ISSN: 3064-9846
Research Article

Journal of Agricultural, Earth and Environmental Sciences

Blowing in the Wind: A Time Series Analysis of Mean UK Summer Temperature

Keith Johnson*

IP Consultant, Thurnbichl 2, A-6345 Kössen Austria

***Corresponding author:** Keith Johnson, IP Consultant, Thurnbichl 2, A-6345 Kössen Austria.

Submitted: 23 March 2024 **Accepted:** 28 March 2024 **Published:** 04 April 2024

https://doi.org/10.63620/MKJAEES.2024.1031

Citation: *Johnson, K. (2024). Blowing in the Wind: A Time Series Analysis of Mean UK Summer Temperature. J of Agri Earth & Environmental Sciences, 3(2), 01-09.*

Abstract

Time series analysis is applied to the mean UK summer temperatures provided by the UK MET Office. First, the statistical significance of the data is determined by comparing with the mean and standard deviation of the whole time series and using the Wald Wolfowitz Runs Test. On this basis, only the rising trend in the last decade or so (> 2009) is possibly significant.

This trend is then compared with various potential causes: atmospheric CO_2, global carbon emissions, China carbon emissions etc. By detrending, using first differences, and computing the cross-correlation function, or CCF, only offshore wind generating capacity gives a significant level of cross-correlation in the CCF. The cross-correlation persists when a different method of detrending is used and autocorrelation is considered using the Cochrane-Orcutt procedure. Hence, if the rising trend is significant, the hypothesis that it is associated with offshore wind generating capacity cannot be rejected.

It follows from a consideration of wind turbine wake dynamics using Bernouilli's principle that extracting large amounts of energy must lead to low pressure down wind of the turbines. With prevailing westerly winds and largely offshore wind farms, this means the creation of a low-pressure region in the North Sea. Perhaps this low-pressure region, sucking hot air from Africa, provides a mechanism for the increase in the mean UK summer temperature? It might also account for the Cerberus heat wave in 2023 and Sahara dust. Hence our attempts at mitigating anthropogenic climate change might be causing deleterious changes in weather patterns.

Keywords: Climate Change mean UK Summer Temperature Time Series Analysis Statistical Significance Cross- correlation CCF Autocorrelation Offshore Wind Generating Capacity Turbine Wake Dynamics Cerberus Heat Wave

Hot on the Trace

Reports by the UK MET office, echoed by the BBC and the Daily Telegraph, suggested that the heat wave Cerberus and other occurrences of exceptional temperature, which affected Europe across the summer of 2023, might well have been due to the Jet Stream lingering unusually in lower latitudes than normal [1]. In their view, this could be taken as further evidence for anthropogenic climate change:

'… One of the elements that might have led to a very hot year in 2022 and may help explain the current wetter summer are changes in the jet stream, the fast-moving winds that carry weather systems across the Atlantic to the UK. In recent years the jet stream has shown a tendency to get stuck, meaning that weather patterns can persist or become blocked in place for weeks. There is a school of thought that a warming climate is causing this change… The heatwave that is happening now across southern Europe, the heatwave that we saw last year, all of these things are fitting into a pattern… The ten-year period from 2013 to 2022 is the warmest ten-year period on record…'.

As further evidence, the Daily Telegraph published the following plot of Mean UK summer temperature:

ORCID 0000-0001-5508-6567

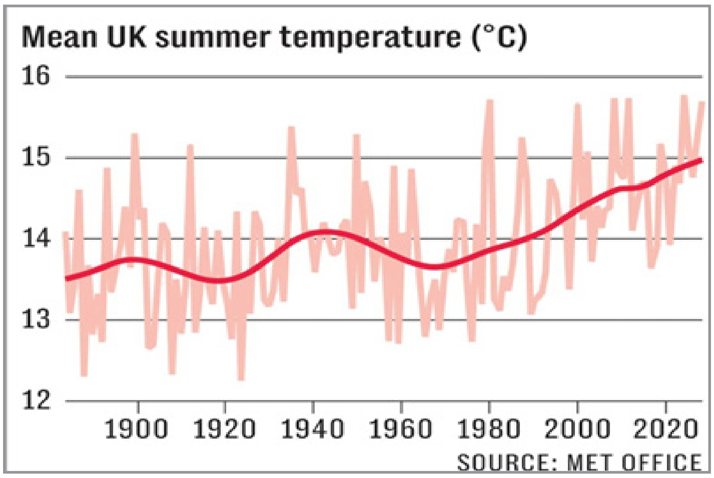

Figure 1: Mean UK Summer Temperature as published

where the red line represents a ten-year running average. How significant is this trend and what might account for it?

Testing for Significance

One way to address the statistical significance is to compute the mean and standard deviation for the whole time series. If the data is just normally distributed about a constant mean, then nearly all the points should fall within two standard deviations from the mean, and the trend has no significance. The analysis is shown in the next graph, where the solid black line represents the mean of the data, and the dashed lines
+/- 2SDs:

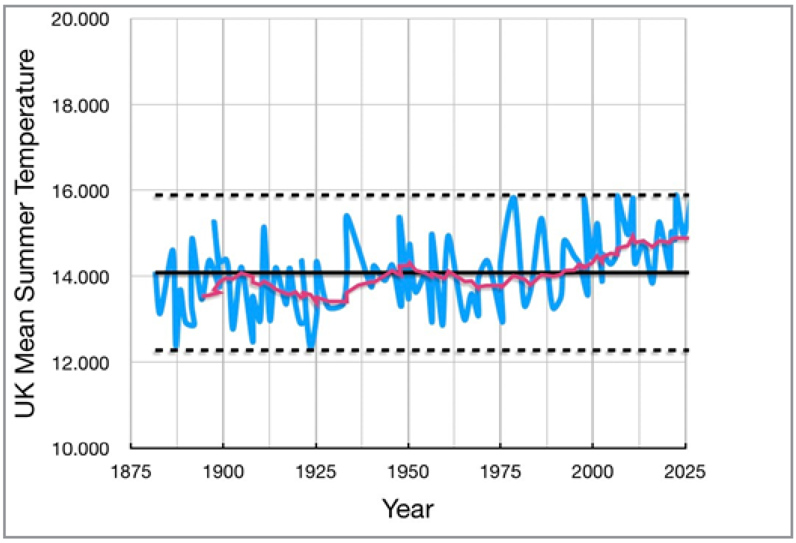

Figure 2: Mean UK Summer Temperature with mean and standard deviations

Clearly, all the points lie within two standard deviations, so there are apparently no grounds for preferring a rising trend over the null hypothesis of a constant mean. This is confirmed by plotting %Deviation from the mean:

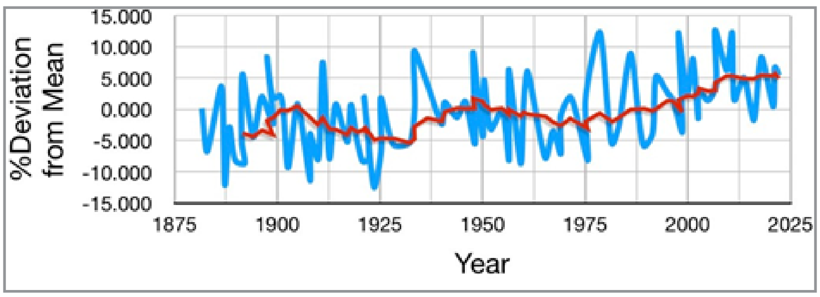

Figure 3: % Deviation from the Mean

The trend line remains within 5% of the mean (which could be deemed the experimental error in the observations), and counting and comparing negative departures from the mean with positive departures, no significant pattern emerges. Indeed, in the last few years, negative departures seem only marginally less common than positive ones.

On a more formal basis, the Wald Wolfowitz Runs Test can be applied [2]. The test is used to test the randomness of a distribution by taking the data in the given order and marking positive and negative deviations from the mean. A run is then defined as a sequence of adjacently marked positive or negative deviations. Under the null hypothesis, the number of runs, R in a sequence of length, N is a random variable whose distribution, given N+ positive deviations and N− negative deviations, is approximately normal with mean $\mu = 2N+. N-/N + 1$ and variance $\sigma^2 = 2(\mu - 1)(\mu - 2)/(N - 1)$. The test statistic:

$$Z = (R - \mu)/\sigma$$

can then be compared with the quantile corresponding to a given level of significance, $Z\alpha$. For $Z > Z\alpha$, the null hypothesis is to be rejected. In the present case, R= 50, N+ = 45, N− = 41 and for a significance level of 5%, $Z\alpha$ =1.96. A little computation then gives μ = 43.906, σ = 4.599, so that Z = 1.501 for these data. Consequently, the null hypothesis of data randomly distributed about a constant mean cannot be rejected at this level of significance.

Thus, there is little evidence in the data to support a rising trend, except perhaps in the last decade or so.

Suppose, however, the trend in the last decade or so is significant: what might then be the cause? According to the current climate science paradigm, the way forward would be to run computer models of climate change for a range of parameters in an attempt to reproduce the observed trend. Yet a simpler approach is to apply time series analysis and seek corroborating correlation in other data sets. Of course, the usual mantra holds that correlation is not causation. On the other hand, a lack of correlation definitely excludes causation. So, candidates for causation can be eliminated by demonstrating a lack of correlation. We take this approach below*.

The Game's Afoot: Cross-Correlations

Given the present consensus on anthropogenic climate change, obvious candidates for review are atmospheric CO_2 concentration, global carbon emissions, and China carbon emissions. Using data from public sources*, plots can be constructed of mean UK summer temperature against these parameters for the period after 2009, and the correlation determined as the coefficient of determination, R^2. The correlation is strongest for atmospheric CO_2 concentration (0.9657), moderate for China emissions (0.7360), and only poor for global carbon emissions (0.4718). So, we can already dismiss global carbon emissions as a candidate.

The results for atmospheric CO_2 concentration are shown in the following figures:

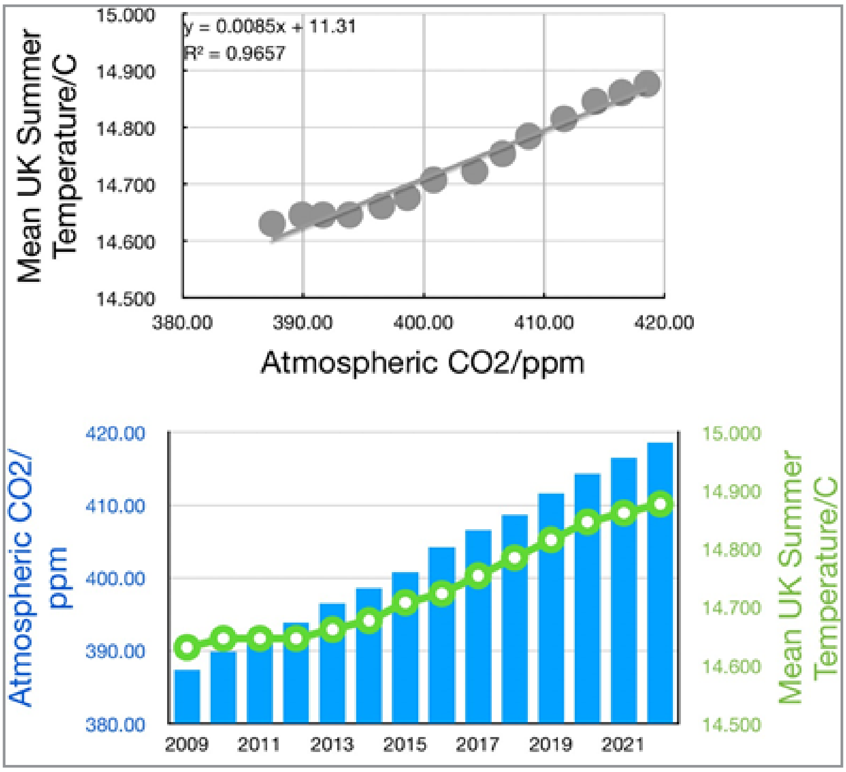

Figure 4: Mean UK Summer Temperature v. Atmospheric CO_2

*Just like Sherlock Holmes, '… after eliminating the impossible, whatever remains, however improbable must be the truth…'.
* See Annex A: Data processing and methods for details.

On the face of it, this would seem to confirm the significance of the temperature data and support the anthropogenic hypothesis. Yet it is well known in time series analysis that one should be wary of correlations between time series which show trends, for, as in the present case, if both sets of data are increasing with time, there is bound to be a strong correlation between them. This is true even if they are not causally related. Thus, when seeking meaningful correlations, it is imperative to remove trends from the data. A simple way to do this is to compute the first differences, i.e. the annual changes, and then determine the cross-correlation function or CCF between the first differences [3]. For the present case, we obtain the following graph:

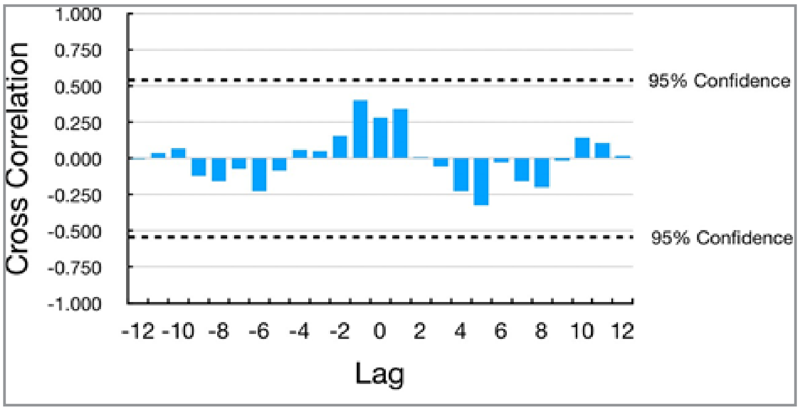

Figure 5: CCF for Mean UK summer Temperature v Atmospheric CO_2 (1st Differences)

where the cross-correlation for lag, is calculated as:

$$\Sigma(x_t - \bar{x}) \,.\, (y_{t-l} - \bar{y})/[\Sigma(x_t - \bar{x})^2]^{1/2} \,.\, [\Sigma(y_t - \bar{y})^2]^{1/2}$$

with x_t the first difference in atmospheric CO_2 at time t, y_t the first difference in mean temperature, and $\bar{x}$, $\bar{y}$,the mean values of these quantities. The 95% confidence limits are then given by $\pm 1.96/\sqrt{N}$ with N the number of values - here 13 [3]. Because none of the sample cross-correlations exceeds this limit, they must be deemed statistically insignificant. Hence atmospheric CO_2 concentration can also be dismissed as a candidate. As similar results obtain for China carbon emissions, these must be rejected as well.

Since these global environmental parameters do not account for the local increase in mean summer temperature, it seems appropriate to search for more local measures such as local UK carbon emissions. Surprisingly, there is a strong correlation (R^2=0.9271) between mean UK summer temperature and the percentage decrease in UK carbon emissions since 2009, as shown in the following graphs:

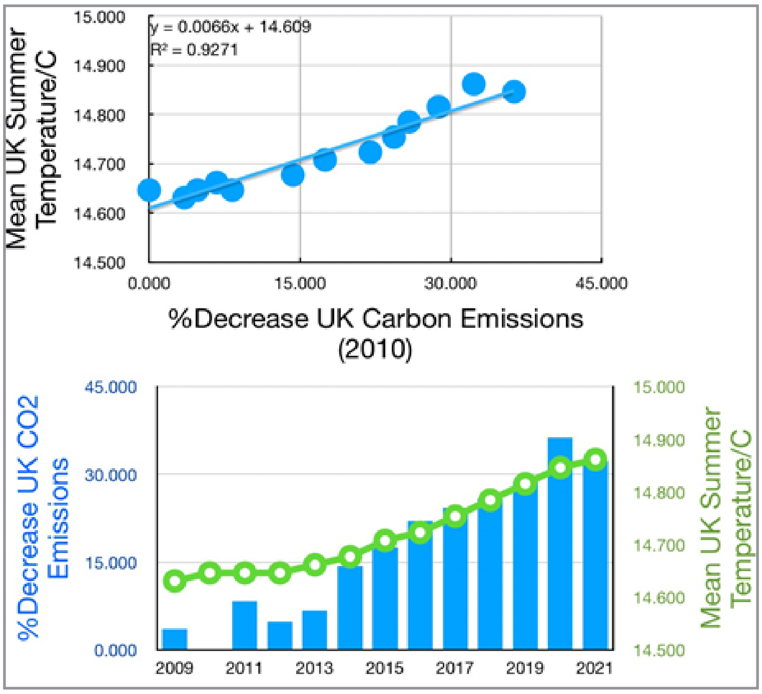

Figure 6: Mean UK Summer Temperature v. % Decreases in UK Carbon Emissions

However, the CCF for the first differences displays no significant cross-correlation:

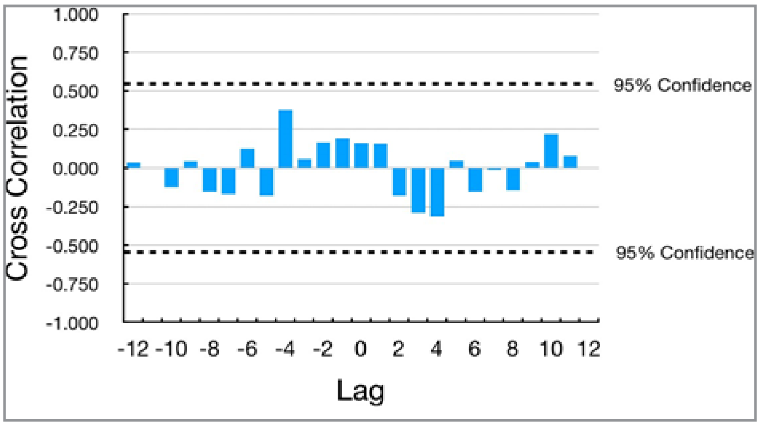

Figure 7: CCF for mean UK summer temperature v. % Decreases in UK Carbon Emissions

So, the correlation is simply due to the positive trend in both series, whereby the series are not causally related.

Nevertheless, the results provide perhaps a pointer to another local candidate, as the decrease in UK carbon emissions is presumably associated with the rise in offshore wind power. As can be seen from the next graphs, the mean UK summer temperature is indeed strongly correlated with offshore wind generating capacity (R^2=0.9721):

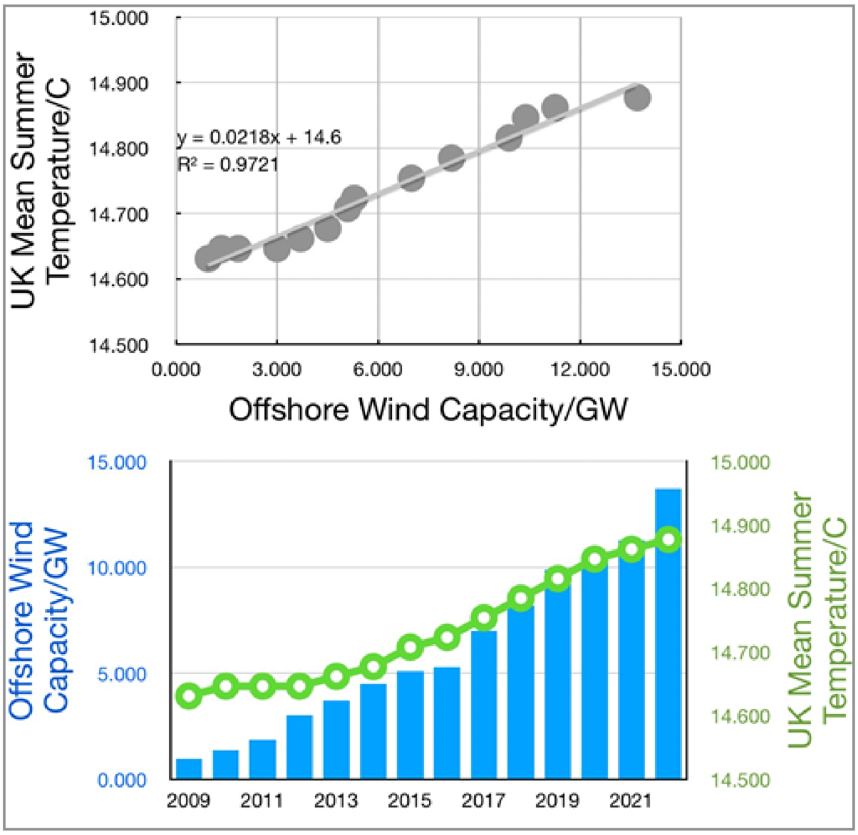

Figure 8: Mean UK Summer Temperature v. OffShore Wind Capacity 2009

Furthermore, the plot for the CCF of first differences just touches the 95% confidence level at lag 4:

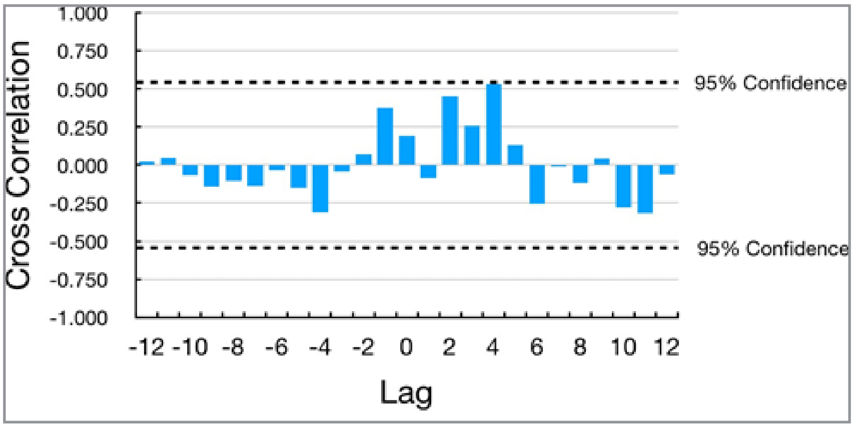

Figure 9: CCF for Mean UK Summer Temperature v. OffShore Wind Capacity (1st Differences)

Is it an artifact? Various consistency tests that have been carried out suggest not (see Annex A for details). In particular, we can take a different approach to removing trends from the data and recalculate the CCF to see whether significant cross- correlation persists.

One such method is to fit straight lines to both series, calculate the residuals as the difference between the actual values and the line of fit, and then determine the CCF from the residuals [3]. The results are shown in the next plot:

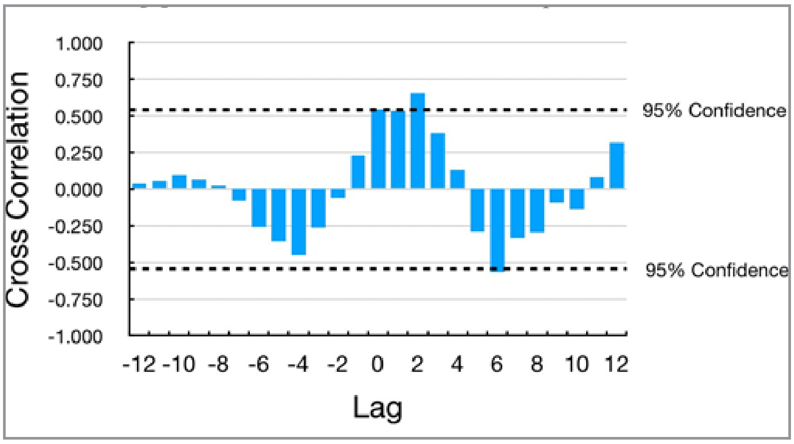

Figure 10: CCF for Mean UK Summer Temperature v. OffShore Wind Capacity (Linear Residuals)

apparently confirming the presence of significant cross-correlation. Yet it is well known in time series analysis that spurious correlations often occur if the time series show autocorrelation, i.e. the series value at time t depends to some extent on earlier values [3].

Fortunately, an advantage of calculating the CCF from the residuals is that the presence of autocorrelation can be tested for using the Durbin Watson statistic, d [4]. This is calculated from the formula:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2},$$

where e_t is the residual from the line of fit at time t etc. and T is the number of values.

The value of d lies between 0 and 4 and can be compared with upper and lower critical values $d_{l,\alpha,}$ $d_{u,\alpha}$ taken from tables for a given level of significance, and degrees of freedom, F, in order to determine the presence of autocorrelation.

However, a value of d substantially less than 2 can be taken as evidence of positive serial correlation. In the present case, d= 0.21236* for the y-values (Mean UK Summer Temperatures) and d = 0.84923 for the x-values (Offshore Wind Capacity). So, both series display considerable autocorrelation.

Nevertheless, autocorrelation in the data can be corrected for using the Cochrane- Orcutt procedure [5]. The residuals in both the x- and y- series are corrected using the following formula:

$$e'_t = e_t - \rho \, . \, e_{t-1}$$

where is the lag-1 autocorrelation in the x-series, here 0.42919. This results in the following CCF:

*Since the y-values are based on a 10-year running average, it is perhaps not surprising there is a large amount of autocorrelation

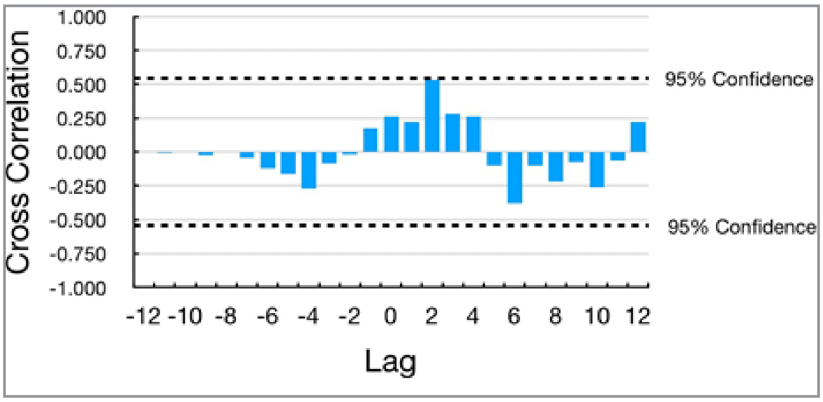

Figure 11: CCF for Mean UK Summer Temperature v. OffShore Wind Capacity (CO-Residuals)

The cross-correlation at lag 2 still just touches the critical value.

Hence if the trend in mean UK summer temperature is significant, we cannot reject the hypothesis that it is associated with the rise in offshore wind generating capacity.

Wind and Weather

At first glance, it might seem improbable that offshore wind power generation could affect the weather. But, as Lorenz first discovered, the nonlinear equations governing the weather have such an incredible sensitivity to initial conditions, that it has been claimed '… a butterfly flapping its wings in Brazil could set off a tornado in Texas…' [6]. Compare the power of a butterfly's wings with 15 GW of wind generating capacity!*

Furthermore, according to Bodini et al, '… Long-term meteorological measurements in the vicinity of wind plants can also be affected by wind plant wakes… aggregated wakes from multiple turbines, i.e., wind plant wakes, can extend more than 50 km downwind of a wind plant, offshore in stable conditions…' [7]. What might be the physical mechanism?

As discussed in in McKay et al and Kulunk, downstream wake effects can be analyzed using rotor disc theory by applying various conservation principles [8, 9]:

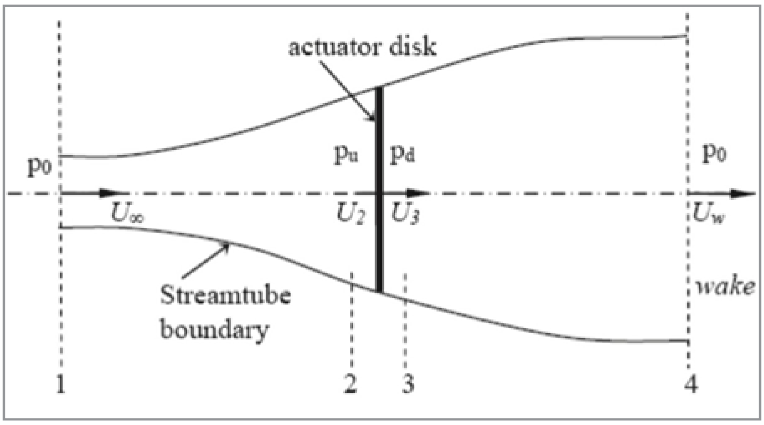

Figure 12: Rotor Disk Theory - taken from Kulunk

'… A decrease in wind speed across the rotor area results in a greater downstream area. From elementary energy conservation principles, it can be shown that a high-pressure area is formed upstream of the rotor disc and a lower pressure area is formed downstream. This pressure change is due to the work of the rotor blades on the air passing over them. The force of the air on the blades results in an opposing force on the air stream causing a rotation of the air column. This low-pressure column of rotating air expands as it moves downstream of the turbine and eventually dissipates as equilibrium is reached with the surrounding airflow. This simplified explanation constitutes what is known as the "wake effect" of a wind turbine. An increase in downstream turbulence is caused by wake rotation, disruption of the air flow across the rotor blades and the vortices formed at the blade tips…'

Using Bernoulli's principle, based on the conservation of energy, the pressure drops across the rotor, p′ can be determined as:

$$p' = 1/2\rho(U_\infty^2 - U_W^2)$$

* See also H. Baumgartner, Letters, Sunday Telegraph edition of 30.01.2022: '… Every wind turbine extracts a tiny amount of energy from the air mass, insignificant in isolation, but there must come a point when a proliferation of these devices will extract sufficient energy to alter the nature of the air mass, a potential climate changing event.'

where ρ is the density, U_∞ and U_W are the wind speeds upstream and downstream of the turbine? The thrust on the turbine is then given by:

$$T = Ap' = 1/2A\rho(U_\infty^2 - U_W^2)$$

and the power generated, as:

$$P = T.1/2(U_\infty + U_W)$$

Thus, extracting large amounts of energy must lead to low pressure down wind of the turbines. Given prevailing westerly winds and largely offshore wind farms, this means the creation of a low-pressure region in the North Sea. Could it not be that this low-pressure region is sucking hot air from Africa, leading to an increase in the mean UK summer temperature?

Indeed, according to weather reports in the Daily Telegraph [1] the Cerberus heat wave was triggered by '… an anticyclone – a large-scale circulation of winds around an area of high atmospheric pressure – pushing north…' while '… A low-pressure system was directed towards the UK… causing the recent wind and rain…'. Finally, might this also be the origin of the Sahara dust that has affected Western Europe in recent years? It would be interesting to plot cumulative dust versus generating power. So, the hypothesis is at least falsifiable in the Popperian sense.

Conclusions

The safest conclusion would seem to be that the trend in UK summer temperatures vaunted by the UK MET Office and the press is not statistically significant. However, if the trend, especially in the last decade or so, is taken as significant, then it cannot be excluded that it is associated with offshore wind generating capacity. Hence our attempts at mitigating anthropogenic climate change might be causing deleterious changes in weather patterns.

References

1. Gatten E, https://www.telegraph.co.uk/news/2023/07/27/heatwave-2022- average-british-summer-40-years-met-office/; https://www.telegraph.co.uk/world- news/2023/07/24/heatwave-europe-why-jet-stream-when-will-it-end/;https://www.telegraph.co.uk/world-news/2023/07/19/europe-char-on-heatwave-weather-how- worried-we-should-be/; https://www.telegraph.co.uk/news/2023/07/13/europe- heatwave-will-see-drizzle-and-cool-weather-in-uk/; https:// digitaleditions.telegraph.co.uk/data/1410/reader/reader.html?#!preferred/0/package/ 1410/pub/1410/page/21/article/NaN
2. https://en.wikipedia.org/wiki/Wald–Wolfowitz_runs_test; See also https:// kindsonthegenius.com/blog/how-to-perform-wald-wolfowitz-test-testing-for-homogeneity-with-run-test/ and https://www.itl.nist.gov/div898/handbook/eda/ section3/eda35d.htm
3. Dean RT, Dunsmuir WTM (2016) Dangers and uses of cross-correlation in analyzing time series in perception, performance, movement, and neuroscience: The importance of constructing transfer function autoregressive models. Behavioral Research Methods 48: 783-802.
4. https://en.wikipedia.org/wiki/Durbin–Watson_statistic
5. https://en.wikipedia.org/wiki/Cochrane–Orcutt_estimation
6. Chodos A (2003) This month in physics history - Circa January 1961: Lorenz and the butterfly effect. APS News 14: 2.
7. Bodini N, Lundquist JK, Moriarty P (2021) Wind plants can impact long-term local atmospheric conditions. Scientific Reports 11: 22939.
8. McKay P, Carriveau R, Ting D S-K, Newson T (2012) Turbine Wake Dynamics Advances in Wind Power. InTech DOI 10.5772/53968.
9. Kulunk E (2011) Chapter 1 Aerodynamics of Wind Turbines in Fundamental and Advanced Topics in Wind Power, Dr. Rupp Carriveau (Ed.), ISBN:978-953-307-508-2, In Tech, 2011.
10. El Hajj A, Kabalan KY, Khoury S (2004) The Use of Spreadsheets to Calculate the Convolution Sum of Two Finite Sequences. International Journal of Engineering Education 20: 867-871.

Annex A: Data Processing and Methods

Data analysis was carried out in a Numbers spreadsheet, 'UK Mean Summer Temperature' on an Apple iPad pro. The contents of the spreadsheet are listed in the table below:

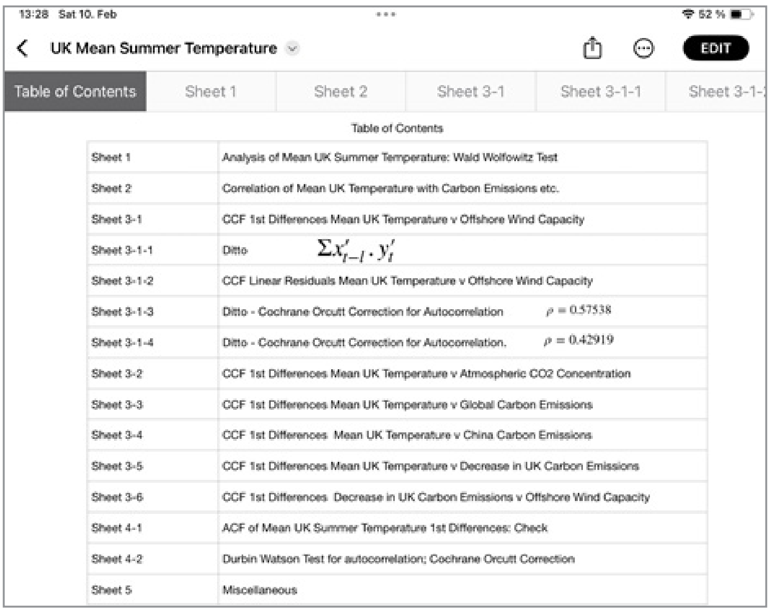

Table of Contents

Sheet 1	Analysis of Mean UK Summer Temperature: Wald Wolfowitz Test
Sheet 2	Correlation of Mean UK Temperature with Carbon Emissions etc.
Sheet 3-1	CCF 1st Differences Mean UK Temperature v Offshore Wind Capacity
Sheet 3-1-1	Ditto $\Sigma x'_{t-l} \cdot y'_t$
Sheet 3-1-2	CCF Linear Residuals Mean UK Temperature v Offshore Wind Capacity
Sheet 3-1-3	Ditto - Cochrane Orcutt Correction for Autocorrelation $\rho = 0.57538$
Sheet 3-1-4	Ditto - Cochrane Orcutt Correction for Autocorrelation. $\rho = 0.42919$
Sheet 3-2	CCF 1st Differences Mean UK Temperature v Atmospheric CO2 Concentration
Sheet 3-3	CCF 1st Differences Mean UK Temperature v Global Carbon Emissions
Sheet 3-4	CCF 1st Differences Mean UK Temperature v China Carbon Emissions
Sheet 3-5	CCF 1st Differences Mean UK Temperature v Decrease in UK Carbon Emissions
Sheet 3-6	CCF 1st Differences Decrease in UK Carbon Emissions v Offshore Wind Capacity
Sheet 4-1	ACF of Mean UK Summer Temperature 1st Differences: Check
Sheet 4-2	Durbin Watson Test for autocorrelation; Cochrane Orcutt Correction
Sheet 5	Miscellaneous

The UK temperature data were obtained by digitising the figure from the Daily Telegraph using the web digitiser https://apps.automeris.io/wpd and downloaded into sheet 1 for analysis. The accuracy of the digitisation was verified by comparing with the original data from the UK Met Office, https://www.metoffice.gov.uk/pub/data/weather/uk/climate/datasets/Tmean/date/ UK.txt. The mean and standard deviation for the whole time series were computed and the Wald Wolfowitz Runs test implemented.

Data for atmospheric CO_2 concentration, global, UK and China carbon emissions, and Offshore wind capacity were downloaded from https://datahub.io/core/co2-ppm, https://data.spectator.co.uk/net-zero, and https://www.statista.com/statistics/792374/cumulative-offshore-wind-capacity-united-kingdom/ respectively. Correlations of these parameters with mean UK summer temperature were determined in sheet 2 of the spreadsheet. In sheets 3.1 - 3.4, the various data sets were detrended by computing first differences and the cross-correlation function, CCF, computed using a tabular method for spreadsheets as discussed in reference [10].

To test the validity of the method, it was used to calculate the autocorrelation of the mean temperature series in sheet 4.1, correctly reproducing a Pearson coefficient R = 1 at lag 0. A further consistency check was to calculate the CCF via the formula Σxt′−l. yt′. with xt′−l = (xt−l − x) and yt′ = (yt − y) thereby inverting the sign of the lag, as in sheet 3-1-1, so that the maximum now appears at lag -4 as required. Then the linear regression equations for mean UK summer temperature and offshore wind capacity, developed in sheet 2, were used as an alternative way to detrend the data and the CCF of the residuals computed in sheet 3-1-2.

In sheet 4.2, the Durbin Watson test was applied to the residuals to determine the extent of autocorrelation. One estimate for can be determined from the Durbin Watson statistic itself (0.5738) but a more accurate estimate is given by the lag 1 autocorrelation, here 0.42919. In sheets 3-1-3, 3-1-4, these values are applied in the Cochrane Orcutt procedure to calculate the CCF compensated for autocorrelation. Sheet 5 contains bits and bobs used in intermediate calculations.

The spreadsheet is available on the iCloud on request to the author and a pdf version can be found on Google Drive: https://drive.google.com/file/d/1RimZ_lcXZwbf39f0ZHisZjsOv_XRdR0A/view?usp=drivesdk