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Investigating long range dependence in temperatures in Siberia

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ABSTRACT

In this paper we examine monthly mean temperatures in 40 selected stations in Siberia for the time period January 1937–December 2020 using long range dependence techniques. In particular, we use a fractionally integrated model that incorporates a linear time trend along with a seasonal structure. Our results show first that long memory is present in all stations with significantly positive values for the differencing parameter, though, at the same time the seasonal component seems to be important in all cases. Performing seasonal unit root tests, the results support nonstationary seasonality and working with the seasonal differenced data, the results differ depending on the structure of the error term: if the errors are uncorrelated, long memory is present; however, allowing autocorrelation, this feature disappears in favor of a short memory pattern.

1. Introduction

Assessing the mechanisms behind the Arctic amplification and the nature of forcings and feedbacks is fundamental due to their impact on global climate system (Yamanouchi and Takata, 2020; AMAP, 2021). According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2021): '*Feedbacks from the loss of summer sea ice and spring snow cover on land have contributed to amplified warming in the Arctic (high confidence), where surface air temperature has likely increased by more than double the global average over the last two decades*' (IPCC, 2021, §1). The concern about this scenario, which is expected to continue throughout the 21st century (IPCC, 2021, §TS.4.3.2.8), is linked to the debate about the possible linkage between the Arctic amplification and the extreme climate anomalies detected at global level, for mid-latitudes (Francis and Vavrus, 2012; Ye et al., 2018; Cohen et al., 2014, 2020) or at local level, for the Siberia region. In this last case, different extreme events have been observed such as the recent heat wave in 2020 (Overland and Wang, 2020) or a 'Warm Arctic-Cold Siberia (WACS)' pattern (Wegmann et al., 2018; Tyrlis et al., 2020; Chen et al., 2021), although this expression could be misleading (Koenigk and Fuentes-Franco, 2019). In fact, Siberia exhibits the highest climatic variability of the entire Northern Hemisphere (NH), that is, 1.39 °C/100 years versus 0.77 °C/100 years in NH (Groisman et al., 2013a, p.72), so could be also considered as a valuable precursor of global climate changes. However, there are few studies focused on Siberia surface air temperature (SAT) trends, and even fewer, from the perspective of long-range dependence (LRD). In fact, we have not found a single study on Siberian temperatures using the methodology of fractional integration used in the present work.

This paper investigates the time trend coefficients in the monthly temperatures of 40 Siberian stations over the period 1937–2020. However, instead of using classical approaches that first remove the deterministic terms and then model the noise term, we use a more efficient approach based on fractional integration, that allows for long memory, a feature widely observed in climatological time series data (Bloomfield, 1992; Percival et al., 2001; Caballero et al., 2002; Franzke, 2010, 2012a; Gil-Alana, 2006, 2012; Rea et al., 2011; Bunde and Ludescher, 2017; Li et al., 2021). According to Franzke (2012a, p.22): '*There is increasing evidence that surface temperatures are long-range dependent*'. In fact, '*long-range dependence has the property that spatially coherent anomalies persist for a long time*' (Franzke et al., 2020, p.3). Some examples based on this approach and referring to high-latitudes, can be found in Franzke (2012b), Gil-Alana (2012), Løvsletten and Rypdal (2016) or Myrvoll-Nilsen et al. (2019), showing all of them clear evidence of warming in this area. The novelty of this work is precisely the econometric specification used to analyze the Siberian data, incorporating in a single framework statistical features such as non-zero means, time trends, seasonality and long range dependence.

The structure of this paper is as follows. Section 2 summarizes the main empirical evidence about this topic. Section 3 describes the

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Table 1
Siberian stations.

Station	Number	Longitude	Latitude
DIKSON	RSM00020674	80.40	73.50
HATANGA	RSM00020891	102.47	71.98
TURUHANSK	RSM00023472	87.93	65.78
VERHNEIMBATSK	RSM00023678	87.95	63.15
BOR	RSM00023884	90.02	61.60
BAJKIT	RSM00023891	96.37	61.67
ALEKSANDROVSKOE	RSM00023955	77.87	60.43
TURA	RSM00024507	100.23	64.27
VANAVARA	RSM00024908	102.27	60.33
TARA	RSM00028493	74.38	56.90
OMSK	RSM00028698	73.38	55.02
NAPAS	RSM00029023	81.95	59.85
SREDNY_VASJUGAN	RSM00029111	78.20	59.20
KOLPASEVO	RSM00029231	82.88	58.30
ENISEJSK	RSM00029263	92.15	58.45
BOGUCANY	RSM00029282	97.45	58.38
PUDINO	RSM00029313	79.43	57.57
BAKCHAR	RSM00029328	82.07	57.00
SEVERNOE	RSM00029418	78.35	56.35
ACHINSK	RSM00029467	90.50	56.28
TAJSHET	RSM00029594	98.00	55.95
TATARSK	RSM00029605	75.97	55.20
BARABINSK	RSM00029612	78.37	55.33
NENASTNAJA	RSM00029752	88.82	54.75
VERHNJAJA_GUTARA	RSM00029789	96.97	54.22
BARNAUL	RSM00029838	83.52	53.43
MINUSINSK	RSM00029866	91.70	53.72
BIJSK_ZONALNAJA	RSM00029939	84.95	52.68
VITIM	RSM00030054	112.58	59.45
KIRENSK	RSM00030230	108.07	57.77
BRATSK	RSM00030309	101.75	56.28
ORLINGA	RSM00030328	105.83	56.05
NIZHNEANGARSK	RSM00030433	109.55	55.78
TULUN	RSM00030504	100.63	54.60
IRKUTSK	RSM00030710	104.35	52.27
HAMAR_DABAN	RSM00030815	103.60	51.53
RUBCOVSK	RSM00036034	81.22	51.50
ZMEINOGORSK	RSM00036038	82.20	51.15
UST_KOKSA	RSM00036229	85.62	50.28
KOSCH_AGACH	RSM00036259	88.68	50.00

methodology applied in the paper. Section 4 presents the data and source used. Section 5 analyses the empirical results obtained, while Section 6 concludes the paper.

2. Literature review

Research on climate variability in the Arctic (poleward of 60° N) warns of a significant and accelerated warming trend in Arctic SAT since the beginning of the 20th century, particularly in the last decades, that exceeds the average trends observed in the Hemisphere North or on a global scale (Bekryaev et al., 2010; Johannessen et al., 2016; Davy et al., 2018; Przybylak and Wyszyński, 2020; Xiao et al., 2020; Cohen et al., 2020; IPCC-AR6, 2021, p.3562). This phenomenon known as Arctic amplification (AA) has been widely debated for decades as it is a key issue for understanding the global climate system (Screen and Simmonds, 2010; Serreze and Barry, 2011; Pithan and Mauritsen, 2014; Franzke et al., 2017; Davy et al., 2018; Yamanouchi and Takata, 2020; Walsh, 2021). Different phases of warming and cooling have been identified during the AA process (see, for example, Fyfe et al., 2013; Johannessen et al., 2016; Xiao et al., 2020). Following Xiao et al. (2020) we distinguish a first phase of warming over the period 1920–1938, known in the literature as the Early Twentieth Century Warming (ETCW) and characterized by very strong positive trends; a subsequent cooling phase (1939–1976); and again, a warming phase from 1977, which exhibits positive trends higher than those registered in the ETCW period (+0.54 °C decade−1 for 1977–2018 versus +0.45 °C decade−1 for 1920–1938). However, in the mid-1990s, an apparent regime change is detected that highlights the rapid warming of the Arctic region (Przybylak, 2007; Bekryaev et al., 2010; Johannessen et al., 2016; Przybylak and Wyszyński, 2020). In particular, Przybylak and Wyszyński (2020) analyze the sub-periods 1976–2015 and 1996–2015, finding positive trends of +0.68 °C decade−1 and + 0.86 °C decade−1, respectively. These results suggest that, from 1996, warming trends in the Arctic become faster and more uniform than those observed in the ECTW period, which is named by Przybylak and Wyszyński (2020) as "*recent rapid Arctic warming*" (RRAW).

Despite these results, there is no clear consensus on the time evolution of Arctic SAT trends due to the disparity of methodologies, models and datasets used. Focusing on the methodology that concerns us, -the study of the LRD-, the references are even more scarce. For example, we can cite the study by Franzke (2012b) referring to the Eurasian Arctic region (>60°N). The author uses daily mean temperatures from 109 stations and applies three different null models –AR (1) as an SRD model; ARFIMA (0, d, 0) as an LRD model (Robinson, 2003); and the phase scrambling method (Theiler et al., 1992), as a non-parametric model–, to introduce different degrees of significance. His results show warming trends in all the stations analyzed. Among them, 16 stations located in the North Atlantic, Scandinavia and Northeast Russia show moderate or weak evidence of these models and only one station located in Iceland shows strong evidence against the 3 null models. For Siberia, the author finds positive but non-significant trends of approximately 0.2–0.3 °C decade–1, which would be within the range of natural climatic fluctuations. In addition, the work of Gil-Alana (2012) based on the Robinson (1994) methodology and applied to the monthly mean temperatures of 19 stations in Alaska, also reveals significant warming trends during the last 50 years for this region. In Løvsletten and Rypdal (2016) the regional linear trends in the 5° × 5°, 2° × 2° grid areas are evaluated for the period 1900–2013 under the null hypothesis of LRD for internal climate variability. Their results show significant warming trends for 80% of the grid cells analyzed, reflecting the observed global warming at a regional level. These results are consistent with Myrvoll-Nilsen et al. (2019). The authors, applying Bayesian inference and assuming LRD noise, find positive trends in much of the land surface (more than 84% of the grid points analyzed), but especially in the Arctic, which is related to the AA phenomenon.

Other related papers to the present one are Yaya and Akintande (2019), Gil-Alana et al. (2019) and Yaya and Vihn (2020). In Yaya and Akintande (2019) the authors investigate global and regional sea surface (SS) and land air surface (LS) temperature series from 1880 to 2016 using fractional integration with the possibility of structural breaks. Nonlinear trends and long memory are found in the two complete series as well as in the numerous subsamples. In Gil-Alana et al. (2019) they look at temperature and rainfall data in several regions in Sub-Saharan Africa. Using I(d) models, they find evidence of anti-persistence ($d < 0$) and short memory ($d = 0$) behaviour for the rainfall data but long memory ($d > 0$) for the temperatures. In Yaya and Vihn (2020) the authors examine average rainfall and temperature readings of Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, and Vietnam, for the time period from 1901 to 2016. They also use fractional integration and found evidence of anti-persistence for the rainfall series of Cambodia, Laos, Myanmar, and Vietnam while long memory is found in the rainfall series of the remaining countries and also in the temperatures.

3. Time trends, seasonality and persistence

Several issues will be examined in the monthly temperatures in Siberia. Firstly, we want to determine if long memory or long-range dependence is present in the data, and, for this purpose, we will make use of a parametric model based on fractional integration, that means that the number of differences required in the series to render it stationary I(0) may be a fractional value. In other words, an integrated of order d process may be specified as:

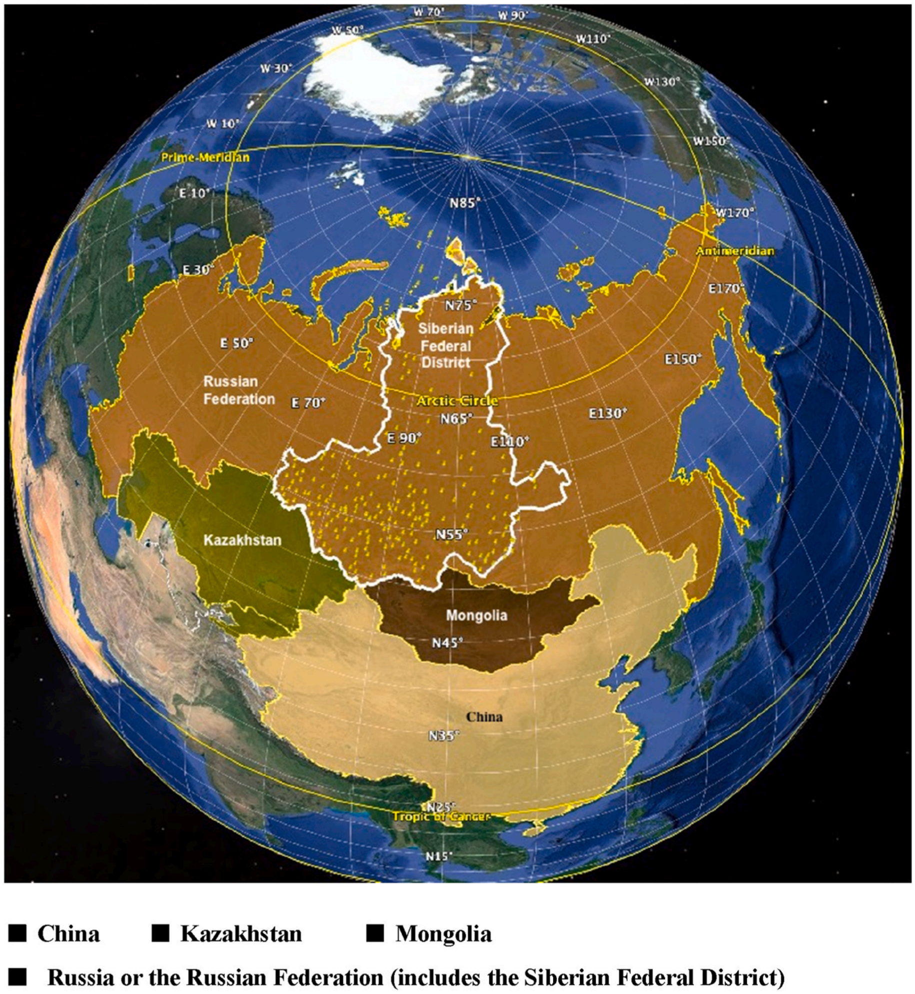

Fig. 1. Latitudinal position of Siberia.

$$(1-B)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

where B refers to the backshift operator, i.e, $B^k x_t = x_{t-k}$, and u_t is an integrated of order 0 or I(0) process. Long range dependence or long memory takes place when d is positive, implying a large degree of association between the observations even if they are far apart. If d = 0, the process is short memory and if d is negative, it shows "anti-persistence" implying that the series reverts to its original trend more often than expected in a pure random series. In addition, we also want to determine if time trends are present in the data and for this purpose we impose a linear time trend model of the form:

$$y_t = \alpha + \beta t + x_t, \quad t = 1, 2, \ldots, \tag{2}$$

where y_t indicates the observed data, and α and β refers respectively to a constant and a linear time trend. In this context, a significant positive value of β indicates support of warming temperatures across time.

Finally, and based on the monthly nature of the data, we also include a seasonal component, that we model throughout a simple autoregressive AR(1) model of the following form.

$$u_t = \varphi u_{t-12} + \varepsilon_t, \quad t = 1, 2, \ldots, \tag{3}$$

where ε_t is a white noise process.

Then, the model specification is the one based on equations (1)–(3), i.e.,

$$y_t = \alpha + \beta t + x_t, (1-B)^d x_t = u_t, \quad u_t = \varphi u_{t-12} + \varepsilon_t, \tag{4}$$

where y_t is the time series we observe, α and β are unknown coefficients for the intercept and the linear trend; the regression errors x_t are I(d), and u_t is a seasonal (monthly) AR(1) process of the form as in Eq. (3) where φ is the AR coefficient and εt is a white noise process.

4. Data

The time series used in this paper are taken from the Global Historical Climatology Network-Monthly (GHCN-M, version 4) temperature dataset which collects the monthly mean temperature of more than 25,000 stations around the world (https://www.ncTdc.noaa.gov/ghcn-monthly). For our paper, we have selected 40 Siberian stations for the period 1937m01–2020m12 -which implies 1008 registers for each time series, which is large enough to justify fractional integration methods-, covering latitudes spanning from 50°N (Kosch-Agach) to 80°N (Ostrov-Oshakova). The choice of the stations is based on data availability. The names of the stations and their location in terms of longitude and latitude are displayed in Table 1. Fig. 1 shows the latitudinal position of Siberia and Fig. 2 displays the geographical location of each of the stations across the region.

As shown in Fig. 1, this paper focuses on the Federal District Siberia, one's of largest district of the Russia Federation which extends along northern Asia. This region borders to the north by the Arctic Ocean; on the south by Kazakhstan, China, and Mongolia; on the west by the Ural Mountains and on the east, by the Pacific Ocean. In particular, 'Siberia is comprised of the entire area of Russian Federation east of the Ural Mountains except for the monsoon climatic areas of the Russian Far East

Fig. 2. Siberian stations.

and Beringia' (Groisman et al., 2013b, p.2). Its vast territory occupies almost 30% of Russia's territory, being its major geographical zones the Central Siberian Plateau and West Siberian Plain. Siberia is also characterized by low population density, severe climate variability, enormous forest area, and a rich diversity of natural resources, which makes it a strategic area to consider (See Portnov, 2006; Naúmov and Collins, 2006; Groisman et al., 2013b; Mueller et al., 2015; Knaub and Ignateva, 2021; Kalikhman and Enkh-Amgalan, 2022).

5. Empirical results

Our first specification is the one based on equation (4). Table 2 displays the estimates of d under the three standard assumptions of i) no deterministic terms, i.e., imposing $\alpha = \beta = 0$ in the first equality in (4); ii) with an intercept ($\beta = 0$) and iii) with an intercept and a linear time trend. We mark in bold in the table the most adequate specification for each case. The first thing we observe in the table is that the time trend is not required in any single case; the intercept in 16 stations, while no terms are required in the remaining ones. Table 3 displays the estimated coefficients for the selected model of each station.

If we focus now on the estimated values of d, in Table 3, the first thing we notice is that all values are significantly positive, thus showing a long memory pattern. The lowest estimate corresponds to Verhnjaja_Gutara ($d = 0.12$) followed by Pudino, Minusinsk, Hamar Daban and Ust Koksa (with $d = 0.14$), while the highest values refer to Nizhneangarsk ($d = 0.26$) and Orlinga (0.30). We notice that the estimates of d are in all cases significantly below 0.5 implying that stationarity holds in all the series examined at least in relation with the zero or long run frequency. However, another interesting feature observed in these results is the one displayed in the last column of the table, showing the estimates of the seasonal AR(1) coefficient, φ, in equation (4). We see that the value is very close to 1 in all cases, ranging between 0.912 (Dikson) and

Table 2
Estimates of the differencing parameter.

Station	No regressors	An intercept	With a linear trend
DIKSON	0.26 (0.18, 0.34)	**0.21 (0.14, 0.28)**	0.20 (0.14, 0.28)
HATANGA	0.22 (0.15, 0.30)	**0.16 (0.10, 0.23)**	0.16 (0.09, 0.23)
TURUHANSK	0.19 (0.12, 0.27)	**0.18 (0.11, 0.25)**	0.17 (0.11, 0.25)
VERHNEIMBATSK	0.21 (0.14, 0.28)	**0.19 (0.12, 0.27)**	0.18 (0.11, 0.26)
BOR	0.18 (0.11, 0.26)	**0.17 (0.10, 0.25)**	0.16 (0.10, 0.24)
BAJKIT	0.21 (0.14, 0.28)	**0.18 (0.12, 0.25)**	0.17 (0.11, 0.25)
ALEKSANDROVSKOE	**0.16 (0.19, 0.23)**	0.15 (0.09, 0.22)	0.14 (0.08, 0.22)
TURA	0.22 (0.15, 0.30)	**0.19 (0.13, 0.26)**	0.18 (0.12, 0.26)
VANAVARA	0.21 (0.14, 0.29)	**0.19 (0.12, 0.26)**	0.18 (0.11, 0.25)
TARA	**0.18 (0.11, 0.25)**	0.18 (0.11, 0.25)	0.17 (0.10, 0.24)
OMSK	**0.18 (0.11, 0.25)**	0.18 (0.12, 0.26)	0.17 (0.11, 0.25)
NAPAS	**0.17 (0.11, 0.25)**	0.17 (0.10, 0.24)	0.16 (0.09, 0.24)
SREDNY_VASJUGAN	**0.16 (0.10, 0.24)**	0.16 (0.10, 0.23)	0.15 (0.09, 0.23)
KOLPASEVO	**0.20 (0.13, 0.27)**	0.19 (0.13, 0.27)	0.19 (0.12, 0.26)
ENISEJSK	**0.19 (0.12, 0.26)**	0.18 (0.12, 0.26)	0.18 (0.11, 0.25)
BOGUCANY	**0.17 (0.10, 0.24)**	0.16 (0.10, 0.24)	0.16 (0.09, 0.23)
PUDINO	**0.14 (0.08, 0.21)**	0.14 (0.08, 0.21)	0.13 (0.07, 0.20)
BAKCHAR	**0.17 (0.10, 0.24)**	0.17 (0.10, 0.24)	0.16 (0.09, 0.23)
SEVERNOE	**0.18 (0.12, 0.25)**	0.18 (0.12, 0.25)	0.17 (0.11, 0.24)
ACHINSK	**0.18 (0.12, 0.26)**	0.19 (0.12, 0.26)	0.18 (0.11, 0.26)
TAJSHET	**0.16 (0.10, 0.23)**	0.16 (0.10, 0.23)	0.15 (0.08, 0.22)
TATARSK	**0.19 (0.13, 0.27)**	0.18 (0.13, 0.27)	0.19 (0.12, 0.27)
BARABINSK	**0.20 (0.13, 0.27)**	0.20 (0.14, 0.27)	0.19 (0.13, 0.27)
NENASTNAJA	0.18 (0.11, 0.26)	**0.18 (0.11, 0.25)**	0.17 (0.10, 0.25)
VERHNJAJA_GUTARA	0.13 (0.07, 0.20)	**0.12 (0.06, 0.19)**	0.11 (0.04, 0.18)
BARNAUL	**0.20 (0.13, 0.27)**	0.21 (0.14, 0.28)	0.20 (0.13, 0.27)
MINUSINSK	**0.14 (0.08, 0.22)**	0.15 (0.09, 0.22)	0.14 (0.07, 0.21)
BIJSK_ZONALNAJA	0.18 (0.11, 0.25)	**0.19 (0.12, 0.26)**	0.18 (0.11, 0.25)
VITIM	0.18 (0.11, 0.27)	**0.16 (0.09, 0.23)**	0.15 (0.08, 0.22)
KIRENSK	0.18 (0.12, 0.27)	**0.17 (0.11, 0.24)**	0.16 (0.10, 0.24)
BRATSK	**0.19 (0.13, 0.26)**	0.19 (0.13, 0.26)	0.18 (0.12, 0.25)
ORLINGA	**0.30 (0.23, 0.20)**	0.29 (0.22, 0.37)	0.29 (0.22, 0.37)
NIZHNEANGARSK	**0.26 (0.20, 0.27)**	0.25 (0.19, 0.32)	0.24 (0.18, 0.31)
TULUN	**0.17 (0.11, 0.22)**	0.17 (0.11, 0.24)	0.16 (0.10, 0.23)
IRKUTSK	**0.18 (0.12, 0.25)**	0.19 (0.13, 0.26)	0.17 (0.11, 0.24)
HAMAR_DABAN	0.15 (0.08, 0.23)	**0.14 (0.08, 0.22)**	0.14 (0.07, 0.21)
RUBCOVSK	**0.23 (0.14, 0.31)**	0.23 (0.16, 0.31)	0.23 (0.14, 0.31)
ZMEINOGORSK	0.18 (0.13, 0.26)	**0.19 (0.12, 0.27)**	0.18 (0.13, 0.26)
UST_KOKSA	**0.14 (0.08, 0.21)**	0.14 (0.08, 0.21)	0.13 (0.07, 0.20)
KOSCH_AGACH	0.22 (0.15, 0.30)	**0.19 (0.13, 0.27)**	0.18 (0.12, 0.27)

In parenthesis the 95% confidence bands and in bold the selected model for the deterministic terms.

Table 3
Estimated coefficients in the selected models for each series.

Station	d (95% band)	Intercept (t-value)	Seasonal AR
DIKSON	0.21 (0.14, 0.28)	−10.6995 (−9.41)	0.912
HATANGA	0.16 (0.10, 0.23)	−12.2834 (−9.26)	0.949
TURUHANSK	0.18 (0.11, 0.25)	−5.9377 (−4.32)	0.933
VERHNEIMBATSK	0.19 (0.12, 0.27)	−4.0843 (−2.88)	0.933
BOR	0.17 (0.10, 0.25)	−2.4570 (−1.92)	0.936
BAJKIT	0.18 (0.12, 0.25)	−5.9747 (−3.95)	0.954
ALEKSANDROVSKOE	0.16 (0.19, 0.23)	–	0.932
TURA	0.19 (0.13, 0.26)	-8-6114 (−4.84)	0.957
VANAVARA	0.19 (0.12, 0.26)	−5.5793 (−3.52)	0.952
TARA	0.18 (0.11, 0.25)	–	0.945
OMSK	0.18 (0.11, 0.25)	–	0.949
NAPAS	0.17 (0.11, 0.25)	–	0.935
SREDNY_VASJUGAN	0.16 (0.10, 0.24)	–	0.934
KOLPASEVO	0.20 (0.13, 0.27)	–	0.936
ENISEJSK	0.19 (0.12, 0.26)	–	0.936
BOGUCANY	0.17 (0.10, 0.24)	–	0.947
PUDINO	0.14 (0.08, 0.21)	–	0.932
BAKCHAR	0.17 (0.10, 0.24)	–	0.941
SEVERNOE	0.18 (0.12, 0.25)	–	0.946
ACHINSK	0.18 (0.12, 0.26)	–	0.937
TAJSHET	0.16 (0.10, 0.23)	–	0.948
TATARSK	0.19 (0.13, 0.27)	–	0.948
BARABINSK	0.20 (0.13, 0.27)	–	0.947
NENASTNAJA	0.18 (0.11, 0.25)	−1.4405 (−1.79)	0.937
VERHNJAJA_GUTARA	0.12 (0.06, 0.19)	−1.7779 (−2.14)	0.960
BARNAUL	0.20 (0.13, 0.27)	–	0.946
MINUSINSK	0.14 (0.08, 0.22)	–	0.953
BIJSK_ZONALNAJA	0.19 (0.12, 0.26)	2.0895 (1.84)	0.943
VITIM	0.16 (0.09, 0.23)	−4.7859 (−3.72)	0.957
KIRENSK	0.17 (0.11, 0.24)	−3.6871 (−2.65)	0.957
BRATSK	0.19 (0.13, 0.26)	–	0.958
ORLINGA	0.30 (0.23, 0.20)	–	0.936
NIZHNEANGARSK	0.26 (0.20, 0.27)	–	0.970
TULUN	0.17 (0.11, 0.22)	–	0.961
IRKUTSK	0.18 (0.12, 0.25)	–	0.967
HAMAR_DABAN	0.14 (0.08, 0.22)	−1.9624 (−2.59)	0.950
RUBCOVSK	0.23 (0.14, 0.31)	–	0.942
ZMEINOGORSK	0.19 (0.12, 0.27)	2.6967 (2.39)	0.937
UST_KOKSA	0.14 (0.08, 0.21)	–	0.964
KOSCH_AGACH	0.19 (0.13, 0.27)	−4.6857 (−3.19)	0.968

0.970 (Nizhneangarsk). Based on these large values, we conduct seasonal unit root tests on the series, following the classical approaches developed in Dickey, Hasza and Fuller (DHF, 1984) and in Beaulieau and Miron (Beaulieu and Miron, 1993) for monthly time series data. The results, though not reported, support the hypothesis of nonstationary unit roots in all series. Thus, in what follows we work with the first monthly differenced series.

Table 4 displays the estimates of d for each station now in the model given by

$$y_t = \gamma + \delta t + x_t, \quad (1 - B)^d x_t = u_t, \tag{5}$$

though the coefficients for γ and δ were found to be insignificant in all cases. Thus, we only report the estimates of d under the assumption that

Table 4
Estimated coefficients of the selected models.

Station	d (white noise)	d (Bloomfield noise)
DIKSON	0.18 (0.12, 0.24)	−0.03 (−0.14, 0.08)
HATANGA	0.14 (0.08, 0.21)	−0.07 (−0.18, 0.08)
TURUHANSK	0.15 (0.09, 0.22)	−0.06 (−0.18, 0.05)
VERHNEIMBATSK	0.15 (0.09, 0.22)	−0.08 (−0.19, 0.07)
BOR	0.14 (0.08, 0.20)	−0.07 (−0.19, 0.06)
BAJKIT	0.15 (0.04, 0.22)	−0.03 (−0.14, 0.09)
ALEKSANDROVSKOE	0.12 (0.12, 0.24)	−0.06 (−0.18, 0.05)
TURA	0.17 (0.06, 0.18)	−0.03 (−0.15, 0.11)
VANAVARA	0.16 (0.11, 0.23)	−0.01 (−0.14, 0.12)
TARA	0.14 (0.10, 0.22)	−0.04 (−0.16, 0.08)
OMSK	0.15 (0.08, 0.21)	−0.04 (−0.16, 0.08)
NAPAS	0.13 (0.07, 0.20)	−0.08 (−0.19, 0.04)
SREDNY_VASJUGAN	0.13 (0.07, 0.19)	−0.06 (−0.18, 0.06)
KOLPASEVO	0.16 (0.10, 0.23)	−0.04 (−0.17, 0.09)
ENISEJSK	0.15 (0.09, 0.21)	−0.03 (−0.17, 0.10)
BOGUCANY	0.13 (0.08, 0.20)	−0.02 (−0.13, 0.12)
PUDINO	0.11 (0.05, 0.17)	−0.03 (−0.14, 0.12)
BAKCHAR	0.13 (0.07, 0.20)	−0.04 (−0.16, 0.09)
SEVERNOE	0.14 (0.09, 0.21)	0.00 (−0.13, 0.14)
ACHINSK	0.18 (0.11, 0.26)	−0.14 (−0.25, 0.03)
TAJSHET	0.13 (0.07, 0.19)	−0.04 (−0.14, 0.09)
TATARSK	0.16 (0.10, 0.23)	−0.04 (−0.16, 0.09)
BARABINSK	0.17 (0.11, 0.24)	−0.02 (−0.14, 0.11)
NENASTNAJA	0.14 (0.08, 0.21)	−0.07 (−0.21, 0.09)
VERHNJAJA_GUTARA	0.09 (0.03, 0.15)	−0.08 (−0.20, 0.04)
BARNAUL	0.17 (0.11, 0.24)	−0.03 (−0.14, 0.12)
MINUSINSK	0.11 (0.05, 0.18)	−0.07 (−0.16, 0.08)
BIJSK_ZONALNAJA	0.16 (0.10, 0.22)	−0.03 (−0.16, 0.11)
VITIM	0.13 (0.07, 0.20)	−0.05 (−0.17, 0.07)
KIRENSK	0.15 (0.09, 0.21)	−0.01 (−0.13, 0.12)
BRATSK	0.16 (0.10, 0.23)	−0.01 (−0.14, 0.14)
ORLINGA	0.27 (0.20, 0.34)	−0.01 (−0.11, 0.12)
NIZHNEANGARSK	0.23 (0.17, 0.30)	0.13 (0.00, 0.25)
TULUN	0.15 (0.09, 0.21)	−0.01 (−0.14, 0.13)
IRKUTSK	0.16 (0.10, 0.28)	0.00 (−0.09, 0.15)
HAMAR_DABAN	0.11 (0.05, 0.18)	−0.10 (−0.21, 0.04)
RUBCOVSK	0.19 (0.13, 0.27)	−0.07 (−0.19, 0.06)
ZMEINOGORSK	0.16 (0.09, 0.23)	−0.11 (−0.23, 0.04)
UST_KOKSA	0.11 (0.05, 0.18)	−0.05 (−0.17, 0.06)
KOSCH_AGACH	0.16 (0.10, 0.23)	−0.07 (−0.16, 0.06)

In parnethesis the 95% confidence band.

Table 5
Estimated coefficients of d for two subsamples: White noise.

Station	1939m01-1976m12	1977m01-2020m12
DIKSON	0.20 (0.12, 0.29)	0.16 (0.08, 0.25)
HATANGA	0.23 (0.15, 0.33)	0.08 (0.00, 0.18)
TURUHANSK	0.24 (0.15, 0.33)	0.07 (−0.02, 0.14)*
VERHNEIMBATSK	0.23 (0.15, 0.33)	0.10 (0.02, 0.20)
BOR	0.20 (0.12, 0.30)	0.10 (0.02, 0.20)
BAJKIT	0.22 (0.14, 0.32)	0.14 (0.06, 0.23)
ALEKSANDROVSKOE	0.17 (0.09, 0.25)	0.08 (0.00, 0.17)
TURA	0.27 (0.19, 0.37)	0.11 (0.04, 0.18)*
VANAVARA	0.21 (0.13, 0.30)	0.15 (0.07, 0.24)
TARA	0.17 (0.09, 0.25)	0.06 (−0.01, 0.15)
OMSK	0.16 (0.08, 0.25)	0.08 (0.01, 0.17)
NAPAS	0.16 (0.08, 0.25)	0.10 (0.02, 0.19)
SREDNY_VASJUGAN	0.16 (0.09, 0.24)	0.08 (0.00, 0.17)
KOLPASEVO	0.16 (0.08, 0.25)	0.13 (0.06, 0.22)
ENISEJSK	0.14 (0.06, 0.24)	0.15 (0.08, 0.23)
BOGUCANY	0.11 (0.03, 0.21)	0.17 (0.09, 0.25)
PUDINO	0.07 (0.01, 0.15)	0.12 (0.04, 0.20)
BAKCHAR	0.13 (0.05, 0.21)	0.12 (0.05, 0.21)
SEVERNOE	0.15 (0.08, 0.23)	0.10 (0.01, 0.18)
ACHINSK	0.13 (0.04, 0.23)	0.15 (0.08, 0.24)
TAJSHET	0.08 (−0.01, 0.18)	0.18 (0.10, 0.26)
TATARSK	0.17 (0.09, 0.26)	0.10 (0.02, 0.18)
BARABINSK	0.18 (0.10, 0.27)	0.11 (0.03, 0.19)
NENASTNAJA	0.17 (0.09, 0.26)	0.07 (0.00, 0.16)
VERHNJAJA_GUTARA	0.06 (−0.02, 0.16)	0.11 (0.04, 0.20)
BARNAUL	0.17 (0.08, 0.25)	0.13 (0.06, 0.21)
MINUSINSK	0.07 (−0.01, 0.16)	0.19 (0.11, 0.28)
BIJSK_ZONALNAJA	0.16 (0.07, 0.25)	0.13 (0.05, 0.21)
VITIM	0.16 (0.08, 0.26)	0.17 (0.08, 0.26)
KIRENSK	0.15 (0.08, 0.25)	0.19 (0.11, 0.28)
BRATSK	0.11 (0.02, 0.21)	0.22 (0.14, 0.31)
ORLINGA	0.08 (0.02, 0.17)	0.39 (0.29, 0.48)*
NIZHNEANGARSK	0.21 (0.13, 0.31)	0.23 (0.15, 0.32)
TULUN	0.08 (0.00, 0.18)	0.18 (0.10, 0.26)
IRKUTSK	0.09 (0.00, 0.19)	0.21 (0.13, 0.29)
HAMAR_DABAN	0.05 (−0.03, 0.16)	0.17 (0.08, 0.26)
RUBCOVSK	0.19 (0.10, 0.29)	0.18 (0.09, 0.26)
ZMEINOGORSK	0.14 (0.06, 0.24)	0.15 (0.08, 0.24)
UST_KOKSA	0.08 (0.01, 0.16)	0.14 (0.07, 0.24)
KOSCH_AGACH	0.22 (0.14, 0.31)	0.21 (0.13, 0.30)

*: Significant differences across the two subsamples at the 5% level.

$\gamma = \delta = 0$. The second column in the table refers to the case where u_t in (5) is a white noise process, while in column 3 we report the results under the assumption of weak autocorrelation, using a non-parametric approach due to Bloomfield (1973). This latter method approximates highly parameterized AR structures with very few parameters and accommodates very well in the context of fractional integration. Starting with the results based on white noise errors, we observe that the estimates of d are significantly positive in all cases, thus, supporting once more the hypothesis of long memory. The lowest estimates are obtained at Verhnjaja Gutara (0.09) and Pudino, Minusinsk, Hamar Daban and Ust Koksa (0.11) while the highest ones correspond to Nizhneangarsk (0.23) and Orlinga (0.27), i.e., the same stations as those reported in Table 3.

Table 6
Estimated coefficients of d for two subsamples: Autocorrelation.

Station	1939m01-1976m12	1977m01-2020m12
DIKSON	−0.01 (−0.16, 0.19)	−0.07 (−0.23, 0.10)
HATANGA	0.03 (−0.13, 0.25)	−0.16 (−0.32, 0.02)
TURUHANSK	0.04 (−0.11, 0.26)	−0.21 (−0.36, −0.01)*
VERHNEIMBATSK	−0.01 (−0.15, 0.21)	−0.16 (−0.30, 0.02)
BOR	−0.05 (−0.22, 0.16)	−0.13 (−0.28, 0.05)
BAJKIT	−0.05 (−0.21, 0.15)	−0.04 (−0.22, 0.12)
ALEKSANDROVSKOE	0.03 (−0.14, 0.24)	−0.16 (−0.33, 0.02)
TURA	0.03 (−0.12, 0.23)	−0.11 (−0.27, 0.07)
VANAVARA	−0.04 (−0.19, 0.17)	−0.02 (−0.17, 0.15)
TARA	0.05 (−0.12, 0.25)	−0.13 (−0.25, 0.05)
OMSK	0.05 (−0.15, 0.24)	−0.13 (−0.27, 0.03)
NAPAS	−0.04 (−0.20, 0.17)	−0.14 (−0.28, 0.04)
SREDNY_VASJUGAN	0.04 (−0.13, 0.23)	−0.16 (−0.30, 0.01)
KOLPASEVO	−0.01 (−0.19, 0.19)	−0.07 (−0.23, 0.08)
ENISEJSK	−0.09 (−0.29, 0.12)	−0.04 (−0.17, 0.16)
BOGUCANY	−0.12 (−0.33, 0.10)	0.05 (−0.14, 0.24)
PUDINO	0.03 (−0.16, 0.23)	−0.07 (−0.22, 0.01)
BAKCHAR	0.00 (−0.20, 0.18)	−0.05 (−0.20, 0.13)
SEVERNOE	0.09 (−0.11, 0.28)	−0.10 (−0.24, 0.07)
ACHINSK	−0.10 (−0.30, 0.11)	−0.04 (−0.19, 0.12)
TAJSHET	0.20 (−0.28, 0.02)	0.07 (−0.25, 0.25)
TATARSK	0.02 (−0.16, 0.24)	−0.12 (−0.25, 0.06)
BARABINSK	0.03 (−0.14, 0.26)	−0.06 (−0.21, 0.10)
NENASTNAJA	−0.05 (−0.25, 0.17)	−0.09 (−0.24, 0.09)
VERHNJAJA_GUTARA	−0.18 (−0.34, 0.01)	−0.03 (−0.19, 0.15)
BARNAUL	−0.01 (−0.20, 0.21)	−0.05 (−0.20, 0.13)
MINUSINSK	0.13 (−0.28, 0.08)	−0.02 (−0.17, 0.14)
BIJSK_ZONALNAJA	0.03 (−0.25, 0.17)	−0.05 (−0.18, 0.13)
VITIM	−0.04 (−0.24, 0.16)	−0.09 (−0.22, 0.10)
KIRENSK	−0.07 (−0.25, 0.11)	−0.03 (−0.18, 0.16)
BRATSK	−0.13 (−0.30, 0.03)	−0.10 (−0.05, 0.10)
ORLINGA	−0.14 (−0.31, 0.07)	0.04 (−0.13, 0.23)
NIZHNEANGARSK	0.00 (−0.17, 0.16)	0.21 (0.03, 0.42)
TULUN	−0.14 (−0.30, 0.07)	0.09 (−0.09, 0.27)
IRKUTSK	−0.17 (−0.26, 0.10)	0.11 (−0.06, 0.33)
HAMAR_DABAN	−0.25 (−0.44, −0.08)*	0.02 (−0.19, 0.21)
RUBCOVSK	−0.09 (−0.25, 0.13)	−0.09 (−0.21, 0.10)
ZMEINOGORSK	−0.12 (−0.29, 0.10)	−0.10 (−0.23, 0.06)
UST_KOKSA	−0.04 (−0.19, 0.16)	−0.10 (−0.22, 0.06)
KOSCH_AGACH	−0.02 (−0.16, 0.14)	−0.10 (−0.12, 0.05)

*: Evidence of anti-persistence ($d > 0$) at the 5% level.

However, if autocorrelation is permitted, a very different picture emerges and the long memory feature observed in the previous column has now disappeared, observing a substantial reduction in the degree of integration of the series. Thus, the estimates of d move now from −0.14 (Achinsk) to 0 (Sernoe) and the only positive value of d is found in the case of Nizhneangarsk ($d = 0.13$). Nevertheless, the null hypothesis of short memory behavior (i.e., $d = 0$) cannot be rejected in any single case. This reduction in the degree of dependence observed when autocorrelation is permitted might be simply a consequence of the competition between the two structures (i.e., the fractional one, measured by d, and the one caused by the Bloomfield model, 1973) in describing the time dependence. However, since Bloomfield (1973) uses a non-parametric method to describe the autocorrelation, no direct comparison is possible between the two structures. Further research should be conducted to investigate this relevant issue.

As a final issue we investigate if the results presented are stable across time. Based on the three subsamples proposed in Xiao et al. (2020), we re-estimate d for the first monthly differences in the model given by equation (5) for the two last subsamples, i.e., 1939m1 – 1976m12, and 1977m1 – 2020m12. (Note that for the first subsample only 24 observations are observable). The results for the case of white noise errors are displayed across Table 5, while those based on AR errors are displayed in Table 6.

In general, as in the previous results, lower values of d are observed under autocorrelation. Starting with the case of white noise errors, we observe a reduction in the value of d in the second subsample (in 23 out of the 40 cases), and if u_t is autocorrelation, the reduction in d takes place in 26 cases. However, the differences are almost insignificant. Thus, with white noise errors, there are only three stations with a significant difference in the estimate of d across the subsamples: Turuhansk and Tura, with a significant reduction in d, from 0.24 to 0.07 in the former station, and from 0.27 to 0.11 in the latter one. On the contrary, for Orlinga, there is an increase from 0.08 to 0.39.

If ut is autocorrelated, using the model of Bloomfield (1973), Table 6, the I(0) hypothesis of short memory cannot be rejected in almost any station (the only two exceptions being Turahansk in the second subsample, and Hamar_Daban in the first subsample, and more importantnly, there are no significant differences across the two subsamples.

As a final issue, and taking into account the results in Przybylak and Wyszyński (2020) that suggest a warming trend from 1996, we also examine the original data starting at 1996m01, no observing substantial differences with the results reported in this work.

6. Conclusions

In this paper we have examined the monthly mean temperatures in 40 selected Siberian stations in order to determine if long memory is present in the data. Along with this, other important features in the data have been examined such as the potential presence of trends and seasonality issues. Our preliminary results support the hypothesis of long memory in all stations with significant positive values of the differencing parameter, though at the same time the seasonal coefficient was found to be very close to 1 in all cases examined. Due to this, seasonal unit root tests were conducted, supporting the hypothesis of nonstationary seasonality. Taking first seasonal differences, the results differ depending on the assumption made on the error term; thus, if the errors follow a white noise process, long memory is still present in the data, however, if autocorrelation is permitted, this evidence disappears in favor of a short memory pattern.

Further results should be conducted on these data to provide definite conclusions about their behavior. Thus, for example, semiparametric methods to identify long memory can be conducted to avoid the need of specification for the error term. In addition, non-linear structures can also be taken into account to determine if the issue of long memory is simply a spurious phenomenon caused by the presence of nonlinearities in the data. In this line, the linear trend can be replaced by Chebyshev polynomials in time, Fourier functions or neural networks in the fractionally integrated model as it has been proposed respectively in Cuestas and Gil-Alana (2016), Gil-Alana and Yaya (2021) and Yaya et al. (2021). Work in these directions is now in progress.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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