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Some new evidence using fractional integration about trends, breaks and persistence in polar amplification

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This paper uses fractional integration methods to obtain new evidence on polar amplification. The adopted modelling framework is very general since it allows the differencing parameter to take any real value, including fractional ones, and provides useful information on both the short and the long run. The analysis is carried out using monthly temperature anomaly data for both the Arctic and the Antarctic, as well as the Northern and Southern Hemisphere, which have been obtained from the NOAA (National Center for Environmental Information) archive. The main findings can be summarised as follows. There is evidence of Arctic amplification, since the upward trend in the Arctic data is more pronounced compared to that in the Northern Hemisphere series, but not of Antarctic amplification, where the opposite holds. Also, the effects of forcings are more long-lived in the Arctic/Northern hemisphere than in the other pole/hemisphere. These results are robust to whether or not seasonality is explicitly modelled. In addition, temperature changes in the poles have bigger effects on those in the corresponding hemisphere if they occur in the Antarctic rather than in the Arctic.

Keywords Polar amplification, Arctic and Antarctic, Northern and Southern Hemispheres, Temperature anomalies, Persistence, Fractional integration

The average temperature increase on the planet has been 1 °C since 1880 (IPCC 2021[1]), but it has been four times higher in the Arctic region (AMAP 2021[2]); in fact in some areas, such as in the northern Barents Sea, warming has been seven times faster[3] This phenomenon, known as polar amplification, is much more pronounced in the Arctic[4–8] than in the Antarctic[1,9–11]. The reason is that the Arctic is an ocean covered by sea ice with a combination of feedback mechanisms that make it particularly vulnerable[12,13], while the Antarctic is a high continent covered by ice and snow, and the ocean water comes from great depths and from such distant sources that it takes centuries before the water reaching the surface warms up[14].

The warming of the Arctic has various effects, such as the decrease in sea ice, which has reached historically low levels[15,16], and in its thickness[17], which causes greater transmission of solar radiation to the ocean, accelerates the migration of ice and favours the formation of cyclones, among other climatic phenomena[18]. Rantanen et al.[19] concluded that the Arctic region has warmed almost four times faster than the rest of the world in the period 1979–2021, which is a higher rate than reported by previous studies based on climate models underestimating the amplification of the warming rate. Researchers have also tried to establish to what extent Arctic amplification is related to an increase in the frequency of extreme weather events in mid-latitudes[20]. The AMAP 2021 report concludes that warming in the Arctic, between 1971 and 2019, has been three times faster than in the rest of the planet, which is affecting global climate change.

The Polar Amplification Model Intercomparison Project (PAMIP) is one of the leading international initiatives exploring Polar Amplification[21]. This project seeks to understand the causes and consequences of Polar Amplification through simulations that address how changes in sea ice and sea surface temperatures influence global and regional climate dynamics. Key results highlight the importance of sea ice and its interaction with the atmosphere in amplifying climate changes in polar regions.

The present paper provides new evidence on the role of polar amplification by analysing the stochastic behaviour of temperature anomaly series for the two poles as well as for the two hemispheres, and then the linkages between developments in the Arctic (Antarctic) and the Northern (Southern) hemisphere as a whole.

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For this purpose, we use techniques based on fractional integration which shed light on the long memory feature observed in most climatological series and their long-run relationships[22,23]; etc.

Rantanen et al.[24] showed that in recent decades warming is accelerating in the Arctic more than in other parts of the world. For their research they analysed temperature data since 1979 and found that the Arctic has warmed on average 0.75°C per decade, i.e. four times faster than the rest of the planet.

The analysis of temperature patterns and anomalies has proven to be crucial for understanding long-term climate dynamics. Varotsos et al.[25] identified two abrupt sea surface temperature (SST) warming events during the last century, occurring in 1925/1926 and 1987/1988, and attributed their origin to the interaction of natural climate cycles with anthropogenic factors. Their study highlights the importance of such events for predicting possible future climate tipping points. As noted by[26] the climate system spans a wide range of temporal and spatial scales influenced by cycles which affect its equilibrium so small alterations in the mean, amplitude or period of these cycles can cause abrupt and even irreversible changes in the climate system. The interaction between the El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) has been shown to cause abrupt changes in the climate system. Events such as those of 1925/1926 and 1987/1988 are cases in point: in 1925/1926, an intense El Niño coincided with a positive phase of the PDO, amplifying its effects[27], while in 1987/1988 the transition to a negative phase of the PDO affected the dynamics of the ENSO and its global impacts[28]. This evidence supports the point made by[26] about the climatic sensitivity to changes in these cycles.

On the other hand, Efstathiou et al.[29] used trendless fluctuation analysis (DFA) to evaluate time series of land and marine temperature anomalies since 1850, and found persistent long-term correlations spanning time scales of up to 39 years. Their approach emphasizes the need to incorporate such correlations into predictive climate models.

Numerous studies have analysed trends in surface air temperature (SAT) variability over the last decades, reaching different conclusions regarding their magnitude and interpretation[30,31]. Some authors[32] have stressed the importance of using an extended observational base to obtain more accurate and representative estimates. While mathematical analyses indicate that Arctic amplification has been detectable since before 1990, recent research has highlighted that, from a physical point of view, this phenomenon has emerged significantly only in the last decades as a result of modern global warming[33–36].

Cai et al.[37] analysed trends between 1850 and 2017 in summer sea ice area variations in six Arctic regions and suggested that their accelerating decrease reflected a combination of global warming and internal climate system variability rather than a single factor. England et al.[38] showed that Arctic amplification is a relatively recent phenomenon; they point out that during much of the twentieth century the Arctic cooled as global mean temperature increased and amplification would not have occurred without historical changes in greenhouse gases or aerosols. Johannessen et al.[39] studied variability and trends in SAT between 1900 and 2014 for the entire Arctic and its different regions using an Arctic Amplification Index (AAI) that relates absolute values of Arctic and Northern Hemisphere (NH) trends calculated over successive 30-year periods, the index being calculated only for years in which both the NH and Arctic trends are significant at the 95% confidence level. They conclude that the amplification is stronger during the early twentieth century warming than during the recent years analysed. Note that since overall temperature changes are somewhat different in the two hemispheres this should be taken into account when making comparisons between developments in the Arctic and elsewhere.

Chylek et al.[7] reported on various simulations using 39 climate models and found that CMIP6 (Coupled Model Intercomparison Project 6) models do not reproduce the observed Arctic amplification behaviour, as they only capture the first increase in Arctic amplification around 1986, but not the second one around 1999. They argue that the former might have been due to external forces (greenhouse gases), while the latter might reflect internal climate variability.

While there are numerous studies confirming the Arctic amplification phenomenon, there is much less evidence concerning Antarctic amplification. Salzmann et al.[9] wondered why Arctic warming differs from Antarctic warming and found that the difference in altitude between the two poles explains this divergence. He used simulation methods to establish how climate would react if the atmospheric concentration of carbon dioxide (CO_2) were doubled and performed the same experiment in a scenario where the Antarctic had a similar height to the surface in the Arctic. His results suggest that if the Antarctic's land height were reduced, temperatures would respond more strongly to an increase in the concentration of greenhouse gases on the continent, thereby contributing to an increase in Antarctic warming and a smaller difference in polar amplification between the Arctic and the Antarctic. Essentially this study found greater 'amplification' when the height of the ice sheet was reduced, a phenomenon which is associated with the meridional heat transport and local radiative feedbacks. Supporting evidence can be found in[40], which identified a related increase in baroclinicity over the continent when elevations are lowered, baroclinicity being the thermo-dynamic process generating cyclones and eddies[41] which are responsible for most of the Southern Hemisphere (SH) meridional heat transport[42].

Wang et al.[43] calculated the annual and seasonal mean surface air temperature (SAT) trend during 1979–2019 for the Antarctic and the mean trend of different southern sectors of Antarctic subregions. The observed temperature anomalies indicate that the smallest fluctuations occur in the austral summer and the largest ones in winter and spring, this being an issue which requires further investigation. Zhu et al.[44] noted that the largest amplification occurs in East Antarctic, followed by West Antarctic, whilst Antarctic amplification is absent in the Antarctic Peninsula. Xie et al.[45] found a positive correlation between temperature changes in East and West Antarctic, but a negative one between Antarctic Peninsula temperatures and those in the SH. It appears therefore that Antarctic amplification is weaker than the Arctic one, which is related to a weaker surface albedo feedback and higher ocean heat uptake in the Southern Ocean[44,46].

Other studies focus on the decrease of sea ice in the Antarctic caused by the warming of this region[47–49]. However, there is still a lack of consensus regarding the processes and mechanisms that determine historical sea ice trends[50].

Both the Arctic and the Antarctic have been shown to influence the climate of the entire planet[18,51–58]; therefore, the study of polar amplification is necessary to estimate the global average temperature change in the future[13]: better knowledge of the climate system of the poles also improves the accuracy of global temperature prediction since what happens in these regions affects future developments in the rest of the planet[16,59].

As can be gathered from the above discussion, the literature on climate change is extensive[60–62]; etc. but there is no common empirical/statistical modelling approach. In the present study we use a fractional integration framework where the differencing parameter d can be any real number (including fractional values); this method provides more accurate information on both the short and the long run[63] than others based on the dichotomy between I(0)[64,65]; etc. and non-stationary I(1) series[66], or against trendless fluctuation models[67], or standard linear regressions[68,69].

The long memory approach will allow us to detect the presence of long-run trends and to analyse the degree of persistence of the Arctic, Antarctic, NH and SH temperature anomaly series, and thus to obtain information on whether or not the series are mean-reverting, i.e. whether exogenous forcings to the series have permanent or transitory effects on its evolution over time. Also, analysing the linkages between temperatures in the poles and the corresponding hemispheres will provide further evidence on how polar amplification has developed over time (possibly affecting the Greenland and/or Antarctic ice sheets) and also be useful to design early warning indicators of climate change. This will result in a deeper understanding of how the climate is evolving and of its impact on the sea level, which is essential to design more effective environmental policies.

The rest of the paper is structured as follows: "Empirical methodology" section outlines the methodology; "Data description and empirical results" section describes the data and discusses the empirical results; "Robustness" section provides some robustness checks based on structural break tests, while "Conclusions" section offers some concluding remarks.

Empirical methodology

The methods used for the empirical analysis are based on the concept of fractional integration and shed light on both the short- and long-memory properties of the series under investigation and their linkages. Below we provide some key definitions.

Short and long memory

A covariance stationary process$\{x(t), t = 0, \pm 1, \ldots\}$ with mean $E(x(t)) = \mu$ is said to exhibit short memory if the infinite sum of the autocovariances, defined as $\gamma(u) = E[(x(t) - \mu)(x(t+u) - \mu)]$, is finite, that is:

$$\sum_{j=-\infty}^{\infty} |\gamma(u)| < \infty. \tag{1}$$

Alternatively, one can define short memory in the frequency domain in terms of the spectral density function, $f(\lambda)$, that is the Fourier transformation of the autocovariances:

$$f(\lambda) = \sum_{j=-\infty}^{\infty} \gamma(u) e^{i\lambda u} = \sum_{j=-\infty}^{\infty} \gamma(u)\cos(\lambda u). \tag{2}$$

In this case, x(t) is said to be characterised by short memory if the spectral density function is positive and bounded at all frequencies, i.e.:

$$0 < \mathrm{f}(\lambda) < \infty. \quad \text{for all } \lambda \in [0, \pi)\,. \tag{3}$$

This category includes the white noise model but also the stationary and invertible AutoRegressive Moving Average (ARMA) class of models in the presence of a time (weak) dependence structure. Short memory processes are sometimes called integrated of order 0 or I(0) processes.

On the other hand, a process is said to exhibit long memory if the infinite sum of autocorrelations becomes unbounded, i.e.:

$$\sum_{j=-\infty}^{\infty} |\gamma\,(u)| = \infty, \tag{4}$$

or, alternative, using the frequency domain definition, if the spectral density function goes to infinity at least at one point in the frequency $[0, \pi)$:

$$f(\lambda) \to \infty, \text{for some}\,\lambda \in [0, \pi). \tag{5}$$

There are many processes that satisfy the above two properties (4) and (5), for example, the Fractional Gaussian noise introduced by[70]. The one based on the concept of fractional integration or integration of order d, or I(d) is most commonly used by time series analysts.

Fractional integration

A process x(t) is said to be I(d) if it can be expressed as:

$$(1-L)^d x(t) = u(t) t = 0 \pm 1, \ldots. \tag{6}$$

where L is the lag operator, i.e., $Lx(t) = x(t-1)$ and u(t) is I(0). Then, as long as d is positive, x(t) in (6) will exhibit long memory in the sense that the infinite sum of the autocovariances becomes infinite. Alternatively, in the frequency domain, its spectral density function will be:

$$f(\lambda) = \frac{\sigma^2}{2\pi} \left| \frac{1}{1 - e^{i\lambda}} \right|^{\mathrm{d}}, \tag{7}$$

and it will tend to infinity as $\lambda \to 0^+$ with $d > 0$.

Using a binomial expansion, the polynomial in L in (6) can be expressed as:

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2, \tag{8}$$

and Eq. (6) can be re-written as

$$x_t = dx_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \frac{d(d-1)(d-2)}{6} x_{t-3} - \cdots + u_t,$$

and thus the differencing parameter d can be interpreted as a measure of the degree of persistence of the series: the higher the value of d is, the greater is the degree of persistence, namely the higher is the association between observations, even if they are far apart in time. Thus, the parameter d is called the memory parameter.

By allowing d to take fractional values, one can consider a wide range of processes including:

1. anti-persistence (if $d < 0$),
2. short memory (if $d = 0$),
3. stationary long memory (if $0 < d < 0.5$),
4. nonstationary with mean reversion (if $0.5 \le d < 1$),
5. unit roots (if $d = 1$),
6. explosive patterns (if $d > 1$).

The fractional integration approach is more flexible and general than the classical methods that only allow for integer degree of differentiation, specifically 0 for stationary series and 1 for nonstationary ones exhibiting unit roots. Reversion to the mean (which implies that forcings only have transitory effects) will occur as long as d is smaller than 1. On the contrary, if d is equal to or higher than 1, the series will not revert to its mean following a forcing, namely the effects of the latter will be permanent.

The estimation of the differencing parameter is carried out by means of the likelihood function in the frequency domain, using a testing approach developed in[71] and widely used in empirical applications. This methodology has numerous advantages with respect to other parametric or semiparametric approaches. More specifically, it has a standard normal limit distribution, and this behaviour holds independently of the inclusion in the model of deterministic terms such as a linear trend (see, Eq. (9) below). In addition, this method is valid for any real d, including values which are outside the stationary region ($d \ge 0.5$). Moreover, it is the most efficient method in the Pitman sense against local departures from the null[70].

Data description and empirical results

We analyse raw temperature anomaly data for both the Arctic and Antarctic, as well as the NH and SH. These provide information about departures from long-term averages, with positive (negative) values indicating warmer (cooler) temperatures than the reference values. The data source, as in several other global climate studies, is the NOAA (National Center for Environmental Information) archive. The series are monthly and span the periods from 1880 to 2022; they are the combined global land and ocean temperature anomalies, i.e., deviations from the 1901–2000 mean for each of the two hemispheres and from the 1910–2000 one for the Arctic and Antarctic (Please note that there exist other sources for Arctic temperatures such as GISS[72], HadCRUT5.0[73] and HadCRUT4/CW[74]; however, despite some slight differences between them, they all imply very similar arctic amplification periods[7].)

The estimated model is the following:

$$\mathrm{y}(t) = \alpha + \beta t + \mathrm{x}(t), \; (1-L)^d x(t) = u(t), \; u(t) = \rho u(t-12) + \varepsilon(t) \tag{9}$$

where α and β are unknown parameters to be estimated, t is time trend, L stands for the lag or backshift operator (i.e., $Lx(t) = x(t-1)$), and d is the required differencing to make x_t a stationary I(0) process, where x_t are the regression errors of order d or I(d); this implies that the d-differenced process, u_t, is short memory or I(0). Given the monthly frequency of the series we assume a monthly seasonal AR process for the error term u(t), where ρ is the seasonal parameter and ε_t is a white noise process. Note that depending on the value of d the series can exhibit short memory (if $d = 0$), long memory ($d > 0$) as well as other types of stochastic behaviour such as I(1) non-stationarity (if $d = 1$), 1/f noise (if $d = 0.5$) which is the boundary between stationary and nonstationary processes, $1/f^{1/2}$ (if $d = 0.25$), etc.

Series	d (95% band)	Intercept (tv)	Time trend (tv)	Seasonality
Arctic	0.32 (0.29, 0.36)	−0.87633 (−4.33)	0.00107 (6.42)	0.0417
Northern Hem	0.50 (0.47, 0.53)	−0.40316 (−4.30)	0.00063 (5.98)	0.0501
Antarctic	0.17 (0.14, 0.20)	−0.15033 (−3.45)	0.00017 (5.08)	0.0073
Southern Hem	0.60 (0.57, 0.63)	−0.11706 (−1.91)	0.00033 (3.30)	b-0.0200

Table 1. Estimated coefficients in the model given by Eq. (9). Seasonal MA errors. The values in column 2 are the estimates of the differencing parameter d along with their 95% confidence bands; those in columns 3 and 4 are the estimates of the constant and the linear trend with their associated t-values; those in the last column are the seasonal coefficients.

Series	d (95% band)	Intercept (tv)	Time trend (tv)
Arctic	0.31 (0.28, 0.35)	−0.88490 (−4.56)	0.00107 (6.74)
Northern Hem	0.52 (0.48, 0.57)	−0.40385 (−4.04)	0.00064 (5.34)
Antarctic	0.20 (0.16, 0.26)	−0.14666 (−2.82)	0.00017 (4.23)
Southern Hem	0.62 (0.57, 0.69)	−0.11275 (−1.77)	0.00034 (3.30)

Table 2. Estimated coefficients in the model given by Eq. (9). Bloomfield errors. The values in column 2 are the estimates of the differencing parameter d along with their 95% confidence bands; those in columns 3 and 4 are the estimates of the constant and the linear trend with their associated t-values.

Series	Arctic	Northern H	Antarctic	Southern H
Arctic	–	–	–	–
Northern H	**0.7906**	–	–	–
Antarctic	0.1836	0.2846	–	–
Southern H	0.5658	0.8421	**0.4897**	–

Table 3. Correlation cofficients among the variables. The values in bold are the correlation coefficient between each poles and the corresponding hemisphere.

Table 1 displays the estimated coefficients from the model given by Eq. (9). It can be seen that the time trend is statistically significant and positive for all the four series examined (Arctic, Antarctic, NH and SH), the highest coefficient being estimated in the case of the Arctic ($\beta = 0.00107$) and being much higher than those of the Antarctic (0.00017) or of the two hemispheres (0.00063 and 0.00033 respectively). These results suggest that amplification occurs in the case of the Arctic (0.00107 versus 0.00063) but not of the Antarctic (0.00017 versus 0.00033). Concerning the degree of persistence, measured by d, the evidence implies that it is much higher in the two hemispheres than in the corresponding poles: the estimates of d are 0.50 and 0.60 respectively for the NH and SH, and 0.32 and 0.17 for the Arctic and the Antarctic. This implies that the effects of forcings disappear at a faster rate in the poles than in the hemispheres. Since the seasonal coefficient appears to be close to 0 and insignificant for all four series, we consider next a model where the error term u(t) displays non-seasonal weak dependence. In particular, we use the exponential spectral model of Bloomfield[75], which is a non-parametric approach that approximates well AR structures with very few parameters. This set of results are reported in Table 2.

As can be seen, the evidence concerning the time trends is very similar to the previous case: the estimated coefficients are 0.00107 and 0.00017 for the Arctic and Antarctic, and 0.00064 and 0.00034 for the NH and SH respectively. The estimates of d are also very close to the previous ones: 0.31 and 0.20 for the Arctic and Antarctic, and 0.52 and 0.62 for the NH and SH respectively. These findings confirm that polar amplification occurs in the Arctic but not in the Antarctic, and also that there is a higher degree of persistence in the NH than in the SH.

Next we analyse the relationship between temperatures in the two poles and the corresponding hemispheres. Table 3 reports the correlation matrix among the four series, which shows a higher correlation between the Arctic and Northern Hemisphere than between the Antarctic and the SH.

Table 4 shows the results of standard OLS regressions for each of the two hemispheres against that of the corresponding pole, first under the assumption of I(0) errors (see the right-hand side panels), and then estimating their order of integration (see the left-hand side panels) and thus allowing for lags in the dynamic relationship. In the former set of regressions, the slope coefficient is positive and similar in the Northern/Arctic and Southern/Antarctic regressions (0.33559 and 0.37299 respectively). When estimating the order of integration, this is found to be significantly positive (0.55 and 0.65 in the Northern/Arctic and Southern/Antarctic regressions respectively), and the slope coefficient is very different, being much higher in the Southern/Antarctic relationship compared to the Northern/Arctic one (0.012413 vis-à-vis 0.14253). In other words, temperature anomalies in

Northern H (t) = α + β Arctic (t) + X(t); $(1 - L)^d$ x(t) = u(t) ~ Bloomfield				
d estimated			d = 0	
d (95% band)	Intercept (tv)	Time trend (tv)	Intercept (tv)	Time trend (tv)
0.55 (0.51, 0.60)	−0.18085 (−2.18)	0.012413 (32.66)	0.03720 (7.41)	0.33559 (72.60)
Southern H (t) = α + β Antarctic (t) + X(t); $(1 - L)^d$ x(t) = u(t) ~ Bloomfield				
d estimated			d = 0	
d (95% band)	Intercept (tv)	Time trend (tv)	Intercept (tv)	Time trend (tv)
0.69 (0.63, 0.75)	−0.06868 (−2.42)	0.14253 (47.22)	0.03659 (10.76)	0.37299 (42.29)

Table 4. Estimated coefficients in a regression model with I(d) errors. The values in column 1 are the integration orders (with their 95% confidence bands); Columns 2 and 4 display the estimated intercept (and t-values), while those in columns 3 and 5 are the estimated time trend coefficients (and t-values). The values in columns 2 and 3 refer to the model with the value of d estimated from the data ; in columns 4 and 5, d = 0 a priori.

the Antarctic appear to have a greater impact on those in the corresponding hemisphere than in the case of the Arctic.

Robustness

Next we allow for the possibility of structural breaks. For this purpose we use an extension of the Bai and Perron's[76] approach to the fractional case as presented in[77]. Following[25] we identify two breaks in the series and report the breaks dates in Table A1 in the Appendix. The breaks occur around 1923(25) and 1984(85, 87) in three of the series, Arctic, NH and SH, while in the case of the Antarctic one the first break seems to take place in 1956m12. These findings are consistent with those of[26], who reported breaks in 1925/26 and 1987/88, and of[78] that found an abrupt warming in the temperatures in the NH in the late 80 s; however, they are in contrast to the results in[79,80] where evidence was found of a change in the Arctic in 2005. This discrepancy might be explained by the different methodology used in those studies along with the different spatiotemporal series examined. Table A1 displays the estimated coefficients for each of the subsamples. Time trends are only found in the cases of the Arctic, NH and SH series in the third subsamples and of the Antarctic one in the second subsample, and the estimates of d are significantly positive in all cases except for the Arctic and Antarctic series in the third subsamples, where the I(0) hypothesis of short memory cannot be rejected. Table A3 displays the estimates of the regression coefficients along with those of d in the model given by Eq. (9) where y(t) refers to the NH and SH temperatures and the time trend has been replaced by Artic and Antarctic data in each subsample. Following[25] and to be consistent across the series next we select for all of them the breaks corresponding to 1925m12 and 1987m12. It can be seen that the estimates of the differencing parameter are positive and significant in all cases, with bigger slope coefficients being obtained from the regression of SH against Antarctic than from that of NH against Arctic.

Future research could also analyse spatial patterns of temperature trends relative to the temperatures in the poles. However, the results in terms of both persistence and trends should not necessarily be heterogenous across regions.

Conclusions

This paper uses fractional integration methods to obtain new evidence on polar amplification, namely the phenomenon that changes in the net radiation balance typically produce larger changes in temperature near the poles than in the corresponding hemisphere or the planet as a whole. The adopted modelling framework is very general since it allows the differencing parameter to take any real value, including fractional ones, and thus it does not impose any restrictions on the stochastic behaviour of the series of interest and provides useful information on both their short- and long-run properties.

The analysis is carried out using monthly temperature anomaly data for both the Arctic and the Antarctic, as well as the NH and SH, which have been obtained from the NOAA (National Center for Environmental Information) archive. The main findings can be summarised as follows. There is evidence of Arctic amplification, since the upward trend in the Arctic data is more pronounced compared to that in the NH series, but not of Antarctic amplification, where the opposite holds. This confirms previous results (see, e.g.[44,46].) and might reflect a difference in altitude[9].

Indeed, the Arctic, being an ocean surrounded by continents, shows stronger albedo feedback due to the loss of sea ice, which intensifies warming. On the contrary, the Antarctic, being an elevated continent surrounded by oceans, exhibits a stronger resistance to climate change, which is influenced by its interaction with deep ocean currents and snow cover.

Also, the effects of forcings are more long-lived in the case of the Arctic/Northern Hemisphere than in the other pole/hemisphere. This is consistent with previous research, for instance by[9], who highlighted the role of altitude and ocean dynamics in the divergence between the two poles. Chylek et al.[7] also pointed out that climate models tend to underestimate the magnitude of Arctic warming, and underlined the need for improved simulations in the case of these critical regions.

These results are robust to whether or not seasonality is explicitly modelled. On the other hand, the effects of forcings disappear faster in the poles than in the hemispheres, which implies that the former have a relatively greater ability to recover from sudden environmental perturbations compared to the latter; consequently, environmental policies should give priority to the protection of the poles given their greater resilience.

In addition, temperature changes at the poles have greater effects on those in the corresponding hemisphere if they occur in the Antarctic than in the Arctic; as a result, Antarctic temperature anomalies may have a more significant impact on the SH due to a combination of geographic, climatic, and ecological factors[81]; however, as indicated by[44], this phenomenon is not uniform and varies between subregions and seasons, being more pronounced in East Antarctica due to a less intense albedo feedback compared to the Arctic[43,44].

Other important issues in this context are the possible presence of structural breaks and nonlinearities. It is well known that both are strongly related to long memory and fractional integration (e.g.[82–84]), and thus not taking them into account might produce biases in the estimation results. Future research will focus on such issues to obtain additional empirical evidence and gain an even deeper understanding of polar amplification.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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G.M.C proposed the idea and took a final visualization of the article. L.A.G.A conducted the empirical results and interpretation; N.C.G. wrote the introduction, literature review and interpretation of results-

Declarations

Competing interests
The authors declare no competing interests.

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