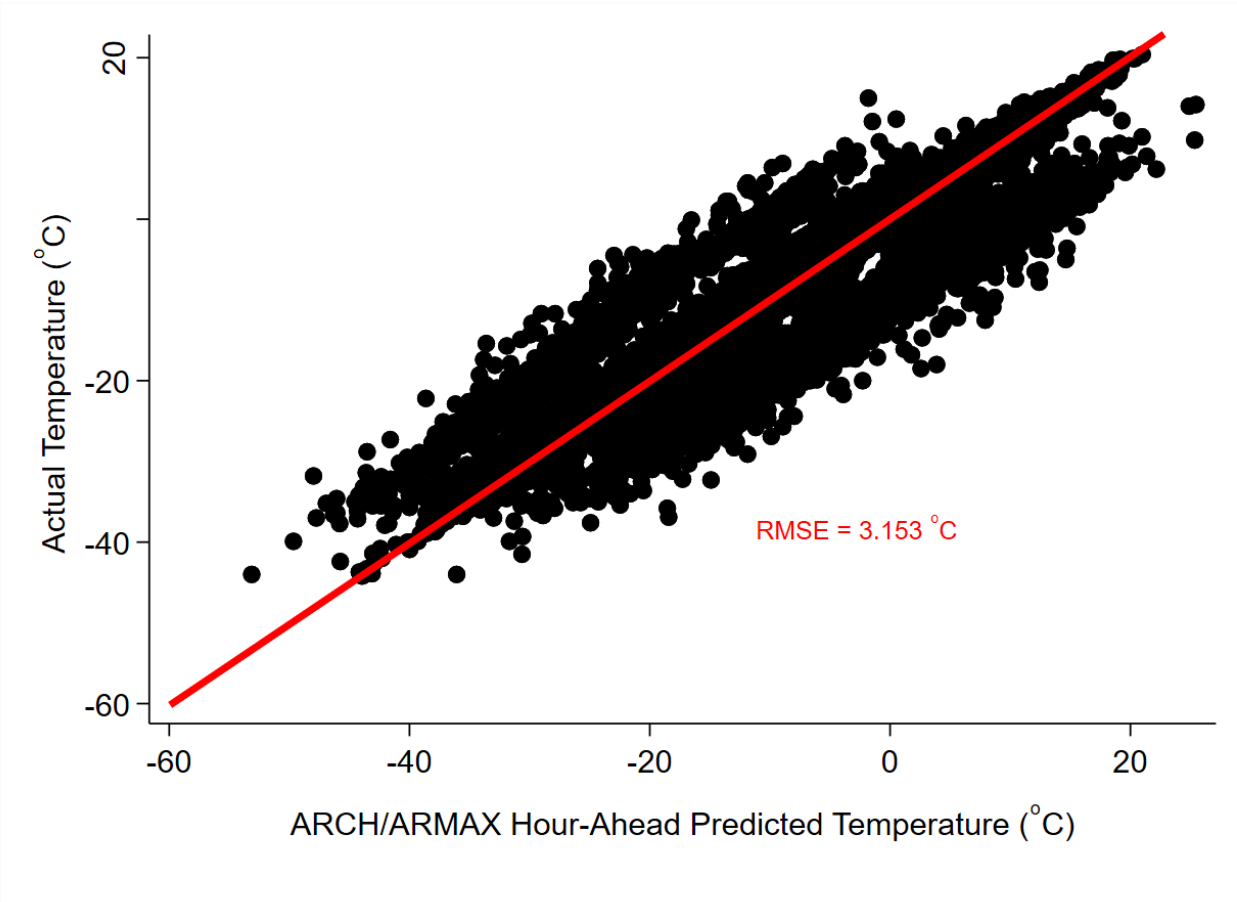

Figure 11. The out-of-sample predicted and actual hourly temperature at BRW when the statistically significant CO_2-related effects are largely ignored, 1 Jan 2016 – 31 December 2021.

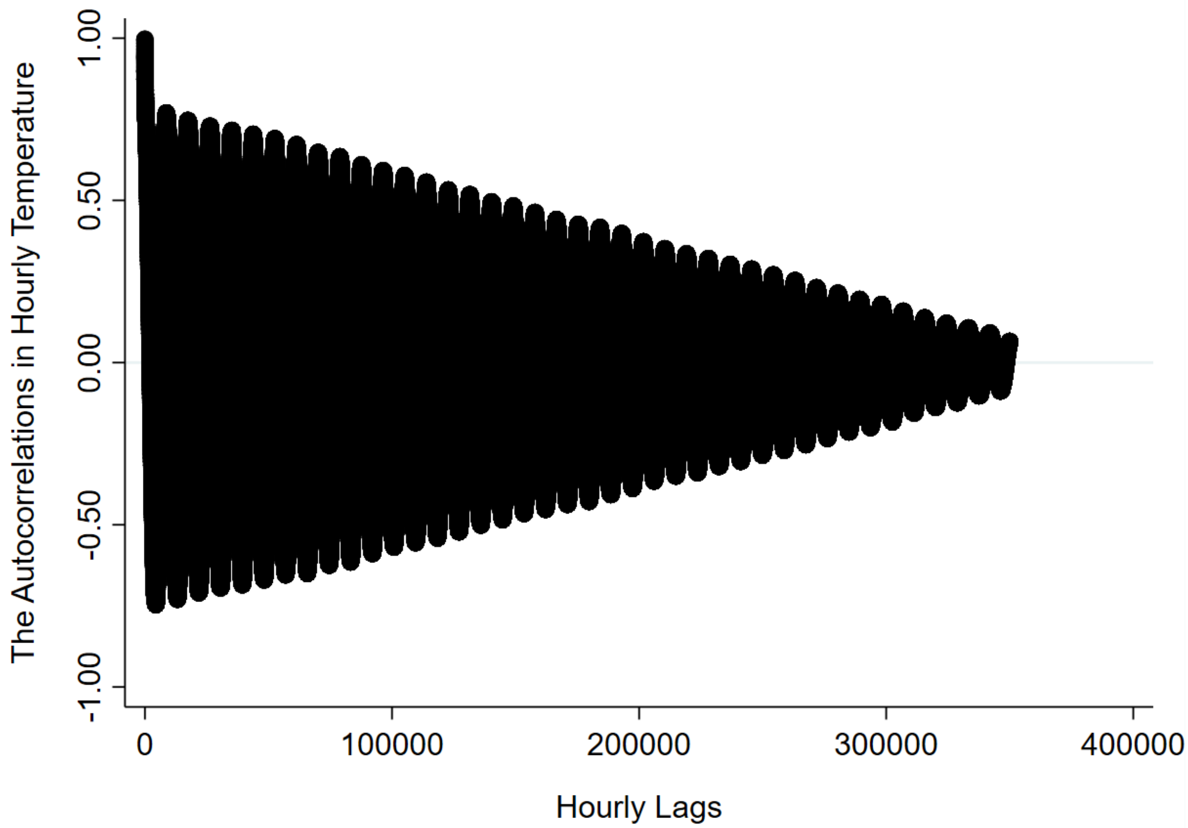

Figure 12. The first 350,000 autocorrelations in hourly temperature at BRW, January 1, 1977, through December 31, 2021.

The out-of-sample analysis supports the earlier discussion indicating the unimportance of factors other than CO_2 and the total downward solar irradiance being drivers of the increase in annual temperature over the sample period. Specifically, using the full model, the mean predicted temperature over the evaluation period equals -8.198850 ^{o}C. The mean predicted temperature over the evaluation period is -8.198851 ^{o}C if the estimated effects of the binary variables for 1985 through 2014 are constrained to equal zero. In short, the binary variables that attempt to control for the possibility of annual temperature being affected by factors other than CO_2 or total downward solar irradiance have virtually no effect on the out-of-sample predicted temperature.

Interestingly, the mean actual temperature over the evaluation period equals -8.189553 ^{o}C, a very close value to the mean of the predicted values.

8. The Implications of the ARCH/ARMAX modeling results for other locations

Based on the methodology used to report the results presented in Table 1, this section examines the implications of the ARCH/ARMAX modeling results for the hourly temperatures at lower latitudes. The analysis proceeds by modeling the hourly temperature at BRW and 17 other locations far from Alaska. The locations include meteorological stations located in Algeria, Australia, Canada, Chile, China, Egypt, India, Indonesia, Ireland, Italy, Japan, Pakistan, South Africa, Tanzania, and Texas in the United States of America. The locations also include MLO and SMO. Using hourly data, pairwise VAR equations (e.g., BRW and KDFW, the ICAO code for the station in Texas) were estimated over the period January 1, 1985, through December 31, 2020 (January 1, 1989, through December 31, 2020, in the case of the Valentia Observatory in Ireland). Some of the spatial correlations in hourly temperature in 2021 at these locations with the hourly temperature at BRW are very low and even negative, which may suggest that the temperatures are largely unrelated(e.g., Dodoma Airport in Tanzania). However, consistent with the findings reported in Table 1, a time-series based data analysis does not support this belief. Specifically, for each of the 17 pairs of data, the null hypotheses of no two-way Granger Causality in hourly temperatures are not supported (Table 3). Consistent with this finding, the lagged temperatures from both locations boost predictive accuracy at the non-BRW location in all cases. For example, the out-of-sample skill score associated with the lagged temperatures at BRW for the station located in Egypt equals 0.577. A skill score of this magnitude is a respectable outcome given that a useless predictive method would have a skill score of zero, while a perfect method would have a score of unity (the value is calculated using a persistence forecast at the non-BRW location as a reference). These results indicate that the hourly temperatures at BRW have significant implications for the hourly temperature at lower latitudes.

Table 3.
Granger Causality Wald test results and out-of-sample predictive accuracy for 17 locations based in part on the lagged temperatures at BRW

Non-BRW Location	Latitude and Longitude of the non-BRW Observatory	The null hypotheses of no two-way Granger Causality in hourly temperature	Correlation with the hourly temperature at BRW in 2021	Skill-Score for the non-BRW 2021 predictions when the data from BRW is used as an input based on a persistence forecast at the non-BRW location as the reference
Mohamed Khider Airport in Algeria	34.801667, 5.741667	Rejected	0.763	0.348
Sydney Airport Australia	-33.946111, 151.177222	Rejected	-0.606	0.333
Ottawa Airport in Canada	45.3225, -75.667222	Rejected	0.787	0.408
La Florida Airport in Chile	-33.533333, -70.583333	Rejected	-0.631	0.370
Beijing Capital International Airport in China	40.0725, 116.5975	Rejected	0.766	0.307
Cairo Airport in Egypt	30.121944, 31.405556	Rejected	0.697	0.567
Begumpet Airport in India	17.453056, 78.4675	Rejected	0.154	0.495
Budiarto Airport in Indonesia	-6.293171, 106.57	Rejected	0.010	0.722

Valentia Observatory in Ireland	51.9394, -10.2219	Rejected	0.669	0.206
Florence Airport in Italy	43.81, 11.203889	Rejected	0.714	0.409
RJTD weather station in Tokyo, Japan	35.6918, 139.7514	Rejected	0.7943	0.385
Walton Airport in Pakistan	31.494722, 74.346111	Rejected	0.663	0.572
Cape Town Airport in South Africa	-33.969444, 18.597222	Rejected	-0.595	0.373
Dodoma Airport in Tanzania	-6.170278, 35.749444	Rejected	-0.277	0.480
Dallas-Fort Worth Airport in the USA	32.896944, -97.038056	Rejected	0.698	0.467
MLO in Hawaii	19.54, -155.58	Rejected	0.382	0.623
SMO in American Samoa	-14.25, -170.56	Rejected	-0.268	0.345

9. Summary and Conclusion

This study estimated an ARCH/ARMAX model with statistical controls for total downward solar irradiance and other factors, including variables that control for the time-series nature of the data, to examine the relationship between CO_2 concentrations and hourly temperature at the Barrow Atmospheric Observatory in Alaska. The model was estimated using hourly data over the time interval of 1 Jan 1985 - 31 Dec 2015. The model was evaluated using hourly data from 1 Jan 2016 through 31 Dec 2021. The predictive R-square equivalence of 0.9966 over the evaluation period suggests that the model has reduced the attribution challenge associated with the significant natural meteorological variability in the Arctic. Consistent with this view, the predictions over the evaluation period are more accurate than the highly regarded ERA5T values for the same general vicinity. Thus, though the model fails to achieve the "white noise" metric in the standardized residuals, the accuracy of its predictions over the evaluation period indicates that the model is "useful." These results are consistent with the physics that indicates that rising CO_2 concentrations have consequences for temperature, a point that even climate deniers such as Richard Lindzen, William Happer, Roy Spencer, Patrick Michaels, and the other members of the CO_2 Coalition have conceded but with the stipulation that a doubling of the CO_2 concentration level will only increase global temperature by about one degree Celsius (CO_2 Coalition, 2015). What is different is that the model also offers useful insights into the magnitude of the relationship between CO_2 concentrations and hourly temperature. Specifically, the predictions over the evaluation period are significantly more accurate when they reflect the actual CO_2 levels estimated and statistically significant CO_2 coefficients compared to when the CO_2 effects on temperature are presumed to be small in magnitude. The out-of-sample results indicate that CO_2 concentrations have nontrivial implications for hourly temperature. The modeling results also addressed the possible contribution of factors other than CO_2 being drivers of increased temperature over the sample. The mean of the out-of-sample predicted temperature over the evaluation period is not materially affected by these variables, even though some are statistically significant.

Given that all models are "wrong," it is a picayune task to dismiss the estimation results reported in Table 2. It is much more challenging to rationally dismiss the implications of the large decline in the out-of-sample predictive accuracy when the estimated CO_2 effects are largely ignored. One possibility is that some unknown natural factor at work is the true culprit of the decline in predictive accuracy. While climate deniers may find this an attractive explanation for the results presented in this paper, the model's high level of predictive out-of-sample accuracy suggests that unknown factors are not an important driver of hourly temperature. There is also the point that attributing the large decline in the out-of-sample predictive accuracy when the estimated CO_2 effects are ignored to an "unknown variable" is highly likely to represent obscurantism as opposed to a conclusion that represents the best of all competing explanations as explained by Lipton (2004, p. 56). In short, the beliefs of climate change deniers are not supported by the hourly temperature data at NOAA's Barrow Observatory in Alaska. Considering the inadequate results on climate action reported by Matthews and Wynes (2022, p. 1404), this suggests that the current outlook for the Earth's future is quite grim. However, research that further illuminates the effects of CO_2 and other greenhouse gases at the hourly level might enable the consilience of evidence to reach a tipping point in terms of public support. One approach being considered is an analysis of the drivers of the hourly surface energy imbalance, a metric that is easily understood as being important but that climate deniers almost never mention. To its credit, the IPCC does acknowledge the importance of this issue. However, an inspection of the latest IPCC report indicates that analysis of the hourly surface energy imbalance is in its infancy. One possible reason for this is that the hourly data are noisy and thus very challenging to work with using the methods typically employed by climate scientists. Interestingly, a preliminary analysis indicates that the hourly surface energy imbalance at Barrow and other locations is autoregressive, heteroskedastic, and Granger Causality related to other locations' imbalances. Given these attributes, it may not be overly optimistic to suspect that an ARCH/ARMAX analysis of this hourly data, complete with an out-of-sample evaluation of the statistical results to ensure credibility, could facilitate an improved understanding of this important topic that could be effectively communicated to the general public.

Acknowledgments

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Conflict of Interest Disclosure

The author is recognized as a contributor to two patents that address the challenges of integrating renewable energy into the power grid. Information about the patents is available at the following links:

> https://patentscope.wipo.int/search/en/detail.jsf;jsessionid=F21BECE874FB500486D2F6CA4C321F02.wapp2nB?docId=WO2017201427&tab=PCTDESCRIPTION
>
> https://patentscope.wipo.int/search/en/detail.jsf?docId=US339099329&docAn=17230201

Data Availability Statement

Data used in this research and reproducing STATA codes are deposited on Zenodo at 10.5281/zenodo.5833580.

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