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ORIGINAL PAPER

Time trends and persistence in the Arctic temperature

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Abstract
Time trends are examined in Arctic temperatures by using a fractionally integrated model. The results indicate that globally, the time trend coefficient is significantly positive and the degree of differentiation is equal to 0.32. Looking at subsamples of 25 years, the time trend is only found to be significantly positive in the last two subsamples, being particularly high in the final one corresponding to data starting at January 2001. For this period, the degree of integration is also the highest across all subsamples. This result supports the hypothesis that temperatures in the Arctic region have increased in recent years.

1 Introduction

The Arctic is experiencing a warming trend greater than that of the rest of the planet (Chylek et al. 2022; IPCC 2021) which is causing melting (Khan et al. 2015; IMBIE 2020), greenhouse gas release and affecting global climate change (Pistone et al. 2019; AMAP 2021). IPPC (2021) projects, with high confidence, indicate that additional warming will intensify permafrost thaw and exacerbate the loss of the seasonal snowpack, continental ice and Arctic Sea ice. It is likely that this area will be without sea ice at least once before 2050, something which could happen more frequently at higher warming levels.

According to the United Nations Environment Programme (2019) Arctic winter temperatures will rise by 3 °C to 5 °C by 2050 and by 5 °C to 9 °C by 2080 even if the Paris Agreement targets are met. Data in the report indicate that since 1979 Arctic Sea ice has shrunk by 40%, glacier melt contributes to one third of global sea level rise, and melting ice will contribute to carbon dioxide and methane emissions which in turn will lead to more melting ice (positive feedback).

Human influence is very likely to be the main driving force behind the global retreat of glaciers since the 1990s, as well as the decrease in Arctic Sea ice area between 1979 and 1988 and 2010–2019 (IPPC 2021; Dai et al. 2019; Mouginot et al. 2019). This phenomenon opens up new shipping routes with negative environmental effects due to air pollution (Chylek et al. 2016).

In recent years, the scientific literature has warned that the Arctic is warming faster than the global average, a phenomenon known as Arctic amplification (Yamanouchi et. a., 2020; Walsh 2021). Rantanen et al. (2022) reports that warming is 3.8 times faster than the global average over the past four decades. The Arctic Monitoring and Assessment Programme (AMAP 2021) report concludes that while the planet has warmed by 0.19 °C per decade, the Arctic has warmed by 0.73 °C. The problem is exacerbated in certain areas of the Arctic, such as the Barents Sea, where warming is seven times faster (Isaksen et al. 2022). Other recent contributions on modelling Arctic climate change include among others Cattle et al. (1995), and more recently, McCrystall et al. (2021), Tian and Hayashi (2024) and Tian et al. (2024).

The literature on climate change is extensive (Brunetti et al. 2001; Gil-Alana 2012, 2018; Lenti et al. 2021; Li et al. 2021; Gil-Alana et al. 2019, 2022) but there is no common approach to modelling it. Our analysis focuses on fractional integration where the differentiation parameter d can be a real number, which provides a more accurate description

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of correlation in both the short and long term, leading to more efficient estimates with less variability (Huang et al. 2022) than those obtained with other methods assuming I(0) (Bloomfeld and Nychka, 1992; Woodward and Gray 1993), or non-stationary I(1) (Woodward and Gray 1995; Mann 2004) or compared to alternative trendless fluctuation analyses (Kantelhardt et al. 2001) and even standard linear regression models (Vogelsang and Franses 2005; Fatichi et al. 2009).

Ultimately the long memory approach will allow us to detect the presence of long-term trends and study the degree of persistence of the Arctic temperature anomaly series, providing information on whether or not the series has reversion to the mean, i.e. whether the shocks have permanent or transient effects and the analysis of temperature trends in this region, which provides early indicators and warning signs of climate change allowing a deeper understanding of how the climate is evolving. This is essential for understanding the impact on sea level, monitoring climate feedbacks such as the release of greenhouse gases and the effects of human activity, among other issues, leading to better designed environmental policies.

2 Methodology and data

In order to measure warming in temperatures, we use a simple linear regression model with an intercept and a time trend coefficient, i.e.,

$$y(t) \ = \alpha + \beta t + x(t), \ t = 1, \ 2, \ldots, \tag{1}$$

where the regression errors, x(t) are integrated of an unknown order d,

$$(1-L)^d x(t) \ = \ u(t), \ t = 1, \ 2, \ldots, \tag{2}$$

and x(t)=u(t)=0 for t≤0, where u(t) is short memory or integrated of order 0.

Thus, a significantly positive value of β will provide evidence of global warming and d>0 will indicate support for the long memory hypothesis widely tested and supported in the context of climatological data (Yuan et al., 2014a, b; 2015; 2022). The property of long memory indicates that the data display a strong degree of dependence across time. Statistically, it implies that the sum of the autocovariances is infinite, a property that is satisfied by many models, including among others the fractionally integrated or I(d) ones with positive values of d. The estimation of the unknown parameters is conducted via Whittle function in the frequency domain, using a well-known technique developed in Robinson (1994).

Note that the two parameters of interest (β and d) are jointly estimated in the joint representation of the Eqs. (1) and (2), i.e.,

$$y^*(t) \ = \alpha 1^*(t) \ + \beta t^*(t) + u(t), \ t = 1, \ 2, \ldots, \tag{3}$$

where $y^*(t) = (1 - L)^d x(t)$; $1^*(t) = (1 - L)^d 1$; and $t^*(t) = (1 - L)^d t$, and since u(t) is I(0) by construction, β can be estimated by any standard least squares procedure. See Gil-Alana and Robinson (1997) for the application of the version of Robinson's (1994) tests used in this work. There are several reasons for using these tests. First, they are valid in the context of any real value d, which implies that they do not require preliminary differentiation in the context of nonstationary data. Secondly, the limit distribution is standard N(0, 1) which facilitates the computation of confidence intervals for the non-rejection values. Moreover, this method is found to be the most efficient one in the Pitman sense against local departures from the null.

Arctic temperature anomaly data are taken from the NOAA series (National Centers for Environmental Information) that combines long-term sea surface temperature and land surface temperature data sets. The data are monthly from 1880 to 2022 and consist of the combined anomalies of global land and ocean temperatures with respect to the average of the period 1901–2000.

Figure 1 displays in the upper part plots of the time series and its first differences. The first thing we observe is a remarkable increase in the temperatures in the last twenty years, also increasing the variability of the data. The second row shows the correlograms of both original and first differences, while the last row displays the periodograms. In both cases, a seasonal pattern becomes apparent along with clear signs of over-differentiation in the first differenced data. To deal with the seasonal component, a monthly AutoRegressive AR(1) process of the form:

$$u(t) \ = \rho\, u(t-12) + e(t), \ t = 1, \ 2, \ldots, \tag{4}$$

is assumed for the u(t) error term in (2), where ρ refers to the AR coefficient and e(t) is an uncorrelated zero mean process with constant variance.

3 Results

As a preliminary step in the empirical analysis, we first conducted the modified R/S statistic as proposed in Lo (1991). This method tests the null hypothesis of no long memory against the alteranative of long memory. However, taking into account that this method is biased in favour of accepting the null as the bandwidth number increases (Teverovsky

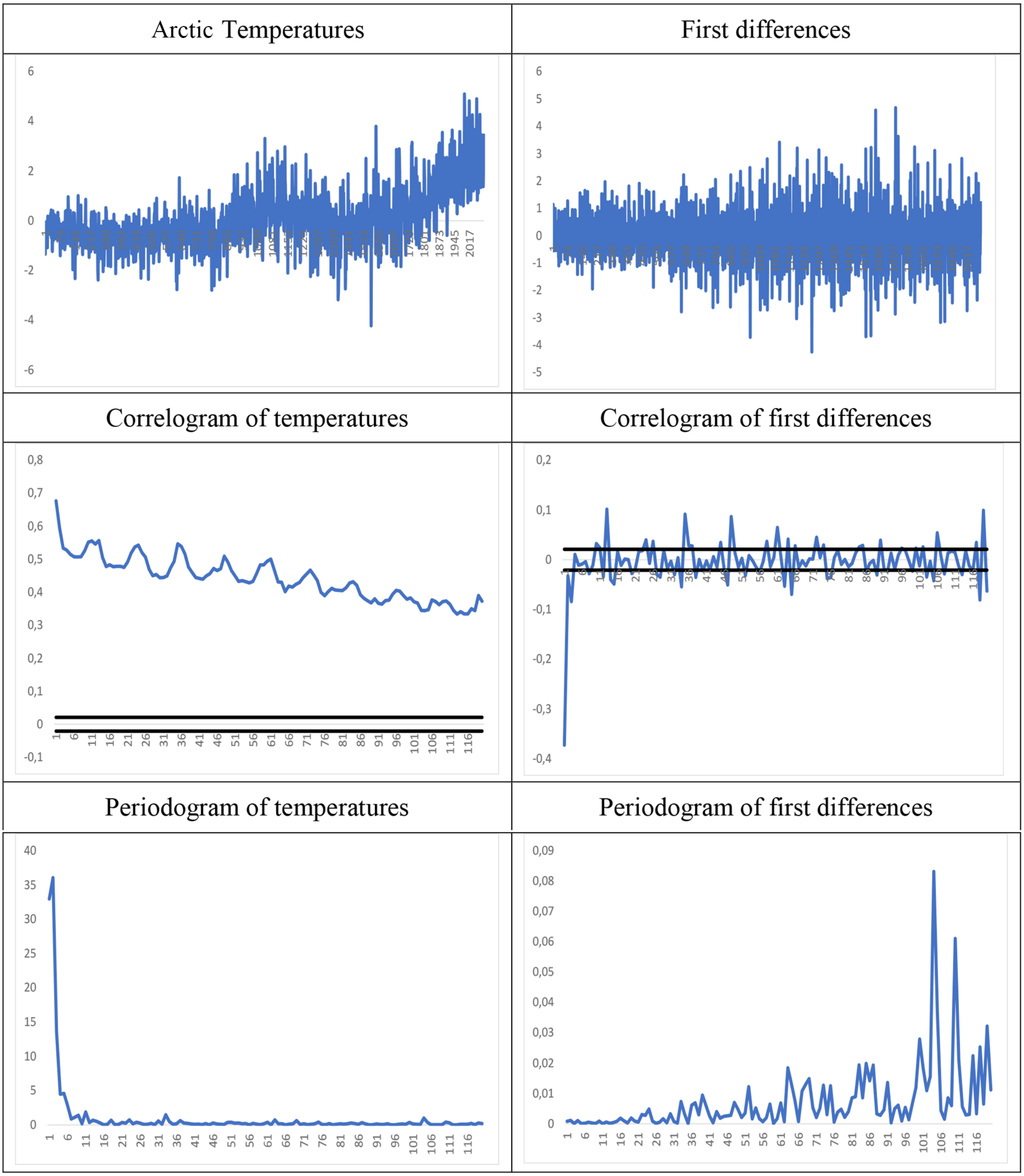

Fig. 1 Time series plots. Notes: The starting date of the data is January 1850 and the last observation corresponds to October 2023. The values in the correlograms and periodograms refer to the first 120 values. The thick lines in the correlograms refer to the 95% confidence bands, and the periodograms are evaluated at the discrete frequencies, $\lambda_j = 2\pi j/T$

et al., 1999; Willinger et al. 1999), we also performed an alternative non-parametric approach based on the rescaled-variance V/S statistic as proposed in Giraitis et al. (2003). The results, though not reported, supported the hypothesis of long memory in all cases examined.

Table 1 Estimates of the model for the whole data period

Series	d (95% band)	α (t-value)	β (t-value)	ρ (Seasonality)
Arctic Temp.	0.32 (0.29, 0.36)	-0.87633 (-4.33)	0.00107 (6.42)	0.041

Notes: The value in column 2 indicates the estimate of d, i.e., the differencing parameter (in parenthesis, its 95% confidence band); the coefficients in columns 3 and 4 are those referring to the intercept and the time trend (in parenthesis, t-values). The last column indicate the coefficient of the seasonal AR(1) model

Table 2 Estimates of the model for 25-year periods

Series	d (95% band)	α (t-value)	β (t-value)	ρ (Seasonality)
1850–1874	0.25 (0.15, 0.37)	-0.30085 (-1.96)	-0.00153 (-1.80)	-0.003
1875–1899	0.24 (0.14, 0.37)	-0.64655 (-2.86)	---	0.151
1900–1924	0.20 (0.12, 0.30)	-0.44481 (-3.53)	---	0.005
1925–1949	0.27 (0.19, 0.37)	0.21343 (1.92)	---	-0.059
1950–1974	0.28 (0.20, 0.38)	-0.11093 (-2.93)	---	-0.042
1975–2000	0.18 (0.09, 0.29)	-0.08764 (-2.42)	0.00107 (6.42)	0.041
2001–2023	0.30 (0.18, 0.47)	0.89719 (2.77)	0.00582 (3.05)	0.182

Notes: The values in column 2 indicate the estimate of d, i.e., the differencing parameter (in parenthesis, its 95% confidence band); the coefficients in columns 3 and 4 are those referring to the intercept and the time trend (in parenthesis, t-values). The last column indicates the coefficient of the seasonal AR(1) model

Table 1 displays the estimates of the model given by Eqs. (1), (2) and (3). We see that the estimate of the differencing parameter is 0.32, being significantly positive and thus supporting the hypothesis of long memory. In addition, the time trend coefficient, β, is also statistically significant, with a value of 0.00107. According to this result, temperatures are increasing about 1.28ºC/year (0.00107×12).The seasonal coefficient seems to be irrelevant for the sample period.

Next, we divide the sample into sub-periods of 25 years, i.e. 300 observations each, and repeat the analysis for each subsample. The results are reported in Table 2.

We observe in Table 2 that for the first 300 observations, corresponding to the period between January 1850 and December 1899, the time trend coefficient was significantly negative at the 5% level (though insignificant at the 10%). For the following four subsamples, it becomes insignificant, becoming again significant for the period between January 1975 and December 2000. The estimate of β is 0.00107, i.e., the same value as for the whole sample; however, this value has increased to 0.00582 over the last 23 years. This implies that for the last subsample, temperatures have increased at a rate of 6.98 C/year. We also observe that the degree of persistence (measured by d) is the highest at this subsample, and the seasonal coefficient also presents the highest value at this period.

4 Conclusions

This paper examines, using fractional integration, the trend and persistence of Arctic temperature anomalies from 1850 to 2023 using NOAA data. The main finding of our study is the significant change in the series analysed from 2001 onwards. The significant increase in temperatures between 2001 and 2023 compared to the previous period implies that the Paris Agreement is far from being reached with respect to the Arctic.

The study confirms the long memory hypothesis. The results indicate for the entire period 1850–2023 an increase in Arctic temperatures of 1.28 °C per year. Dividing the sample into 25-year periods shows that for the period 1850–1899 the trend coefficient is negative first and then insignificant until the period between January 1975 and December 2020 when it becomes statistically significant.

The last subsample analysed (2001–2023) shows the highest degree of persistence in the period analysed and the seasonal coefficient is also the highest for that period. The results of the study indicate that temperatures have increased at a rate of 6.98 °C per year. This result is more pessimistic than that obtained by the United Nations Environment Programme (2019) or IPPC (2021).

The results are in line with previous studies such as Chylek et al. (2022) who note that in 1999 Arctic temperatures peaked probably due to internal climate variability or Isaksen (2022) who warns that the Arctic climate is moving away from its 20th century state towards an unprecedented state with accelerated warming since 2005. This suggests that current environmental policies are not working and may even aggravate the situation of Arctic warming and, therefore, of the planet, as pointed out by the United Nations Environment Program (2023) in its report prior to the Climate Summit COP28, which underlined the discrepancy between intentions to comply with what was agreed in Paris and to limit global warming to a 1.5ºC rise and the reality of the results. The aforementioned target having only a 14% likelihood of being met.

Future lines of research may incorporate alternative modelling approaches based on nonlinear models. In fact, this is an issue that is intimately related with the line of work used in this work and that should examined in future papers.

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Declarations

Competing interests The contact author has declared that none of the authors has any competing interests.

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