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Time Trends and Persistence in European Temperature Anomalies

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TIME TRENDS AND PERSISTENCE IN EUROPEAN TEMPERATURE ANOMALIES

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ABSTRACT

This paper looks at the level of persistence in the temperature anomalies series of 114 European cities. Once this level of persistence has been identified, the time trend coefficients are estimated and the results indicate that most of the series examined display positive trends, supporting thus climate warming. Moreover, the results obtained confirm the hypothesis that long-memory behaviour cannot be neglected in the study of temperatures time series, changing therefore, the estimated effect of global warming.

Keywords: Time trends; persistence; temperatures; Europe; long memory

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1. Introduction

It is a well-known fact that temperatures are increasing (Nicholls et al., 1996; Percival et al,, 2001; Caballero et al., 2002; Gil-Alana, 2003, 2005; Jones and Wigley, 2010; Franzke, 2012; Bunde et al., 2014; Ludescher et al., 2016; Folland et al., 2018; etc.). On a global scale, organizations such as the National Oceanic and Atmospheric Administration (NOAA) and NASA have shown that since 2010, we have had the warmest years on record as compared to the baseline average of the 20th century and of 1951–1980 respectively. Authors such as Hansen et al. (2010) and Cahill et al. (2015) argue that this trend is likely to continue in the long-term due to the continuous greenhouse gas concentration increases.

In spite of the wide literature dealing with this problem, modelling climatological time series is still a controversial topic that has no unique answer. In past years, it was common to examine trends in global and regional mean temperatures over time assuming temperatures time series were stationary I(0) (Bloomfield and Nychka, 1992; Woodward and Gray, 1993; etc.) or, alternatively, assuming nonstationary I(1) models (Woodward and Gray, 1995; Stern and Kaufmann, 2000**;** etc.), where in the I(d) representation, d indicates the number of differences required to get stationarity I(0)[1]. However, the I(0) and I(1) models are only two particular cases of a wider class of I(d) models, where d is assumed to be a real number. These processes are said to be fractionally integrated or integrated of order d, and if d is positive, the process belongs to a wider category of models denominated long memory.

[1] A stationary process is said to be integrated of order 0, and denoted by I(0) if the infinite sum of its autocovariances is finite. Examples are the white noise and the stationary and invertible ARMA-type of models. Another definition, this time in the frequency domain, is provided in Section 3. A nonstationary process is I(1) if it requires first differences to render it stationary I(0).

In recent years, with the development of new methods including spectral analysis (Malamud and Turcottr, 1999; Weber and Talkner, 2001), the structure function method (Lovejoy and Schertzer, 2012), wavelet analysis (Arneodo et al., 1995; Abry and Veitch, 1998), detrended fluctuation analysis (Peng et al., 1994; Kantelhardt et al., 2001), etc., the research on long-term memory has spread considerably, spanning many different fields.

In previous research, long-term memory behavior has been observed in many climate variables, such as precipitation (Kantelhardt et al., 2006; Jiang et al., 2017), relative humidity (Chen et al., 2007), wind fields (Feng et al., 2009), atmospheric general circulations (Vyushin and Kushner, 2009) and total ozone anomalies (Vyushin et al., 2007).

In this paper we focus on the analysis of the temperature anomalies time series across Europe, with monthly observations ranging over 45 years. We use 114 stations for a time period starting in 1970 and ending in 2016. We are mainly interested in the analysis of the degree of persistence of the data (measured by the order of integration of the series, d) and its effect on the estimation of the time trends coefficients.

The paper is structured as follows. Section 2 deals with a review of the analysis of the temperatures in Europe. Section 3 describes the methodology used in the paper, while Section 4 presents the data and the empirical results. Section 5 concludes the paper.

2. Temperatures in Europe

Many recent studies have focused on the impact of global warming on a regional scale, assessing that the trend of temperature anomalies is very different according to the different locations and different time ranges. They all agree that during the last decades there has been a large acceleration of warming, but they found different results for its rate and about the period of highest interest.

To mention just a few of the more recent papers, Mikkonen et al. (2015) studied long time series in Finland, finding a rapid increase of the warming after 1960s, with an increase of +0.14 °C/decade between 1847 and 2013, and a rise of between 0.2 and 0.4 °C/decade after the 1960s; Delveux et al. (2019) examined the temperatures in Belgium and found a warming of +0.15 °C/decade between 1880 and 2015, and +0.3 °C/decade between 1954 and 2015, with an abrupt increase during the 1980s; Klingbjer and Moberg (2003) focus on 200-year temperature time series in Sweden starting in 1802, and detect an anomalous warming period in the last 3 decades. Brunet et al. (2007) studied time series covering the period 1901-2005, concentrating on the geographical pattern of warming across Spain, and found that the period 1973-2005 was the one with the highest rate of change and the strongest acceleration of warming. Ribes et al. (2016) measured an overall warming of +1.5 ± 0.5 °C during the period 1959-2009 in France. Mamara et al. (2015) explore temperature time series during the period 1960-2004 in 52 stations in Greece, obtaining a negative trend before 1976 and an increasing one of 0.2-0.4 °C/decade between 1977 and 2004.

A large part of the most recent research is now studying the evolution of temperatures taking into account the long-memory property of the series, both at a global scale, Gil-Alana (2005), dealing with Northern Hemisphere temperatures, and at a local scale, such as Franzke (2010), who explored eight stations in Antarctica, observing long-range memory behavior. Jiang et al. (2015) also observed long-memory in the air temperatures in 552 Chinese stations; Massah and Kantz (2016) and Yuan et al. (2014, 2015) used detrended fluctuation analysis (DFA) to detect long-memory behavior of temperature series in Europe and in Antarctica respectively. Gil-Alana and Sauci (2019) compared the persistence across US states, obtaining a positive persistence parameter for all of the States, with an increase in the temperatures between 1.5 °F and 2.5 °F for most of them.

3. Methodology

Long memory is a feature in time series data that means that observations are highly dependent even if they are far apart in time. Within this category, widely observed in climatological data (Yuan et al., 2014; Jiang et al., 2015; Gil-Alana and Sauci, 2019), a well-known parametric model is the one based on fractional integration that means that the number of differences required in a series to render it stationary I(0) is a fractional value.

Since this paper deals with climate warming and time trends in the temperatures, the model examined will be the following one:

$$y_t = \beta_0 + \beta_1 t + x_t, \quad t = 0, \pm 1, \ldots, \tag{1}$$

where y_t refers to the temperature anomalies and x_t is an error term that is supposed to be integrated of order d, or I(d), and described as:

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

where B is the backshift operator, i.e., $B^k x_t = x_{t-k}$ and u_t is I(0) defined as a process with a spectral density function that is positive and finite at all frequencies over the spectrum.

Based on (1) and (2), we test the null hypothesis:

$$H_o : d = d_o , \tag{3}$$

for any real value d_o. Thus, under H_o (3), the null model becomes:

$$(1 - B)^{d_o} y_t = \beta_0 \widetilde{1}_t + \beta_1 \widetilde{t}_t + u_t , \quad t = 0, 1, ..., \tag{4}$$

where $\widetilde{1}_t = (1 - B)^{d_o} 1,$ and $\widetilde{t}_t = (1 - B)^{d_o} t,$ and noting that u_t in (4) is I(0) by construction, we can test the significance of β_1 by using standard methods.

In the empirical application carried out in the following section, we will display the values of d_o where H_o (3) cannot be rejected along with the estimates of the deterministic terms, β_0 and β_1, the latter showing us if the temperatures have increased across time. For this purpose, we use a simple version of a testing procedure developed by Robinson (1994) and that has been widely used in the analysis of I(d) models (see, e.g., Gil-Alana and Robinson, 1997). It is based on the Lagrange Multiplier (LM) method and uses the Whittle function expressed in the frequency domain.

4. Data and Empirical Results

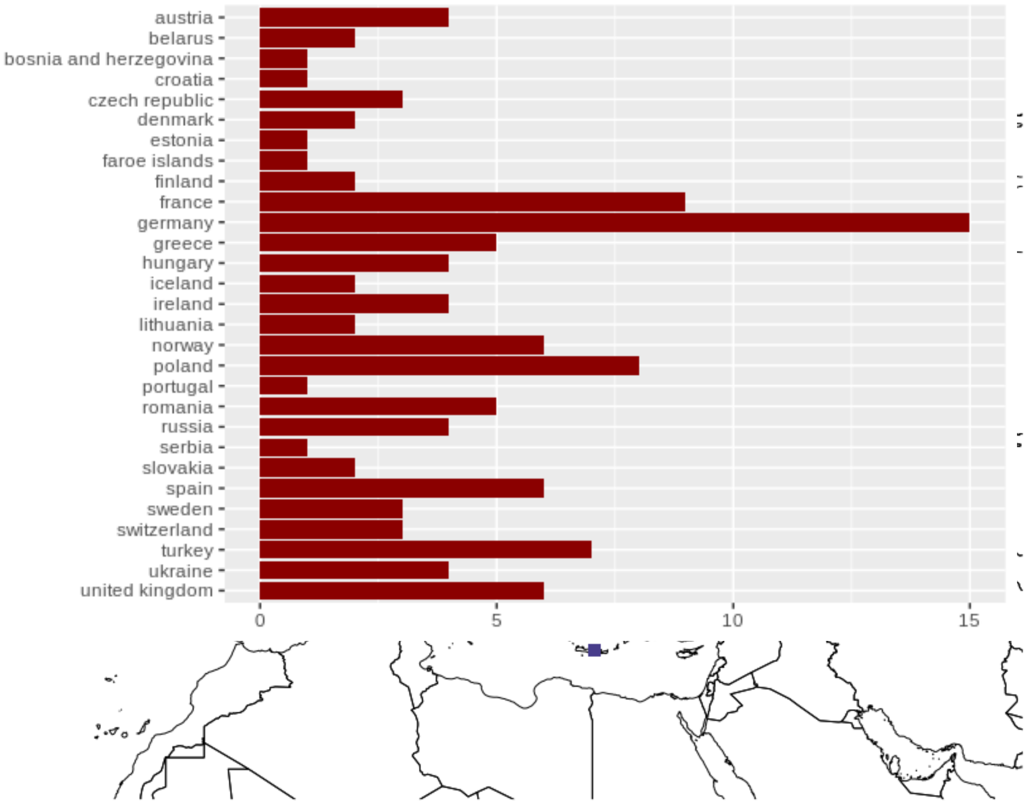
Monthly data anomalies of mean temperatures are obtained from free datasets from KNMI Climate Explorer, ECA&D. Data span 114 stations across 29 different countries in Europe, with starting points in January 1971 and ending points in November 2016. We focused on these stations and this time range in order to have the most complete time series. We have chosen the dataset in such a way that we have no more than 5 missing data in each of the series, and no more than one consecutive missing data: in these cases missing data were substituted with arithmetic mean of observations of the same month of the previous and following years. The specific stations are displayed in Figure 1.[2] As we can see from Figure 2, Germany is the country with the largest coverage, with 15 stations, followed by other large countries such as France, Poland, Spain, Turkey and the United Kingdom. Central Europe is the region with the highest density in terms of number of stations. 69 of the stations come from continental areas, while 45 are located next to the sea. They are both from large metropolitan areas (15 stations from cities with more than 1 million inhabitants), from urban areas (71 of them are cities with a population greater than 100.000 people), small towns (12 are cities with more than 10,000 inhabitants, and rural area (16 stations are located in towns with fewer than 10,000 people); 12 stations are located in mountain places, with an altitude higher than 600 metres; in particular the stations of Saentis and Zugspitze are located at more than 2,000 metres above sea level, so we can consider them as high mountain areas.

Figure 1: Distribution of the stations

The distribution of the stations is quite heterogeneous, with a higher density in Central Europe and a lower density in Southern Europe and poor-inhabited areas in Northern Europe.

Figure 2: Number of stations displayed by country.

[2] The distribution of the stations is quite heterogeneous, due to the difficulty in finding complete series from some countries like Italy, Albania and Bulgaria.



The bar chart depicts the number of stations by country. 29 countries are represented in our study. The country with the highest number of stations is Germany (15).

The increase of temperatures is evident in our dataset: focusing on the yearly average temperatures, nine out of ten of the warmest years are after 2000. Winter months are more influenced by these events, in fact, the top 15 months experiencing the largest temperature increase during the period under consideration fell between December and March; indeed, considering the average temperature anomalies among the 114 stations, we observed that these months experiencing the largest temperature increase.

Table 1 displays the estimated coefficients under the assumption that u_t in equation (2) is a white noise process. Thus, all the dependence between the observations is captured by the differencing parameter d. The first thing we observe here is that the estimated values of d are positive and statistically significant for all except two stations: Saentis (CH) and Zugspitze (D), implying the existence of long memory, and thus being consistent with most studies in this area. The highest levels of persistence are observed in Alborg (DK) (d = 0.30); Kobenhavn (DK) (0.28) and Oslo and Stavanger (N) and Visby (S) (d = 0.27), all corresponding to Scandinavian countries. We also observe that in all cases the highest values at the confident bands are below 0.5, implying a stationary though long memory pattern. Focusing now on the time trend coefficients, we observe that they are significantly positive in 108 out of the 114 stations examined, being insignificant only for Alborg (DK), Kovenhavn (DK), Tallin (EST), Linkoeping and Visby (S), and Oslo (N), all them Northern European stations. On the other extreme, the highest time trend coefficients correspond to Cuenca (E) (+0.59 °C/decade), and Graz (A) and Belgrade (SRB) (+0.50 °C/decade), along with Sodankyla

(FIN) (+0.48 °C/decade), Burgos (E) (+0.47 °C/decade) and Wlodawa (PL) (+0.47 °C/decade).

Table 2 extends the results to the case of autocorrelated errors by using the exponential spectral model of Bloomfield (1973). This is a non-parametric method that approximates fairly well highly parameterized AR(MA) models.[3] In addition it allows us to describe the potential seasonality that might be present in the data. Under this specification, the first thing we observe is that the estimated values of the differencing parameter are smaller than in the previous case, clearly due to the competition between the two structures (fractional integration and Bloomfield (1973)) in describing the time dependence. In fact, the I(0) hypothesis of short memory behaviour, i.e., d = 0, cannot be rejected in 76 stations, while long memory (d > 0) is found in the remaining 38, in all cases displaying again a stationary (d < 0.5) pattern. Among these, the highest levels of persistence are found in the cases of Vardo (N) (d = 0.21), Lerwick (UK) and Thorsnavn (DK), both with estimated values of d equal to 0.20, and then, followed by Vishy (S) (d = 0.18), Malinhead (IRE, d = 0.16), Greitswald (D) and Rostock (D) with d = 0.15, Alborg and Kobenhavn (DK), Reykjavik (IS), Stavanger (N) and Linkoeping (S) with d = 0.14.

Table 1: Estimated coefficients: White noise errors

City	d (95% band)	Intercept (t-	Time trend[4] (t-
Aberdeen (UK)	0.18 (0.12, 0.27)	**-0.73885 (-3.34)**	**0.2472 (3.09)**
Afyon (TK)	0.12 (0.05, 0.20)	**-1.09225 (-3.99)**	**0.3766 (3.77)**
Akureyri (IS)	0.12 (0.05, 0.21)	**-0.77300 (-3.04)**	**0.3032 (3.27)**
Alborg (DK)	0.30 (0.22, 0.40)	-0.71536 (-1.32)	0.2654 (1.33)
Alencon (F)	0.12 (0.05, 0.20)	**-0.82984 (-3.74)**	**0.2592 (3.21)**

[3] See Gil-Alana (2004) for the specification of this model in the context of fractional integration.

Almeria (E)	0.23 (0.17, 0.32)	**-1.27293 (-5.30)**	**0.3616 (4.16)**
Ankara (TK)	0.13 (0.05, 0.22)	**-1.22732 (-4.20)**	**0.3766 (4.04)**
Athens (GR)	0.16 (0.09, 0.26)	**-1.12073 (-4.90)**	**0.3308 (3.99)**
Belfast (UK)	0.19 (0.12, 0.28)	**-0.64199 (-2.79)**	**0.2020 (2.43)**
Belgrade (SRB)	0.14 (0.06, 0.24)	**-1.39786 (-4.47)**	**0.4990 (4.39)**
Bistrita (RO)	0.17 (0.09, 0.27)	**-1.08282 (-3.06)**	**0.4175 (3.25)**
Bodo (N)	0.16 (0.09, 0.26)	**-0.83926 (-2.83)**	**0.3270 (3.05)**
Bourges (F)	0.09 (0.02, 0.18)	**-1.17550 (-5.61)**	**0.4003 (5.20)**
Brest (BY)	0.16 (0.09, 0.24)	**-1.09978 (-2.86)**	**0.4072 (2.92)**
Brest (F)	0.17 (0.10, 0.25)	**-0.87223 (-3.88)**	**0.2721 (3.34)**
Brno (CZ)	0.15 (0.09, 0.24)	**-1.03105 (-3.37)**	**0.3665 (3.30)**
Budapest (H)	0.14 (0.07, 0.24)	**-1.09231 (-3.78)**	**0.3775 (3.59)**
Burgos (E)	0.18 (0.11, 0.23)	**-1.35656 (-4.78)**	**0.4720 (4.59)**
Caen (F)	0.13 (0.07, 0.22)	**-0.90114 (-4.26)**	**0.2842 (3.69)**
Cluj (RO)	0.13 (0.06, 0.23)	**-1.08124 (-3.78)**	**0.3960 (3.80)**
Cork (IRE)	0.20 (0.13, 0.29)	**-0.71542 (-3.05)**	**0.2272 (2.67)**
Coruna (E)	0.19 (0.12, 0.28)	**-1.18437 (-6.07)**	**0.3677 (5.21)**
Cuenca (E)	0.13 (0.04, 0.24)	**-1.60427 (-7.47)**	**0.5873 (7.35)**
Debrecen (H)	0.17 (0.10, 0.26)	**-1.13413 (-3.32)**	**0.4173 (3.37)**
Edirne (TK)	0.13 (0.06, 0.22)	**-1.03946 (-4.16)**	**0.3311 (3.64)**
Elblag (PL)	0.17 (0.10, 0.26)	**-0.99661 (-2.48)**	**0.3551 (2.44)**
Erfurt (D)	0.15 (0.08, 0.23)	**-0.97915 (-2.96)**	**0.3464 (2.88)**
Eskdalemuir	0.18 (0.11, 0.26)	**-0.66889 (-2.72)**	**0.2261 (2.54)**
Essen (D)	0.13 (0.07, 0.22)	**-0.85376 (-3.05)**	**0.2803 (2.75)**
Falun (S)	0.25 (0.17, 0.35)	**-0.91001 (-1.57)**	**0.3806 (1.80)**
Fichtelberg (D)	0.09 (0.03, 0.18)	**-0.90584 (-3.65)**	**0.3627 (3.99)**
Goerlitz (D)	0.16 (0.09, 0.24)	**-0.89994 (-2.60)**	**0.3157 (2.51)**
Graz (A)	0.17 (0.10, 0.25)	**-1.34253 (-4.51)**	**0.4988 (4.63)**
Greifswald (D)	0.25 (0.18, 0.34)	**-0.91138 (-2.13)**	**0.3197 (2.06)**
Hamburg (D)	0.20 (0.13, 0.29)	**-0.91196 (-2.39)**	**0.3183 (2.31)**
Hannover (D)	0.16 (0.09, 0.25)	**-0.98406 (2.93)**	**0.3415 (2.80)**
Helsinki (FIN)	0.24 (0.16, 0.34)	-0.86899 (-1.59)	**0.3478 (1.76)**
Heraklyon (GR)	0.20 (0.13, 0.30)	**-1.04605 (-5.17)**	**0.3013 (4.12)**
Iasi (RO)	0.14 (0.06, 0.23)	**-1.15611 (-3.35)**	**0.4146 (3.30)**
Kalamata (GR)	0.15 (0.08, 0.25)	**-0.94868 (-5.68)**	**0.2616 (4.32)**
Kastamonu	0.14 (0.06, 0.24)	**-0.80206 (-3.01)**	**0.2643 (2.73)**

Kaunas (LT)	0.19 (0.13, 0.28)	**-0.82186 (-1.85)**	**0.2993 (1.86)**
Kharkiv (UA)	0.17 (0.10, 0.27)	**-1.14450 (2.54)**	**0.4401 (2.70)**
Klagenfurt (A)	0.18 (0.10, 0.28)	**-1.09318 (-3.59)**	**0.3991 (3.62)**
Kobenhavn	0.28 (0.20, 0.37)	-0.49393 (-1.04)	0.1447 (0.83)
Krakow (PL)	0.14 (0.08, 0.23)	**-1.19842 (-3.81)**	**0.4458 (3.00)**
Kyiv (UA)	0.17 (0.10, 0.26)	**-1.18052 (-2.84)**	**0.4463 (2.96)**
Larissa (GR)	0.11 (0.03, 0.21)	**-1.27952 (-6.45)**	**0.4130 (5.70)**
Leba (PL)	0.23 (0.14,	**-1.18031 (-2.25)**	**0.4219 (2.22)**
Leipzig (D)	0.17 (0.10,	**-0.98446 (-2.76)**	**0.3435 (2.66)**
Lerwick (UK)	0.21 (0.15,	**-0.63429 (-3.08)**	**0.2241 (3.00)**
Lindenberg (D)	0.16 (0.10,	**-0.98526 (-2.84)**	**0.3941 (2.78)**
Linkoeping (S)	0.26 (0.19, 0.36)	-0.16821 (-0.30)	0.0591 (0.29)
Lisboa (P)	0.15 (0.07,	**-1.10520 (-5.85)**	**0.3187 (4.65)**
Lugano (CH)	0.13 (0.06,	**-1.16079 (-6.02)**	**0.3933 (5.60)**
Lviv (UA)	0.14 (0.07,	**-1.06354 (-3.27)**	**0.3994 (3.38)**
Madrid (E)	0.20 (0.13,	**-1.13171 (-3.87)**	**0.3275 (3.10)**
Malinhead (IRE)	0.21 (0.14,	**-0.53641 (-2.50)**	**0.1516 (1.95)**
Marseille (F)	0.16 (0.08,	**-0.81883 (-3.27)**	**0.2211 (2.44)**
Minsk (BY)	0.16 (0.09,	**-1.11263 (-2.73)**	**0.4299 (2.91)**
Moscu (RUS)	0.15 (0.09,	**-0.98484 (-2.33)**	**0.3824 (2.49)**
Mugla (TK)	0.13 (0.06, 0.23)	**-0.92469 (-4.46)**	**0.2691 (3.57)**
Murmansk (RUS)	0.15 (0.08,	**-1.024452 (-2.47)**	**0.4422 (2.95)**
Nice (F)	0.22 (0.13,	**-1.06964 (-4.35)**	**0.3269 (3.67)**
Nurenberg (D)	0.11 (0.05,	**-1.03969 (-4.09)**	**0.3679 (3.96)**
Odesa (UA)	0.23 (0.15,	**-1.11663 (-2.52)**	**0.4109 (2.56)**
Orland (N)	0.23 (0.16,	**-0.75230 (-1.94)**	**0.2969 (2.11)**
Oslo (N)	0.27 (0.19, 0.37)	-0.73585 (-1.36)	0.2918 (1.47)
Ostrava (CZ)	0.15 (0.08,	**-0.88525 (-2.70)**	**0.3121 (2.63)**
Pecs (H)	0.12 (0.05,	**-1.06034 (-3.85)**	**0.3638 (3.62)**
Perpignan (F)	0.15 (0.07,	**-1.00115 (-4.77)**	**0.2938 (3.85)**
Poprad (SK)	0.14 (0.07,	**-0.84625 (-2.81)**	**0.3189 (2.91)**
Postdam (D)	0.17 (0.11,	**-0.95606 (-2.70)**	**0.3342 (2.62)**
Poznan (PL)	0.16 (0.10,	**-1.01505 (-2.87)**	**0.3671 (2.86)**
Praha (CZ)	0.13 (0.07,	**-0.97528 (-3.34)**	**0.3518 (3.31)**
Reykjavik (IS)	0.17 (0.11,	**-0.82488 (-3.37)**	**0.3296 (3.72)**
Rostock (D)	0.25 (0.18,	**-0.91138 (-2.14)**	**0.3197 (2.06)**

Saentis (CH)	0.05 (-0.02,	**-0.92004 (-4.44)**	**0.4080 (5.31)**
Salzburg (A)	0.09 (0.03,	**-1.17615 (-5.01)**	**0.4233 (4.91)**
Sarajevo (BH)	0.14 (0.05,	**-1.05884 (-3.51)**	**0.3725 (3.40)**
Schleswig (D)	0.24 (0.16,	**-0.79083 (-1.89)**	**0.2770 (1.83)**
Shannon (IRE)	0.17 (0.10,	**-0.73769 (-3.30)**	**0.2309 (2.85)**
Sibiu (RO)	0.12 (0.05,	**-1.10310 (-3.90)**	**0.4069 (3.95)**
Sivas (TK)	0.19 (0.11, 0.30)	**-0.93265 (-2.13)**	**0.3397 (2.14)**
Sliak (SK)	0.17 (0.10,	**-1.02840 (-3.08)**	**0.3784 (3.13)**
Sodankyla (FIN)	0.15 (0.08,	**-1.09408 (-2.21)**	**0.4847 (2.70)**
Split (HR)	0.14 (0.06,	**-1.18599 (-5.11)**	**0.3731 (4.42)**
Stavanger (N)	0.27 (0.19,	-0.70342 (-1.52)	**0.2820 (1.67)**
S.Petersburg	0.18 (0.11,	**-1.00006 (-2.08)**	**0.3938 (2.27)**
Strasbourg (F)	0.11 (0.05,	**-1.01213 (-4.16)**	**0.3398 (3.82)**
Szczecin (PL)	0.20 (0.13,	**-0.87732 (-2.18)**	**0.3055 (2.10)**
Szeged (H)	0.17 (0.09,	**-1.06187 (-3.06)**	**0.3719 (2.96)**
Tallin (EST)	0.23 (0.16,	-0.76665 (-1.47)	0.3015 (1.59)
Tessalonica (GR)	0.14 (0.06,	**-1.32416 (-6.08)**	**0.4329 (5.47)**
Thorshavn (DK)	0.18 (0.13,	**-0.80754 (-4.14)**	**0.3058 (4.43)**
Timisoara (RO)	0.14 (0.06,	**-1.07717 (-3.62)**	**0.3736 (3.46)**
Tolousse (F)	0.12 (0.05,	**-1.125810 (-4.89)**	**0.3661 (4.35)**
Trier (D)	0.12 (0.06,	**-1.04497 (-4.02)**	**0.3636 (3.83)**
Tromso (N)	0.17 (0.10, 0.26)	**-0.85765 (-2.86)**	**0.3504 (3.22)**
Urfa (TK)	0.18 (0.11, 0.27)	**-1.28170 (-4.46)**	**0.3982 (3.83)**
Valentia (IRE)	0.20 (0.13, 0.30)	**-0.62299 (-2.89)**	**0.1769 (2.27)**
Valley (UK)	0.24 (0.17, 0.33)	**-0.62755 (-2.27)**	**0.1931 (1.93)**
Vardo (N)	0.25 (0.19, 0.32)	**-1.03911 (-2.97)**	**0.4492 (3.54)**
Vilnius (LT)	0.19 (0.12, 0.28)	**-1.04937 (-2.33)**	**0.3914 (2.40)**
Visby (S)	0.27 (0.20, 0.36)	-0.58310 (-1.27)	0.2107 (1.26)
Vytegra (RUS)	0.14 (0.07, 0.23)	**-0.91294 (-1.92)**	**0.3705 (2.14)**
Waddington (UK)	0.19 (0.12, 0.28)	**-0.90617 (-3.39)**	**0.3086 (3.19)**
Warsaw (PL)	0.15 (0.09, 0.23)	**-1.05587 (-2.99)**	**0.3914 (3.05)**
Wien (A)	0.13 (0.06, 0.21)	**-1.08121 (-3.98)**	**0.3752 (3.79)**
Wlodawa (PL)	0.15 (0.07, 0.24)	**-1.26161 (-3.27)**	**0.4691 (3.34)**
Wroclaw (PL)	0.15 (0.09, 0.23)	**-1.11910 (-3.39)**	**0.3996 (3.34)**
Zaragoza (E)	0.17 (0.10, 0.26)	**-1.19749 (-4.53)**	**0.3570 (3.73)**
Zugspitze (D)	0.05 (-0.02, 0.13)	**-0.78448 (-3.80)**	**0.3781 (4.94)**

Zurich (CH)	0.07 (0.00, 0.16)	**-1.09273 (-5.35)**	**0.3866 (5.14)**

All of the trend coefficients in the following tables have °C/decade as unit.

Table 2: Estimated coefficients: Autocorrelated errors

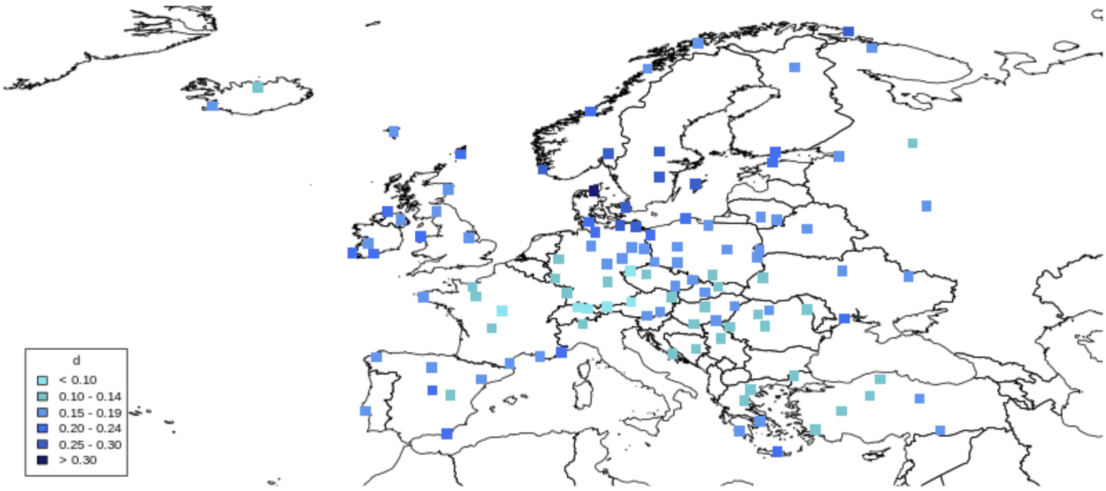
City	d (95% band)	Intercept (t-value)	Time trend[4] (t-
Aberdeen (UK)	0.11 (0.01, 0.25)	**-0.77439 (-4.84)**	**0.2530 (4.45)**
Afyon (TK)	0.02 (-0.07, 0.16)	**-1.113508 (-6.71)**	**0.3864 (6.10)**
Akureyri (IS)	0.04 (-0.06, 0.17)	**-0.78368 (-4.53)**	**0.3045 (4.73)**
Alborg (DK)	0.14 (0.04, 0.28)	**-0.82598 (-3.09)**	**0.2942 (3.03)**
Alencon (F)	0.05 (-0.03, 0.19)	**-0.83451 (-5.25)**	**0.2613 (4.44)**
Almeria (E)	0.13 (0.07, 0.23)	**-1.21308 (-7.97)**	**0.3464 (6.25)**
Ankara	-0.04 (-0.13, 0.10)	**-1.31722 (-10.31)**	**0.4562 (9.35)**
Athens (GR)	0.04 (-0.08, 0.18)	**-1.16228 (-9.01)**	**0.3395 (7.07)**
Belfast (UK)	0.09 (-0.01, 0.26)	**-0.69884 (-4.83)**	**0.2198 (4.14)**
Belgrade (SRB)	0.00 (-0.12, 0.15)	**-1.46170 (-9.18)**	**0.5166 (8.61)**
Bistrita (RO)	0.02 (-0.06, 0.14)	**-1.22661 (-7.10)**	**0.4500 (6.96)**
Bodo (N)	-0.01 (-0.09, 0.12)	**-0.90486 (-6.95)**	**0.3435 (6.98)**
Bourges(F)	0.00 (-0.10, 0.15)	**-1.18197 (-8.72)**	**0.4055 (7.94)**
Brest (BY)	0.09 (-0.01, 0.24)	**-1.12339 (-4.05)**	**0.4129 (4.05)**
Brest (F)	0.09 (-0.01, 0.24)	**-0.87349 (-5.63)**	**0.2739 (4.81)**
Brno (CZ)	0.10 (-0.01, 0.23)	**-1.04648 (-4.33)**	**0.3692 (4.17)**
Budapest (H)	0.08 (-0.04, 0.22)	**-1.11484 (-5.12)**	**0.3832 (4.79)**
Burgos (E)	0.10 (0.01, 0.23)	**-1.31764 (-6.74)**	**0.4658 (6.51)**
Caen (F)	0.06 (-0.02, 0.18)	**-0.89779 (-5.92)**	**0.2858 (5.10)**
Cluj (RO)	-0.03 (-0.11, 0.11)	**-1.16831 (-8.90)**	**0.4181 (8.36)**
Cork (IRE)	0.12 (0.02, 0.26)	**-0.74792 (-4.60)**	**0.2392 (4.03)**
Coruna (E)	0.11 (0.01, 0.24)	**-1.16604 (-8.66)**	**0.3673 (7.47)**
Cuenca (E)	-0.10 (-0.22, 0.07)	**-1.57835 (-22.2)**	**0.5662 (20.44)**
Debrecen (H)	0.08 (-0.02, 0.21)	**-1.20996 (-5.41)**	**0.4353 (5.29)**
Edirne (TK)	0.00 (-0.08, 0.11)	**-1.10186 (-8.28)**	**0.3446 (6.88)**
Elblag (PL)	0.07 (-0.05, 0.22)	**-0.94885 (-3.78)**	**0.3418 (3.69)**
Erfurt (D)	0.09 (-0.01, 0.24)	**-0.98042 (-3.93)**	**0.3461 (3.78)**
Eskdalemuir	0.13 (0.03, 0.26)	**-0.70220 (-3.60)**	**0.2380 (3.35)**
Essen (D)	0.04 (-0.05, 0.19)	**-0.87943 (-4.83)**	**0.2882 (4.25)**
Falun (S)	0.09 (0.01, 0.23)	**-1.06364 (-3.81)**	**0.4180 (4.08)**
Fichtelberg (D)	0.02 (-0.07, 0.17)	**-0.92699 (-5.25)**	**0.3677 (5.56)**
Goerlitz (D)	0.11 (0.01, 0.26)	**-0.91266 (-3.30)**	**0.3180 (3.17)**
Graz (A)	0.07 (-0.02, 0.20)	**-1.35905 (-7.32)**	**0.5041 (7.36)**
Greifswald (D)	0.15 (0.05, 0.29)	**-0.94731 (-3.47)**	**0.3300 (3.33)**

Hamburg (D)	0.08 (-0.02, 0.23)	**-0.94544 (-4.33)**	**0.3279 (4.08)**
Hannover (D)	0.07 (-0.03, 0.20)	**-1.00368 (-4.56)**	**0.3477 (4.28)**
Helsinki (FIN)	0.07 (-0.04, 0.20)	**-1.02552 (-4.12)**	**0.3913 (4.26)**
Heraklyon (GR)	0.10 (0.00, 0.24)	**-1.09710 (-8.62)**	**0.3115 (6.68)**
Iasi (RO)	0.01 (-0.09, 0.18)	**-1.19964 (-6.49)**	**0.4249 (6.12)**
Kalamata (GR)	0.03 (-0.08, 0.16)	**-0.99482 (-10.60)**	**0.2727 (7.78)**
Kastamonu	-0.02 (-0.11, 0.11)	**-0.85969 (7.00)**	**0.2783 (5.98)**
Kaunas (LT)	0.12 (0.03, 0.24)	**-0.87984 (-2.74)**	**0.3179 (2.71)**
Kharkiv (UA)	0.05 (-0.05, 0.16)	**-1.26205 (-4.95)**	**0.4727 (5.00)**
Klagenfurt (A)	0.02 (-0.08, 0.17)	**-1.13217 (-7.97)**	**0.4068 (7.65)**
Kobenhavn	0.14 (0.03, 0.28)	**-0.56054 (-2.20)**	**0.1618 (1.75)**
Krakow (PL)	0.11 (-0.02, 0.26)	**-1.20536 (-4.41)**	**0.4474 (4.48)**
Kyiv (UA)	0.07 (-0.04, 0.19)	**-1.23743 (-4.77)**	**0.4600 (4.81)**
Larissa (GR)	-0.09 (-0.18, 0.03)	**-1.31156 (-17.76)**	**0.4193(14.60)**
Leba (PL)	0.04 (-0.07,	**-1.09484 (-5.09)**	**0.4002 (5.01)**
Leipzig (D)	0.08 (-0.02,	**-0.99275 (-4.25)**	**0.3442 (4.00)**
Lerwick (UK)	0.20 (0.10,	**-0.64388 (-3.26)**	**0.2268 (3.18)**
Lindenberg (D)	0.10 (0.00,	**-1.00472 (-3.84)**	**0.3537 (3.69)**
Linkoeping (S)	0.14 (0.05, 0.26)	-0.31497 (-0.96)	0.0909 (0.76)
Lisboa (P)	0.00 (-0.09,	**-1.06063 (-11.58)**	**0.3082 (8.93)**
Lugano (CH)	0.01 (-0.07,	**-1.19865 (-11.08)**	**0.4045 (9.96)**
Lviv (UA)	0.08 (-0.02,	**-1.09746 (-4.47)**	**0.4073 (4.51)**
Madrid (E)	0.07 (-0.02,	**-1.05927 (-6.66)**	**0.3153 (5.38)**
Malinhead (IRE)	0.16 (0.05,	**-0.56831 (-3.32)**	**0.1622 (2.61)**
Marseille (F)	-0.02 (-0.12,	**-0.86519 (-8.27)**	**0.2337 (5.89)**
Minsk (BY)	0.08 (-0.02,	**-1.15552 (-4.13)**	**0.4410 (4.28)**
Moscu (RUS)	0.10 (-0.01,	**-1.01909 (-3.05)**	**0.3915 (3.20)**
Mugla (TK)	-0.02 (-0.11,	**-0.97434 (9.73)**	**0.2826 (7.44)**
Murmansk (RUS)	0.07 (-0.02,	**-1.01459 (-3.57)**	**0.4333 (4.14)**
Nice (F)	-0.05 (-0.18,	**-1.08842 (-16.11)**	**0.3286 (12.69)**
Nuernberg (D)	0.08 (-0.03,	**-1.03955 (-4.71)**	**0.3670 (4.52)**
Odesa (UA)	0.06 (-0.03,	**-1.27359 (-6.34)**	**0.4551 (6.12)**
Orland (N)	0.10 (0.02,	**-0.87047 (-4.09)**	**0.3269 (4.19)**
Oslo (N)	0.11 (0.02, 0.24)	**-0.91611 (-3.47)**	**0.3403 (3.53)**
Ostrava (CZ)	0.09 (-0.01,	**-0.89872 (-3.64)**	**0.3125 (3.45)**
Pecs (H)	0.03 (-0.09,	**-1.08692 (-6.07)**	**0.3692 (5.53)**
Perpignan (F)	-0.01 (-0.11,	**-1.00921 (-9.90)**	**0.2958 (7.70)**

Poprad (SK)	0.10 (0.00,	**-0.86890 (-3.48)**	**0.3234 (3.54)**
Postdam (D)	0.08 (-0.02,	**-0.96887 (-4.19)**	**0.3366 (3.96)**
Poznan (PL)	0.10 (0.00,	**-1.03684 (-3.87)**	**0.3719 (3.79)**
Praha (CZ)	0.10 (0.01,	**-0.98295 (-3.88)**	**0.3529 (3.80)**
Reykjavik (IS)	0.14 (0.06,	**-0.84983 (-4.18)**	**0.3341 (4.53)**
Rostock (D)	0.15 (0.05,	**-0.94731 (-3.47)**	**0.3300 (3.33)**
Saentis (CH)	-0.04 (-0.13,	**-0.93448 (-7.03)**	**0.4140 (8.15)**
Salzburg (A)	0.02 (-0.10,	**-1.15956 (-6.93)**	**0.4174 (6.67)**
Sarajevo (BH)	-0.06 (-0.17,	**-1.11002 (-9.77)**	**0.3842 (8.80)**
Schleswig (D)	0.10 (0.01,	**-0.84334 (-3.83)**	**0.2899 (3.59)**
Shannon (IRE)	0.12 (0.01,	**-0.76214 (-4.30)**	**0.2396 (3.71)**
Sibiu (RO)	0.00 (-0.07,	**-1.17143 (-7.41)**	**0.4213 (7.08)**
Sivas (Turkey)	0.01 (-0.09, 0.13)	**-1.08552 (-5.84)**	**0.3829 (5.48)**
Sliak (SK)	0.07 (-0.02, 0.21)	**-1.05760 (-5.08)**	**0.3812 (4.96)**
Sodankyla (FIN)	-0.03 (-0.11, 0.08)	**-1.14716 (-5.57)**	**0.4904 (6.25)**
Split (HR)	-0.01 (-0.12, 0.15)	**-1.24172 (-10.51)**	**0.3896 (8.74)**
Stavanger (N)	0.14 (0.05, 0.27)	**-0.86224 (-3.32)**	**0.3207 (3.40)**
S.Petersburg	0.10 (0.00, 0.25)	**-1.06645 (-3.22)**	**0.4125 (3.40)**
Strasbourg (F)	0.05 (-0.03, 0.19)	**-1.01267 (-5.54)**	**0.3395 (5.01)**
Szczecin (PL)	0.11 (0.01, 0.25)	**-0.90775 (-3.41)**	**0.3130 (3.22)**
Szeged (H)	0.04 (-0.07, 0.17)	**-1.11388 (-5.96)**	**0.3821 (5.49)**
Tallin (EST)	0.13 (0.01, 0.27)	**-0.88178 (-2.66)**	**0.3349 (2.77)**
Tessalonica (GR)	-0.04 (-0.14, 0.10)	**-1.13725 (-15.12)**	**0.4462 (12.87)**
Thorsnavn (DK)	0.20 (0.10, 0.32)	**-0.79118 (-3.71)**	**0.3015 (3.91)**
Timisoara (RO)	-0.01 (-0.12, 0.12)	**-1.14408 (-7.95)**	**0.3897 (7.17)**
Tolouse (F)	0.02 (-0.07, 0.15)	**-1.13918 (-7.99)**	**0.3702 (6.94)**
Trier (D)	0.05 (-0.04, 0.19)	**-1.05694 (-5.68)**	**0.3679 (5.33)**
Tromso (N)	0.05 (-0.05, 0.16)	**-0.87675 (-5.16)**	**0.3516 (5.58)**
Urfa (TK)	0.08 (-0.04, 0.23)	**-1.33183 (-7.39)**	**0.4097 (6.18)**
Valentia (IRE)	0.10 (-0.01, 0.27)	**-0.64254 (-4.73)**	**0.1842 (3.70)**
Valley (UK)	0.13 (0.04, 0.26)	**-0.70083 (-4.17)**	**0.2152 (3.52)**
Vardo (N)	0.21 (0.12, 0.33)	**-1.03660 (-3.53)**	**0.4452 (4.19)**
Vilnius (LT)	0.11 (0.01, 0.23)	**-1.09032 (-3.51)**	**0.4074 (3.59)**
Visby (S)	0.18 (0.08, 0.33)	**-0.66390 (-2.15)**	**0.2317 (2.07)**
Vytegra (RUS)	0.09 (-0.03, 0.24)	**-0.94392 (-2.51)**	**0.3786 (2.74)**
Waddington (UK)	0.09 (0.00, 0.22)	**-0.94932 (-5.65)**	**0.3231 (5.24)**

Varsaw (PL)	0.11 (0.01, 0.24)	**-1.07177 (-3.66)**	**0.3938 (3.68)**
Wien (A)	0.10 (-0.02, 0.23)	**-1.08164 (-4.58)**	**0.3741 (4.33)**
Wlodawa (PL)	0.01 (-0.11, 0.16)	**-1.23510 (-6.26)**	**0.4608 (6.22)**
Wroclaw (PL)	0.09 (-0.01, 0.25)	**-1.12137 (-4.51)**	**0.3993 (4.37)**
Zaragoza (E)	0.06 (0.01, 0.16)	**-1.12648 (-7.19)**	**0.3395 (5.86)**
Zugspitze (D)	-0.04 (-0.13, 0.11)	**-0.80452 (-6.07)**	**0.3838 (7.58)**
Zurich (CH)	-0.02 (-0.12, 0.14)	**-1.09537 (-8.33)**	**0.3878 (7.78)**

Figure 3: Persistence in Europe.



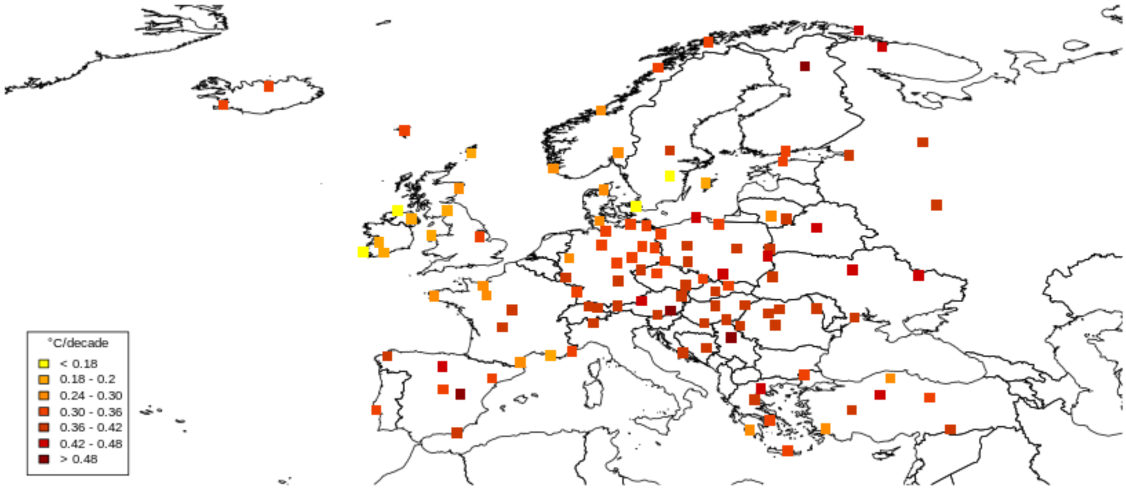
Darker stations represent stations with stronger long-memory behavior. Darker points are located especially next to Baltic Sea and Atlantic Ocean. Continental stations are characterized by weaker long-memory behavior

If we focus on the time trend coefficients, these are statistically significant in all cases, and the highest increments correspond to Cuenca (E) with a value of +0.57 °C/decade, followed by Belgrade (SRB), Sodankyla (FIN) and Graz (A). To resume, we obtained an overall average increase of the temperatures of +0.34 °C/decade during the period 1971-2016 under white noise assumption for the error term, and +0.35 °C/decade under autocorrelated disturbances.

As previous papers state (Fraedrich and Blender, 2003; Eichner et al., 2003, Blender and Fraedrich, 2006; Yuan et al., 2014; etc.), our study confirms that the temperatures over the sea are found to be characterized by stronger long-term memory, while the persistence parameters are found to be weaker over the inner continent. It has been proposed that one possible origin of climate memory may come from the slow-varying effects of the ocean, where the huge heat storage capacity is thought to be the key factor (Monetti et al., 2003; Yuan et al., 2015). In fact, the average persistence parameter for the continental stations is equal to 0.15, while it is 0.20 for the sea stations. (See, Figure 3)

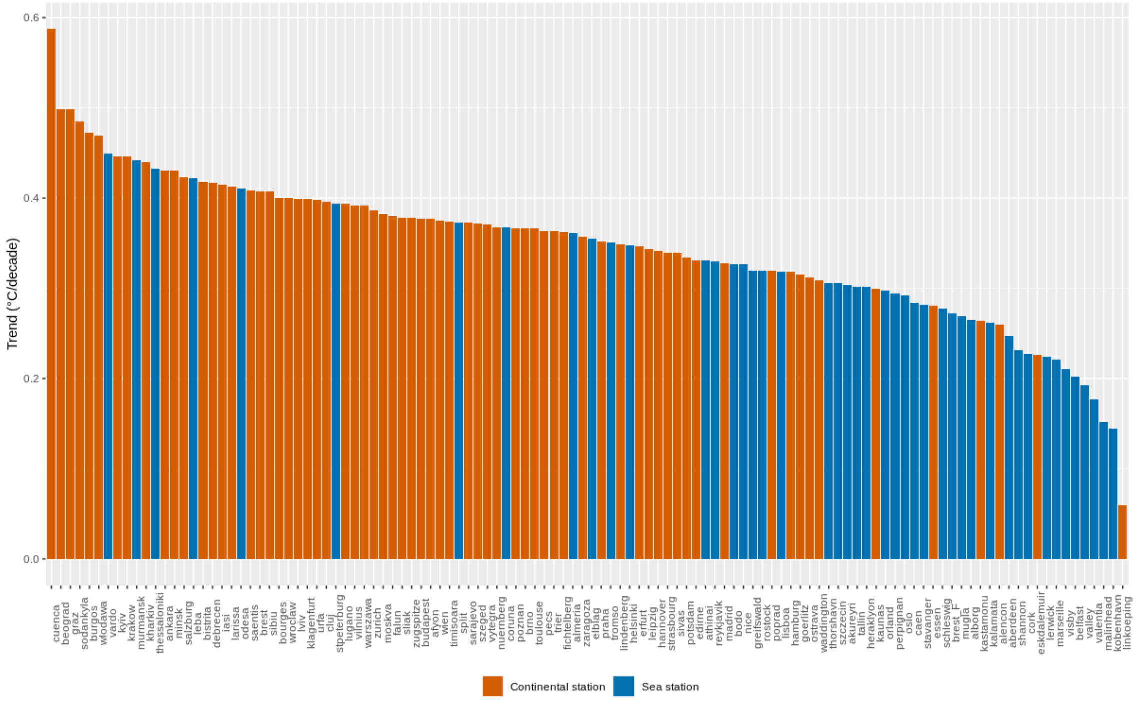
On the other hand, the time trend parameters of the continental series are higher than the ones of sea stations, highlighting the role of the closeness to sea in climate change, with an average increase of +0.3 °C/decade for the stations next to the sea, and an average increase of +0.37 °C/decade measured in the continental stations. (Figures 4, 5 and 6).

Figure 4: Trends in Europe



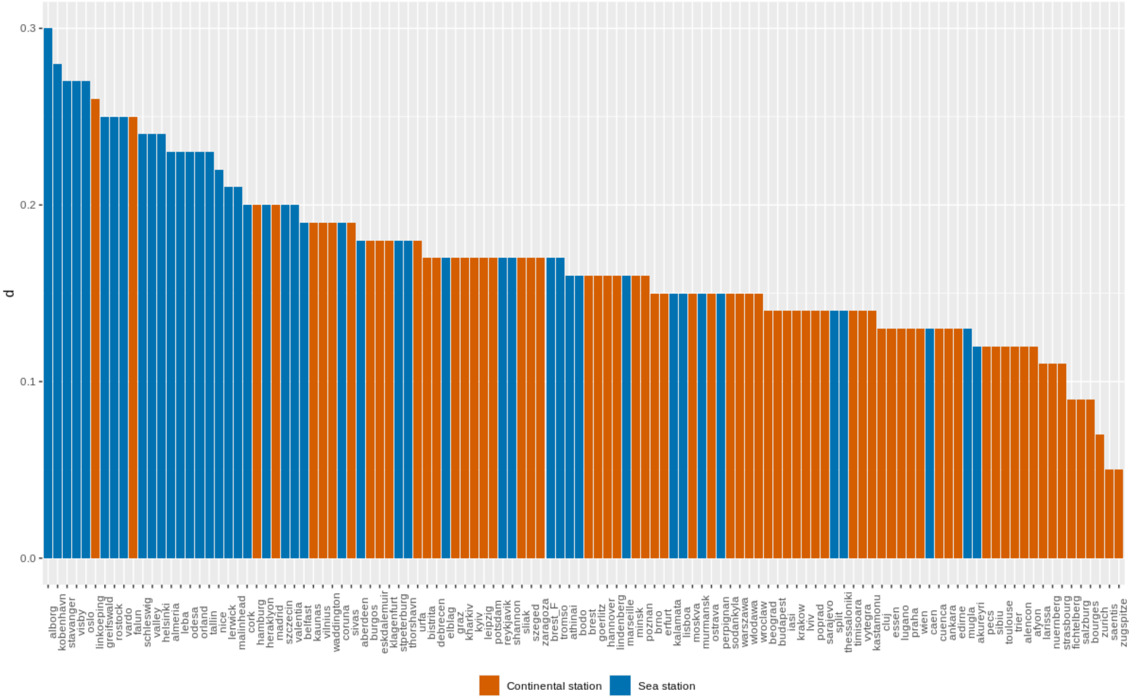
Darker points represent stations with higher trend parameter. The increment of the temperatures is more prominent in continental regions, while it is less severe in sea stations, Great Britain and Ireland.

Figure 5: Trends and sea proximity.



Comparison of the trend parameter of the temperatures between sea stations (blue) and continental stations (brown). Most of the highest positions are occupied by continental stations. The pattern is the opposite of the persistence parameter.

Figure 6: Persistence and sea proximity



Comparison of *d* parameter (that characterize I(d)) between sea stations and continental stations. In agreement with previous research, the strength of long-memory is higher in temperature time series for stations close to oceans and seas.

We finally compare in Table 3 the estimates of the time trend coefficients under three potential scenarios: the one based on the assumption of I(0) errors (4th column in the table), and those based on estimated values of d, under both white noise (2nd column) and autocorrelated (3rd column) errors.

Table 3: Estimated coefficients for the time trend under different assumptions

City	d estimated (WN)	d estimated (BL)	d = 0
Aberdeen (UK)	0.2472 (3.09)	0.2530 (4.45)	0.2745 (7.49)
Afyon (TK)	0.3766 (3.77)	0.3864 (6.10)	0.3872 (6.60)
Akureyri (IS)	0.3032 (3.27)	0.3045 (4.73)	0.3062 (5.62)
Alborg (DK)	----	0.2942 (3.03)	0.3065 (5.48)
Alencon (F)	0.2592 (3.21)	0.2613 (4.44)	0.2628 (5.53)
Almeria (E)	0.3616 (4.16)	0.3464 (6.25)	0.3311 (10.14)
Ankara (TK)	0.3766 (4.04)	0.4562 (9.35)	0.4529 (7.57)
Athens (GR)	0.3308 (3.99)	0.3395 (7.07)	0.3406 (8.30)

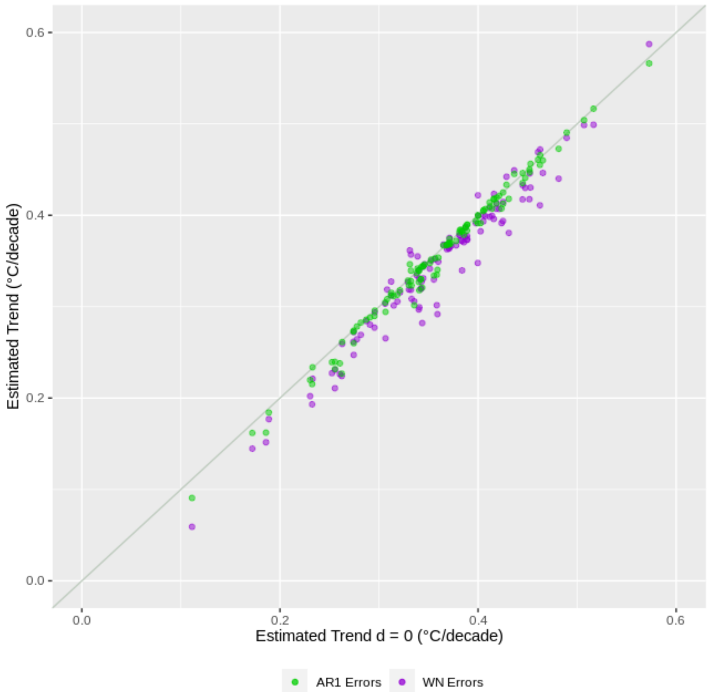
Belfast (UK)	0.2020 (2.43)	0.2198 (4.14)	0.2304 (6.33)
Belgrade (SRB)	0.4990 (4.39)	0.5166 (8.61)	0.5166 (8.43)
Bistrita (RO)	0.4175 (3.25)	0.4500 (6.96)	0.4518 (7.42)
Bodo (N)	0.3270 (3.05)	0.3435 (6.98)	0.3428 (6.46)
Bourges (F)	0.4003 (5.20)	0.4055 (7.94)	0.4055 (7.88)
Brest (BY)	0.4072 (2.92)	0.4129 (4.05)	0.4182 (6.05)
Brest (F)	0.2721 (3.34)	0.2739 (4.81)	0.2745 (7.09)
Brno (CZ)	0.3665 (3.30)	0.3692 (4.17)	0.3727 (6.48)
Budapest (H)	0.3775 (3.59)	0.3832 (4.79)	0.3888 (6.86)
Burgos (E)	0.4720 (4.59)	0.4658 (6.51)	0.4627 (9.86)
Caen (F)	0.2842 (3.69)	0.2858 (5.10)	0.2871 (6.61)
Cluj (RO)	0.3960 (3.80)	0.4181 (8.36)	0.4158 (7.10)
Cork (IRE)	0.2272 (2.67)	0.2392 (4.03)	0.2524 (7.07)
Coruna (E)	0.3677 (5.21)	0.3673 (7.47)	0.3680 (11.92)
Cuenca (E)	0.5873 (7.35)	0.5662 (20.44)	0.5717 (12.77)
Debrecen (H)	0.4173 (3.37)	0.4353 (5.29)	0.4450 (7.55)
Edirne (TK)	0.3311 (3.64)	0.3446 (6.88)	0.3446 (6.74)
Elblag (PL)	0.3551 (2.44)	0.3418 (3.69)	0.3389 (4.92)
Erfurt (D)	0.3464 (2.88)	0.3461 (3.78)	0.3460 (5.57)
Eskdalemuir	0.2261 (2.54)	0.2380 (3.35)	0.2605 (6.42)
Essen (D)	0.2803 (2.75)	0.2882 (4.25)	0.2909 (5.06)
Falun (S)	0.3806 (1.80)	0.4180 (4.08)	0.4310 (5.96)
Fichtelberg (D)	0.3627 (3.99)	0.3677 (5.56)	0.3687 (6.06)
Goerlitz (D)	0.3157 (2.51)	0.3180 (3.17)	0.3211 (5.16)
Graz (A)	0.4988 (4.63)	0.5041 (7.36)	0.5070 (9.91)
Greitswald (D)	0.3197 (2.06)	0.3300 (3.33)	0.3423 (6.4)
Hamburg (D)	0.3183 (2.31)	0.3279 (4.08)	0.3322 (5.74)
Hannover (D)	0.3415 (2.80)	0.3477 (4.28)	0.3514 (5.82)
Helsinki (FIN)	0.3478 (1.76)	0.3913 (4.26)	0.3997 (5.68)
Heraklyon (GR)	0.3013 (4.12)	0.3115 (6.68)	0.3149 (10.25)
Iasi (RO)	0.4146 (3.30)	0.4249 (6.12)	0.4253 (6.30)
Kalamata (GR)	0.2616 (4.32)	0.2727 (7.78)	0.2741 (8.76)
Kastamonu (TK)	0.2643 (2.73)	0.2783 (5.98)	0.2777 (5.32)
Kaunas (LT)	0.2993 (1.86)	0.3179 (2.71)	0.3407 (4.84)
Kharkiv (UA)	0.4401 (2.70)	0.4727 (5.00)	0.4813 (6.20)
Klagenfurt (A)	0.3991 (3.62)	0.4068 (7.65)	0.4073 (8.14)
Kobenhavn (DK)	----	0.1618 (1.75)	0.1721 (3.27)

Krakow (PL)	0.4458 (3.00)	0.4474 (4.48)	0.4522 (7.32)
Kyiv (UA)	0.4463 (2.96)	0.4600 (4.81)	0.4654 (6.51)
Larissa (GR)	0.4130 (5.70)	0.4193(14.60)	0.4188 (9.44)
Leba (PL)	0.4219 (2.22)	0.4002 (5.01)	0.3999 (5.72)
Leipzig (D)	0.3435 (2.66)	0.3442 (4.00)	0.3444 (5.62)
Lerwick (UK)	0.2241 (3.00)	0.2268 (3.18)	0.2623 (8.65)
Lindenberg (D)	0.3941 (2.78)	0.3537 (3.69)	0.3598 (5.77)
Linkoeping (S)	----	----	----
Lisboa (P)	0.3187 (4.65)	0.3082 (8.93)	0.3082 (8.71)
Lugano (CH)	0.3933 (5.60)	0.4045 (9.96)	0.4053 (10.25)
Lviv (UA)	0.3994 (3.38)	0.4073 (4.51)	0.4141 (6.49)
Madrid (E)	0.3275 (3.10)	0.3153 (5.38)	0.3122 (7.05)
Malinhead (IRE)	0.1516 (1.95)	0.1622 (2.61)	0.1859 (5.93)
Marseille (F)	0.2211 (2.44)	0.2337 (5.89)	0.2329 (5.20)
Minsk (BY)	0.4299 (2.91)	0.4410 (4.28)	0.4476 (6.12)
Moscu (RUS)	0.3824 (2.49)	0.3915 (3.20)	0.4025 (5.07)
Mugla (TK)	0.2691 (3.57)	0.2826 (7.44)	0.2816 (6.64)
Murmansk (RUS)	0.4422 (2.95)	0.4333 (4.14)	0.4287 (5.51)
Nice (F)	0.3269 (3.67)	0.3286 (12.69)	0.3292 (9.65)
Nuernberg (D)	0.3679 (3.96)	0.3670 (4.52)	0.3651 (6.40)
Odesa (UA)	0.4109 (2.56)	0.4551 (6.12)	0.4624 (7.80)
Orland (N)	0.2969 (2.11)	0.3269 (4.19)	0.3402 (6.50)
Oslo (N)	----	0.3403 (3.53)	0.3590 (5.73)
Ostrava (CZ)	0.3121 (2.63)	0.3125 (3.45)	0.3123 (5.08)
Pecs (H)	0.3638 (3.62)	0.3692 (5.53)	0.3702 (6.27)
Perpignan (F)	0.2938 (3.85)	0.2958 (7.70)	0.2957 (7.53)
Poprad (SK)	0.3189 (2.91)	0.3234 (3.54)	0.3302 (5.59)
Postdam (D)	0.3342 (2.62)	0.3366 (3.96)	0.3380 (5.57)
Poznan (PL)	0.3671 (2.86)	0.3719 (3.79)	0.3778 (5.93)
Praha (CZ)	0.3518 (3.31)	0.3529 (3.80)	0.3567 (5.95)
Reykjavik (IS)	0.3296 (3.72)	0.3341 (4.53)	0.3553 (8.38)
Rostock (D)	0.2472 (3.09)	0.3300 (3.33)	0.3423 (6.43)
Saentis (CH)	0.3197 (2.06)	0.4140 (8.15)	0.4116 (6.71)
Salzburg (A)	0.4080 (5.31)	0.4174 (6.67)	0.4161 (7.22)

Sarajevo (BH)	0.4233 (4.91)	0.3842 (8.80)	0.3826 (6.50)
Schleswig (D)	0.3725 (3.40)	0.2899 (3.59)	0.2954 (5.48)
Shannon (IRE)	0.2770 (1.83)	0.2396 (3.71)	0.2556 (6.64)
Sibiu (RO)	0.2309 (2.85)	0.4213 (7.08)	0.4213 (6.96)
Sivas (TK)			0.3839 (5.54)
Sliak (SK)	0.4069 (3.95)	0.3829 (5.48)	0.3811 (6.65)
Sodankyla (FIN)	0.3397 (2.14)	0.3812 (4.96)	0.4895 (5.28)
Split (HR)	0.3784 (3.13)	0.4904 (6.25)	0.3889 (8.56)
Stavanger (N)	0.4847 (2.70)	0.3896 (8.74)	0.3436 (6.42)
S.Petersburg	0.3731 (4.42)	0.3207 (3.40)	0.4252 (5.37)
Strasbourg (F)	0.2820 (1.67)	0.4125 (3.40)	0.3400 (6.22)
Szczecin (PL)	0.3938 (2.27)	0.3395 (5.01)	0.3186 (5.21)
Szeged (H)	0.3398 (3.82)	0.3130 (3.22)	0.3838 (6.44)
Tallin (EST)	0.3055 (2.10)	0.3821 (5.49)	0.3586 (5.09)
Tessalonica (GR)	0.3719 (2.96)	0.3349 (2.77)	0.4451 (10.45)
Thorsnavn (DK)	----	0.4462 (12.87)	0.3355 (10.34)
Timisoara (RO)	0.4329 (5.47)	0.3015 (3.91)	0.3891 (6.69)
Tolousse (F)	0.3058 (4.43)	0.3897 (7.17)	0.3709 (7.50)
Trier (D)	0.3736 (3.46)	0.3702 (6.94)	0.3709 (6.65)
Tromso (N)			0.3526 (6.83)
Urfa (TK)			0.4118 (8.69)
Valentia (IRE)	0.3661 (4.35)	0.3679 (5.33)	0.1887 (5.77)
Valley (UK)	0.3636 (3.83)	0.3516 (5.58)	0.2325 (6.49)
Vardo (N)	0.3504 (3.22)	0.4097 (6.18)	0.4365 (9.91)
Vilnius (LT)	0.3982 (3.83)	0.1842 (3.70)	0.42327 (5.94)
Visby (S)	0.1769 (2.27)	0.2152 (3.52)	0.2555 (4.81)
Vytegra (RUS)	0.1931 (1.93)	0.4452 (4.19)	0.3857 (4.13)
Waddington (UK)	0.4492 (3.54)	0.4074 (3.59)	0.3329 (7.87)
Warsaw (PL)	0.3914 (2.40)	0.2317 (2.07)	0.3977 (5.99)
Wien (A)	----	0.3786 (2.74)	0.3711 (6.66)
Wlodawa (PL)	0.3705 (2.14)	0.3231 (5.24)	0.4605 (6.37)
Wroclaw (PL)	0.3086 (3.19)	0.3938 (3.68)	0.4002 (6.47)
Zaragoza (E)	0.3914 (3.05)	0.3741 (4.33)	0.3322 (7.31)
Zugspitze (D)	0.3752 (3.79)	0.4608 (6.22)	0.3817 (6.25)
Zurich (CH)	0.4691 (3.34)	0.3993 (4.37)	0.3875 (7.05)

We observe in this table that imposing d = 0 produces a bias in the estimation of the time trend in favor of higher coefficients for the time trend. Thus, comparing d = 0 with the case of estimated d and white noise errors, in 95 out of the 114 stations, the time trend is higher under the (wrong) assumption of short memory or I(0) behaviour. That means that imposing a priori this restriction produces a higher increase in the temperatures than the one obtained when we estimate this differencing parameter, being in many cases, significantly higher than 0. Comparing now this case (d = 0) with the estimated d under autocorrelation, the time trend parameter is lower in 72 stations under the estimation of d with Bloomfield (1973) errors.

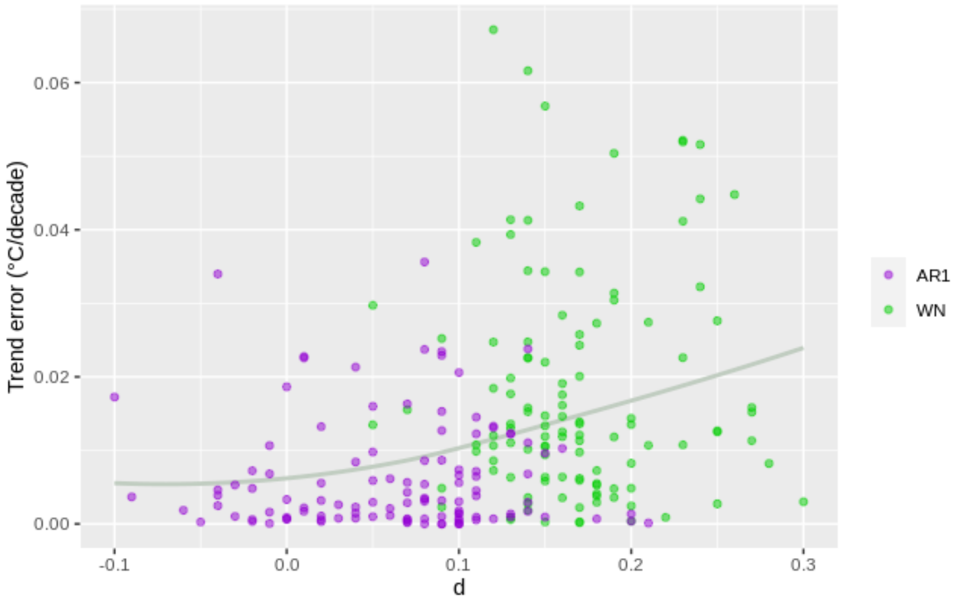
Figure 7: Models comparison



In the plot, the trend estimates obtained are compared: for each station, the x axis represents the trend under short memory assumption and the y axis the trend under the two models. Most of the observations fall below the bisector, meaning that the $d = 0$ assumption overestimates the trend.

In particular we can see that, as expected, the larger the persistence parameter is, the higher the difference between the I(0) scenario and the other two scenarios is. If we call δ the difference between the slope under d = 0, and the slope under another estimation of d, we obtain that the correlation between δ and d is 51% with white noise errors, and 60% with autocorrelated errors. Thus, long-memory has the effect of relaxing the increase of temperatures in our model.

Figure 8: Trends errors



Comparison of the absolute values of the differences between trends estimates under the assumption *d*=0, and under long-memory assumption. As we can observe, the increment of *d* has significant consequences on the estimation of the trend. The white noise assumption leads to higher estimates of *d* (on average, *d*=0.17 under white noise and *d*=0.06 with autocorrelated errors).

5. Concluding comments

We have examined in this paper the temperature anomalies in 114 European stations, examining the degree of persistence of the series by estimating the differencing parameter d. Our results indicate that under the white noise specification for the error term, most of the series display a long memory (stationary) pattern, presented in terms of a significantly positive order of integration. Allowing autocorrelation in the error term, the degree of persistence decreases, probably due to the competition between the I(d) and the autocorrelated I(0) structures in describing the time dependence. Nevertheless, positive values of d are found in most of the stations. This long memory feature also has an influence on the estimation of the time trend coefficients, generally observing lower values when the differencing parameter is estimated rather than imposed at zero. In other words, not taking into account the long memory feature in the data produces a bias in favor of higher coefficients in relation to the temperature warming. Even though the memory parameters measured under the white noise specification for the error term are higher than those based on the autocorrelation structure, the two models return similar results concerning the warming, concluding that the overall average increase of temperatures is about 0.35 °C/decade.

Dealing with the temperature trend, many people feel it is determined by the change in temperature, regardless of the reasons for the change. Part of these changes may be due to change in radiative forcing (global warming), while the other part may be due to persistence. Therefore, the time trend may be non-linear, an issue of great interest, noting that fractional integration and non-linear structures are intimately related (Diebold and Inoue, 2001; Granger and Hyung, 2004). In this context, tests like those proposed in Qu (2011) for testing spuriuos long memory can be implemented in the data, along with the examination of potential nonlinear structures using, for instance, Chebyshev polynomials in time (Cuestas and Gil-Alana, 2016), Fourier transform (Gil-Alana and Yaya, 2020) or even neural network structures as in Yaya et al. (2021), still in the context of fractional integration. Finally, the presence of inhomogeneities in the data, caused for instance by station rellocation or changes in the methods of observations, has not been investigated in this paper. The analysis based on homogeneized versions of the 114 series examined would allow us to compare the results between the raw and the homogeneized series, and this would permit us to evaluate the uncertainty of the persistence and trends due to the presence of non-climatic perturbations in the temperature series.

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