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RESEARCH

Trends and persistence in the number of hot days: some multi-country evidence

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Abstract

This paper uses fractional integration methods to obtain comprehensive evidence on the evolution of the number of hot days, defined as those with temperatures above 35 °C, in 54 countries from various regions of the world over the period from 1950 to 2022. The variable analysed is a key indicator of global warming, and the chosen modelling approach is most informative about the behaviour of the series as it provides evidence on the possible presence of time trends, on whether or not mean reversion occurs, and on the degree of persistence. In brief, the findings indicate the presence of considerable heterogeneity among the countries studied and highlight the importance of tailored climate policies based on both global and local factors.

1 Introduction

Analysing the evolution of maximum temperatures and the frequency of hot days is crucial to understand the impact of climate change. Existing studies point to a significant increase in average maximum temperature in several regions of the world (Yan et al. 2020; Francis and Fonseca 2024; Ogunrinde et al. 2024; etc.). This increase, combined with more frequent heat waves, is transforming weather patterns dramatically. The regions most affected include North Africa, sub-Saharan Africa, Central and West Asia, the Mediterranean and parts of the Americas. These changes are exacerbating aridity over vast tracts of land, with profound implications for food security, water resource availability, and both local and transnational migration patterns (Sun et al. 2018; Linares et al. 2020; Issa et al. 2023).

In particular, in Central Asia, North Africa and West Africa there has been a marked increase in maximum temperatures from previous ranges of 36–39 °C to new ones of 39–42 °C in several areas (Ogunrinde et al. 2024). In sub-Saharan Africa and the Sahel, models project even more extreme temperature increases between 3 and 6 °C by the end of the 21 st century (Weber et al. 2018; Ofori et al. 2021).

Heat waves, a climatic phenomenon associated with significant risks to public health and the economy, are also on the rise. In West and Central Africa, a considerable increase in both their frequency and duration is expected, especially in the most arid and vulnerable areas (Diedhiou et al. 2018). Similarly, in North Africa and West Asia, extreme temperatures not only affect the quality of life, but are also closely linked to an increase in the likelihood of socio-political conflicts and forced migrations (Abdel, 2024).

In East Africa, climate records highlight concerning upward trends in both maximum and minimum temperatures, underscoring the urgent need to implement sustainable, local-scale adaptation measures. These strategies must be based on a thorough understanding of the specific needs of the affected communities (Gebrechorkos et al. 2019).

The Mediterranean and the Middle East, regions which are particularly vulnerable to climate change, are also experiencing warming at an increasing rate. This phenomenon is more pronounced during the spring and summer seasons (Hadjinicolaou et al. 2023; Francis and Fonseca 2024). These trends affect local ecosystems, agricultural production and water resources, aggravating living conditions in communities already facing climate challenges.

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In China, there has also been a sharp increase in maximum temperatures and the frequency of hot days, especially since the 1990 s (Yan et al. 2020; Zhou and Lu 2021). In Australia, positive trends of more than 0.6 °C per decade have been detected in the highest temperatures of the year, and heat waves are becoming more intense, prolonged and frequent, affecting human health, agriculture and urban systems (Papari et al. 2020). Frederiksen and Osbrough (2022) analyse the systematic changes in precipitation and temperatures, both mean and extreme, in Australia since the beginning of the 20th century, identifying transitions towards a warmer and drier climate. They conclude that, over the last two decades, there has been a significant increase in the frequency of temperature extremes and a marked decrease in precipitation in the southwest and southeast of the country due to alterations in atmospheric circulation and possible climate tipping points. The same is happening in the US, where the frequency of extreme heat events is also increasing (Ombadi and Risser., 2022; Ibebuchi et al. 2024).

This context requires the development and implementation of region-specific adaptation strategies. These should consider the characteristics of agricultural, water and social systems, as well as the intrinsic vulnerability of each area to projected climate changes. Therefore, there is a need for studies evaluating the evolution and long-term patterns of maximum temperatures and extreme events. These are essential to identify trends, validate climate models and design informed and sustainable adaptation policies.

The present study contributes to this area of the literature by analysing annual data on the evolution of days with temperatures above 35 °C over the period from 1950 to 2022 in 54 countries from different regions of the world, including sub-Saharan Africa (Benin, Burkina Faso, Cameroon, Chad, Eritrea, Ethiopia, Gambia, Ghana, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, South Africa, Somalia, South Sudan, Sudan, Sudan and Togo), Central Asia (Kazakhstan, Tajikistan, Uzbekistan), South Asia (Afghanistan, Bangladesh, India, Nepal, Pakistan), North Africa (Algeria, Djibouti, Egypt, Libya, Morocco and Tunisia), West Asia and the Middle East (Bahrain, Iran, Iraq, Syria, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates and Yemen), East Asia and Pacific (Australia, China, Myanmar and Thailand), as well as parts of the Americas (Argentina, Mexico, Paraguay and the United States). The analysis uses fractional integration methods, which are ideally suited to our purposes. Note that most of the existing literature on this topic is based on the classical dichotomy between stationary (or integrated of order 0, denoted as I(0) and non-stationary (or I(1) series (see, e.g., Woodward and Gray 1993; Stern and Kaufmann 2000; Kaufmann et al. 2006, 2010; etc.). Such studies are based on standard unit roots tests that are now known to have very low power against fractional integration alternatives (see, e.g., Diebold and Rudebusch 1991; Hassler and Wolters, 1994; Lee and Schmidt 1996; etc.). By contrast, a fractional integration framework (see Granger 1980; Granger and Joyeux 1980; and Hosking 1981) is much more general and flexible, since the differencing parameter d is allowed to take any real value, including fractional ones. Consequently, it encompasses a much wider range of stochastic processes, including the unit root case, and provides key information about whether or not the series of interest are mean-reverting (and thus on whether exogenous shocks have permanent or transitory effects) and on their degree of persistence, with crucial implications for climate change policies.

The remainder of the paper is structured as follows: Section 2 briefly reviews the relevant literature; Section 3 introduces the modelling framework; Section 4 describes the data and presents the empirical results; Section 5 offers some concluding remarks.

2 Literature review

Understanding the evolution of temperatures and climatic conditions and their long-term trends, as well as changes in the frequency and intensity of extreme events, is essential to develop models generating reliable forecasts (Papacharalampous et al. 2018; Bahari and Hamid 2019; Liu et al. 2021; Domonkos et al. 2021; etc.). For this purpose, various methods have been used.

O'Kane et al. (2024) investigate climate regime shifts and tipping points in the Southern Hemisphere over the past few decades using observational data, reanalyses, numerical simulations and machine learning techniques. Their results reveal a marked transition in atmospheric circulation and climate stability since the late 1970 s, associated with oceanic warming and an increase in extreme events. These changes are directly linked to anthropogenic forcing and, under high-emission scenarios, are expected to intensify in the future.

Classical models, such as the autoregression integrated moving average (ARIMA) one, are widely employed due to their versatility in analysing and modelling stationary and non-stationary series. ARIMA specifications allow to decompose time series into trend, seasonal and noise components, providing a useful framework for making short-term temperature forecasts (Lai and Dzombak 2020; Dimri et al. 2020). However, this approach has limitations in the presence of long-range dependence between the observations, as in the case of temperature data, since past weather events may have persistent effects on future conditions (Chen et al. 2023).

Other common methods include exponential smoothing techniques (Taylor 2004), which prioritise recent observations to capture dynamic changes, and decomposition-based approaches such as seasonal or Fourier analysis (Yang 2013). These methods are useful for identifying periodic or cyclical patterns in the series, such as seasonal temperature variations. However, they are less suitable for capturing long-term trends and for distinguishing between stationary and non-stationary components in the series.

Regression analysis is another common tool, which is often used for exploring relationships between temperatures and variables such as greenhouse gas emissions, land use or geographic factors. However, this approach assumes linearity in the relationships, which may not be appropriate for climate data that exhibit complex and nonlinear behaviour (Deb and Jana 2021).

As already mentioned, a framework which is ideally suited to model the behaviour of temperature series is the autoregressive fractional integrated fractional moving average (ARFIMA) model (Granger and Joyeux 1980; Hosking 1981); this allows the differencing parameter d to be any real number, including fractional ones as opposed to integers only, and thus provides a more accurate description of both short- and long-range dependence (Huang et al. 2022), and it also yields more efficient estimates (Bhardwaj et al. 2020). Its generality and flexibility are particularly useful to distinguish between stationary and non-stationary processes, which is crucial to avoid erroneous conclusions about the evolution of weather patterns, and to capture the long-range dependence or long memory typically exhibited by temperatures (Caporale et al. 2024, 2025; Gil Alana et al., 2022, 2024, 2025). Climate series are often influenced by long-term phenomena, such as global warming, climate cycle variability or the cumulative impact of anthropogenic changes (Twaróg 2024), and therefore fractional integration techniques can shed light on their degree of persistence. Finally, these methods are a powerful tool for long-term forecasting of temperatures (Lenti and Gil-Alana 2021; Gil-Alana et al. 2022, 2024, 2025; Chibuzor and Gil-Alana 2024; Vyushin and Kushner 2009; Yuan et al. 2013) as they integrate system memory, and thus generate more accurate predictions reflecting underlying trends and persistence dynamics. The main features of this approach are described in the next section.

3 Fractional integration

Fractional integration can be defined in terms of the degree of differencing required to produce stationary *I(0)* behaviour in a series. Specifically, a process *x(t)*, *t* = *0*, *1*, *2* ... is said to be integrated of order *d*, and denoted as *I(d)*, if it can be written as:

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

where L stands for the lag operator, i.e., Lx(t) = x(t-1); *d* is a real positive value, and *u(t)* is an *I(0)* process that can be assumed to be a white noise process or alternatively a weakly autocorrelated one as in the stationary AutoRegressive Moving Average class of models.

The parameter *d* is called the differencing parameter; for non-integer values of *d*, one can use the following Binomial expansion of *L*, such that

$$(1-L)^{d}\;=\sum\nolimits_{j=1}^{\infty}\frac{\Gamma\;(d-1)\;(-L)^{j}}{\Gamma\;(d-j+1)\;\Gamma\;(j+1)}\,,$$

.

where Γ is the gamma function, which is defined as:

$$\Gamma\;(z)=\int_{0}^{\infty}t^{z-1}e^{-t}d\,(t)\,.$$

Alternatively, $(1-L)^{d}$ can be expressed as a Taylor expansion such that

$$(1-L)^{d}\;=\;\sum\nolimits_{j=0}^{\infty}\left(\begin{array}{c}d\\ j\end{array}\right)(-1)^{j}L^{j}\;=\;1\;-\;dL\;+\;\frac{d\,(d-1)}{2}L^{2}\;-\;\ldots$$

and thus Eq. (1) becomes:

$$x\,(t)\;\;=\;\;d\,x\,(t-1)\;-\;\frac{d\,(d-1)}{2}\,x\,(t-2)\;\;+\;\;...\;\;+\;\;u\,(t)\,.$$

Thus, for any non-integer *d*, *x(t)* becomes a function of all its past history, and the higher the value of *d* is, the higher the level of dependence between the observations.

Several cases can occur depending on the value of *d*, namely:

i) antipersistence, if d < 0, (e.g., when a process reverses itself more often than a pure random process; pink noise or 1/f noise),
ii) short memory, if *d* = 0, (e.g., a white noise process, stationary ARMA, etc.),

iii) stationary long memory, if $0<d<0.5$,
iv) nonstationary mean reversion, if $0.5 \le d<1$,
v) *I(1)* behaviour, if $d=1$, (e.g., a random walk process, ARIMA(p, 1, q), etc.)

In the empirical application carried out in the following section, we assume that *x(t)* are the errors in a regression model including a linear time trend, i.e.,

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

where *y(t)* is the observed series.

The estimation of *d* (and of the coefficients of the deterministic terms, i.e., *α* and *β*) is based on a maximum likelihood function expressed in the frequency domain. In fact, we use a simple version of a testing approach developed in Robinson (1994) and whose functional form can be found in Gil-Alana and Robinson (1997). It considers of testing the null hypothesis H_o: $d=d_o$, in the model given by Eqs. (1) and (2) for any d_o-values = −1 to 2 with 0.01 increments. The test statistic selects the 95% confidence interval, while the close value to zero approximates the maximum likelihood estimate. A fundamental reason for using this approach is that it is not restricted to the stationary range $d>0.5$) and therefore it does not require preliminary differentiation in case of nonstationary data. In addition, it is the most efficient method in the "Pitman" when directed against local departures from the null.

4 Data and empirical results

Data on the number of days per year with maximum temperature above 35 °C are taken from the World Bank Climate Change Knowledge Portal (2024), https://climateknowledgeportal.worldbank.org/); they are based on a heat index, which is a measure of temperature including the influence of atmospheric humidity and is constructed as explained in World Bank Group (2025).

We recognize that there is no universally accepted definition of a hot day. The decision to use an absolute threshold of 35 °C is based on methodological and practical reasons as it allows homogeneous comparability across countries and over time, which is essential for trend and persistence analysis by fractional integration. In addition, this variable, already calculated in the World Bank's Climate Change Portal database, is widely available and covered for 54 countries over the period 1950–2022. The portal is based on preconstructed climate indicators, including the annual number of days with maximum temperatures above 35 °C. The indicators are calculated from sources such as reanalyses and climate models. We should notice that the aggregation at the national level may mask internal climate variations, especially in large countries, and we note this as a limitation of the study in the conclusions.

Regarding the selection of countries and data sources, it is important to note that the sample of 54 countries was determined exclusively by the complete and continuous availability of annual data for the period 1950–2022, according to the records offered by the World Bank's Climate Change Knowledge Portal. While we recognize that this database may not reach the level of climatological accuracy of sources such as ERA5 or MERRA2, its main advantage lies in offering harmonized time series, comparable across countries and open access, which allows for a robust and reproducible implementation of the econometric methods used. In future research, the integration of alternative sources of higher geoscientific resolution could be considered, as well as the use of local thresholds derived from climate reanalyses.

The selected countries are all those for which data are available for the entire period from 1950 to 2022; the sample covers sub-Saharan Africa (Benin, Burkina Faso, Cameroon, Chad, Eritrea, Ethiopia, Gambia, Ghana, Mali, Mauritania, Mozambique, Niger, Nigeria, Senegal, South Africa, Somalia, South Sudan, Sudan and Togo), Central Asia (Kazakhstan, Tajikistan and Uzbekistan), South Asia (Afghanistan, Bangladesh, India, Nepal, Pakistan), North Africa (Algeria, Djibouti, Egypt, Libya, Morocco and Tunisia), West Asia and Middle East (Bahrain, Iran, Iraq, Syria, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, United Arab Emirates and Yemen), East Asia and Pacific (Australia, China, Myanmar and Thailand), as well as parts of the Americas (Argentina, Mexico, Paraguay and the United States).

Table 1 reports the estimates of *d* in Eqs. (1) and (2) under the assumption of white noise errors and for three different model specifications. The estimation is carried out using a general to specific approach. Column 4 shows the estimates of *d* (and the corresponding 95% confidence bands) from the most general model including both an intercept and a linear time trend. If the latter is found to be statistically insignificant, it is dropped from the regression, namely *β* is set equal to 0 in Eq. (2) and the model is re-estimated including only an intercept as the deterministic component; the corresponding estimates of *d* with their 95% confidence bands are displayed in column 3. Finally, if the intercept is also found to be insignificant, the model is re-estimated setting $\alpha=\beta=0$; column 2 reports the results obtained in this case.

Table 1 shows the estimates of *d*, with those corresponding to the selected models in bold. It can be seen that only

Table 1 Estimates of d under three deterministic specifications. White noise errors

North Africa			
Country	No terms	A constant	A constant and a linear trend
ALGERIA	0.39 (0.30, 0.56)	0.45 (0.38, 0.54)	**0.19 (0.08, 0.35)**
DJIBOUTI	0.33 (0.23, 0.48)	0.39 (0.29, 0.53)	**0.13 (−0.05, 0.39)**
EGYPT	0.34 (0.26, 0.46)	0.39 (0.31, 0.51)	**0.20 (0.09, 0.37)**
LIBYA	0.14 (0.07, 0.24)	0.19 (0.10, 0.32)	**−0.27 (−0.44, −0.02)**
MOROCCO	0.35 (0.27, 0.48)	0.41 (0.33, 0.52)	**0.15 (0.02, 0.34)**
TUNISIA	0.30 (0.22, 0.41)	0.34 (0.25, 0.44)	**0.16 (0.02, 0.33)**
Sub-Saharian Africa			
BENIN	0.27 (0.19, 0.40)	0.33 (0.24, 0.46)	**−0.09 (−0.28, 0.46)**
BURKINA FASO	0.29 (0.22, 0.40)	0.36 (0.28, 0.47)	**−0.07 (−0.24, 0.47)**
CAMEROON	0.23 (0.16, 0.35)	0.28 (0.19, 0.40)	**−0.05 (−0.18, 0.40)**
CHAD	0.49 (0.49, 0.60)	0.52 (0.45, 0.61)	**0.36 (0.25, 0.61)**
ERITREA	0.48 (0.39, 0.59)	0.52 (0.45, 0.64)	**0.29 (0.16, 0.64)**
ETHIOPIA	0.36 (0.27, 0.57)	0.47 (0.37, 0.62)	**0.26 (0.00, 0.62)**
GAMBIA	0.21 (0.13, 0.31)	0.24 (0.15, 0.35)	**−0.14 (−0.28, 0.35)**
GHANA	0.19 (0.09, 0.35)	0.21 (0.10, 0.38)	**0.04 (−0.12, 0.25)**
MALI			
MALI	0.30 (0.24, 0.38)	0.45 (0.38, 0.55)	**0.31 (−0.54, 0.03)**
MAURITANIA	0.30 (0.24, 0.42)	0.47 (0.39, 0.59)	**−0.04 (−0.23, 0.25)**
MOZAMBIQUE	0.28 (0.14, 0.47)	**0.28 (0.14, 0.48)**	0.25 (0.12, 0.46)
NIGER	0.41 (0.34, 0.52)	0.48 (0.41, 0.58)	**0.11 (−0.02, 0.31)**
NIGERIA	0.21 (0.14, 0.30)	0.26 (0.18, 0.36)	**−0.42 (−0.57, −0.17)**
SENEGAL	0.30 (0.23, 0.40)	0.37 (0.30, 0.47)	**−0.09 (−0.27, 0.14)**
SOUTH AFRICA	−0.01 (−0.12, 0.16)	−0.01 (−0.14, 0.18)	**−0.15 (−0.32, 0.09)**
SOMALIA	0.32 (0.24, 0.45)	0.40 (0.31, 0.52)	**0.08 (−0.11, 0.35)**
SOUTH SUDAN	0.26 (0.16, 0.41)	0.28 (0.18, 0.42)	**0.12 (−0.01, 0.32)**
SUDAN	0.47 (0.38, 0.63)	0.51 (0.43, 0.64)	**0.33 (0.17, 0.57)**
TOGO	0.08 (−0.01, 0.23)	0.10 (−0.01, 0.26)	**−0.17 (−0.37, 0.09)**
Central Asia			
KAZAKHSTAN	0.25 (0.15, 0.38)	0.26 (0.16, 0.39)	**0.17 (0.04, 0.33)**
TAJIKISTAN	0.49 (0.38, 0.64)	0.48 (0.37, 0.63)	**0.48 (0.37, 0.63)**
UZBEKISTAN	0.23 (0.13, 0.37)	0.25 (0.14, 0.38)	**0.18 (0.05, 0.33)**
South Asia			
AFGHANISTAN	0.24 (0.17, 0.34)	0.31 (0.23, 0.40)	**0.07 (−0.03, 0.21)**
BANGLADESH	0.13 (−0.01, 0.32)	0.11 (−0.01, 0.30)	**−0.01 (−0.18, 0.23)**
INDIA	−0.04 (−0.09, 0.34)	**−0.11 (−0.29, 0.16)**	−0.14 (−0.32, 0.14)
NEPAL	0.05 (−0.12, 0.26)	0.04 (−0.09, 0.20)	**−0.12 (−0.32, 0.15)**
PAKISTAN	0.43 (−0.04, 0.62)	**0.02 (−0.08, 0.16)**	−0.01 (−0.11, 0.14)
West Asia and Middle East			
BAHRAIN	0.31 (0.17, 0.52)	0.33 (0.19, 0.54)	**0.24 (0.06, 0.50)**
IRAN	0.47 (0.38, 0.61)	0.53 (0.46, 0.63)	**0.34 (0.23, 0.49)**
IRAQ	0.42 (0.32, 0.60)	0.46 (0.38, 0.56)	**0.31 (0.17, 0.50)**
SYRIA	0.05 (−0.04, 0.17)	0.06 (−0.04, 0.19)	**−0.12 (−0.24, 0.06)**
JORDAN	0.09 (−0.01, 0.20)	0.10 (−0.01, 0.22)	**−0.06 (−0.18, 0.10)**
KUWAIT	0.50 (0.36, 0.75)	0.45 (0.36, 0.55)	**0.34 (0.20, 0.53)**
OMAN	0.17 (0.12, 0.36)	0.36 (0.28, 0.49)	**−0.10 (−0.26, 0.18)**
QATAR	0.54 (0.42, 0.73)	0.54 (0.45, 0.69)	**0.46 (0.34, 0.66)**
SAUDI ARABIA	0.50 (0.43, 0.62)	0.56 (0.50, 0.65)	**0.37 (0.26, 0.54)**
SYRIA	0.25 (0.17, 0.37)	0.28 (0.19, 0.40)	**0.15 (0.04, 0.30)**
TURKEY	0.22 (0.13, 0.36)	0.24 (0.14, 0.38)	**0.15 (0.03, 0.32)**
U.A.E.	0.51 (0.41, 0.67)	0.52 (0.44, 0.64)	**0.43 (0.32, 0.59)**
YEMEN	0.54 (0.45, 0.70)	0.62 (0.53, 0.76)	**0.46 (0.28, 0.71)**
East Asia and Pacific			
AUSTRALIA	0.20 (0.06, 0.48)	0.25 (0.10, 0.48)	**0.14 (−0.06, 0.44)**
CHINA	0.45 (0.28, 0.70)	**0.36 (0.23, 0.55)**	0.36 (0.23, 0.55)

Table 1 (continued)

North Africa			
MYANMAR	0.03 (−0.06, 0.17)	0.04 (−0.08, 0.21)	**−0.29 (−0.52, 0.02)**
THAILAND	−0.06 (−0.16, 0.10)	−0.07 (−0.20, 0.12)	**−0.24 (−0.42, 0.01)**
America			
ARGENTINA	0.11 (−0.02, 0.33)	0.12 (−0.01, 0.32)	**0.08 (−0.10, 0.38)**
MEXICO	0.24 (0.14, 0.42)	0.31 (0.20, 0.47)	**0.13 (−0.03, 0.37)**
PARAGUAY	−0.02 (−0.14, 0.17)	**−0.02 (−0.15, 0.16)**	−0.01 (−0.15, 0.17)
U.S.A.	0.35 (0.24, 0.55)	0.41 (0.30, 0.57)	**0.27 (0.10, 0.50)**

In bold the selected specification on the basis of the statistical significance of the deterministic components. The reported values are the estimates of d, and in brackets the corresponding 95% confidence intervals

in five countries, namely Mozambique, India, Nepal, China and Paraguay, the time trend is not statistically significant and is not included in the preferred specification. The entire set of estimated coefficients corresponding to the latter is instead shown for each country in Table 2.

Concerning the estimates of d, it can be seen that the highest degrees of persistence are found in the cases of Tajikistan ($d = 0.48$), Qatar (0.46), Yemen (0.46), UAE (0.43) and Saudi Arabia (0.37). This parameter is significantly positive in 24 countries in total, the additional

Table 2 Estimated coefficients from the selected models. White noise errors

North Africa			
Country	diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
ALGERIA	0.19 (0.08, 0.35)	19.1234 (8.46)	0.4739 (9.31)
DJIBOUTI	0.13 (−0.05, 0.39)	−0.7466 (−0.46)	0.2413 (6.58)
EGYPT	0.20 (0.09, 0.37)	0.3750 (0.41)	0.1073 (5.30)
LIBYA	−0.27 (−0.44, −0.02)	0.2672 (2.28)	0.0687 (12.68)
MOROCCO	0.15 (0.02, 0.34)	1.3111 (2.97)	0.0848 (8.50)
TUNISIA	0.16 (0.02, 0.33)	−0.2058 (−2.21)	0.1334 (6.27
Sub-Saharian Africa			
BENIN	−0.09 (−0.28, 0.46)	−0.3268 (−1.99)	0.0448 (11.29)
BURKINA FASO	−0.07 (−0.24, 0.47)	−0.7746 (−1.71)	0.1574 (12.79)
CAMEROON	−0.05 (−0.18, 0.40)	−0.1669 (−1.94)	0.0181 (8.84)
CHAD	0.36 (0.25, 0.61)	−1.8865 (−1.09)	0.2409 (6.00)
ERITREA	0.29 (0.16, 0.64)	−0.5539 (−0.81)	0.1166 (7.56)
ETHIOPIA	0.26 (0.00, 0.62)	0.5729 (2.11)	0.0436 (7.14)
GAMBIA	−0.14 (−0.28, 0.35)	−0.4767 (−3.49)	0.0362 (10.74)
GHANA	0.04 (−0.12, 0.25)	−0.0906 (−1.98)	0.0074 (4.19)
MALI			
MALI	0.31 (−0.54, 0.03)	14.9884 (25.38)	0.6218 (39.82)
MAURITANIA	−0.04 (−0.23, 0.25)	15.4798 (12.34)	0.5061 (16.95)
MOZAMBIQUE	0.28 (0.14, 0.48)	0.0419 (1.76)	------
NIGER	0.11 (−0.02, 0.31)	−1.5606 (−1.07)	0.4072 (12.35)
NIGERIA	−0.42 (−0.57, −0.17)	−0.3132 (−6.08)	0.0384 (27.02)
SENEGAL	−0.09 (−0.27, 0.14)	−0.2115 (−0.35)	0.2294 (16.03)
SOUTH AFRICA	−0.15 (−0.32, 0.09)	−0.0047 (−1.94)	0.0003 (3.18)
SOMALIA	0.08 (−0.11, 0.35)	0.0069 (0.20)	0.0062 (8.10)
SOUTH SUDAN	0.12 (−0.01, 0.32)	−0.8026 (−1.66)	0.0466 (4.24)
SUDAN	0.33 (0.17, 0.57)	0.5948 (0.32)	0.2848 (6.82)
TOGO	−0.17 (−0.37, 0.09)	−0.0731 (−1.80)	0.0058 (5.74)
Central Asia			
KAZAKHSTAN	0.17 (0.04, 0.33)	−0.0136 (−0.19)	0.0058 (3.77)
TAJIKISTAN	0.48 (0.37, 0.63)	−0.0324 (−2.23)	0.0095 (2.72)
UZBEKISTAN	0.18 (0.05, 0.33)	0.0828 (0.15)	0.0433 (3.84)
South Asia			
AFGHANISTAN	0.07 (−0.03, 0.21)	3.0462 (5.66)	0.0938 (7.59)
BANGLADESH	−0.01 (−0.18, 0.23)	0.2836 (3.73)	−0.0046 (−2.60)

Table 2 (continued)

North Africa			
INDIA	−0.11 (−0.29, 0.16)	0.7991 (42.00)	------
NEPAL	−0.12 (−0.32, 0.15)	0.2355 (6.90)	−0.0026 (−3.08)
PAKISTAN	0.02 (−0.08, 0.16)	22.3880 (54.49)	-----
West Asia and Middle East			
BAHRAIN	0.24 (0.06, 0.50)	0.1026 (0.04)	0.1257 (2.49)
IRAN	0.34 (0.23, 0.49)	6.9583 (6.78)	0.1636 (6.91)
IRAQ	0.31 (0.17, 0.50)	19.6346 (4.44)	0.6325 (6.28)
SYRIA	−0.12 (−0.24, 0.06)	−0.0125 (−1.27)	0.0010 (4.11)
JORDAN	−0.06 (−0.18, 0.10)	−0.1473 (−2.81)	0.0188 (4.56)
KUWAIT	0.34 (0.20, 0.53)	51.8854 (7.81)	0.8274 (5.40)
OMAN	−0.10 (−0.26, 0.18)	26.7653 (25.71)	0.3002 (11.85)
QATAR	0.46 (0.34, 0.66)	24.0736 (3.05)	0.6784 (3.39)
SAUDI ARABIA	0.37 (0.26, 0.54)	12.7233 (3.03)	0.7463 (7.84)
SYRIA	0.15 (0.04, 0.30)	0.6866 (2.74)	0.0820 (3.93)
TURKEY	0.15 (0.03, 0.32)	0.0666 (1.61)	0.0022 (2.36)
U.A.E.	0.43 (0.32, 0.59)	30.68761 (3.99)	0.6339 (3.36)
YEMEN	0.46 (0.28, 0.71)	1.8171 (2.30)	0.1815 (5.14)
East Asia and Pacific			
AUSTRALIA	0.14 (−0.06, 0.44)	3.5900 (4.74)	0.0406 (2.35)
CHINA	0.36 (0.23, 0.55)	0.1342 (2.63)	------
MYANMAR	−0.29 (−0.52, 0.02)	0.0091 (2.42)	0.0038 (6.82)
THAILAND	−0.24 (−0.42, 0.01)	−0.0085 (−0.39)	0.0020 (3.68)
America			
ARGENTINA	0.08 (−0.10, 0.38)	0.0134 (2.26)	0.0039 (3.48)
MEXICO	0.13 (−0.03, 0.37)	0.1212 (3.11)	0.0041 (4.72)
PARAGUAY	−0.02 (−0.15, 0.16)	0.4142 (4.47)	------
U.S.A.	0.27 (0.10, 0.50)	0.0988 (2.06)	0.0054 (5.04)

Column 2 reports the estimate of d and in brackets the corresponding 95% confidence intervals, whilst column 3 and 4 report the estimates of the intercept and of the coefficient on the time trend respectively as well as the corresponding t-values in brackets; --- indicates lack of statistical significance

19 being Chad and China (0.36), Iran and Kuwait (0.34), Sudan (0.33), Iraq (0.31), Eritrea (0.29), Mozambique (0.28), USA (0.27), Ethiopia (0.26), Bahrain (0.24), Egypt (0.20), Algeria (0.19), Uzbekistan (0.18), Kazakhstan (0.17), Tunisia (0.16), Morocco, Syria and Turkey (0.15). In another 24 countries the estimated values of *d* are either positive or negative and the *I(0)* hypothesis of short memory cannot be rejected – these are Mali (0.31), Australia (0.14), Djibouti and Mexico (0.13), South Sudan (0.12), Niger (0.11), Argentina and Somalia (0.08), Afghanistan (0.07), Ghana (0.04), Pakistan (0.02), Bangladesh (−0.01), Paraguay (−0.02), Cameroon and Mauritania (−0.04), Jordan (−0.06), Burkina Faso and Afghanistan (−0.07), Benin and Senegal (−0.09), Oman (−0.10), India (−0.11), Syria and Nepal (−0.12), Gambia (−0.14), Togo (−0.17), Thailand (−0.24) and Myanmar (−0.29). Finally, two countries exhibit significant anti-persistent patterns, specifically Libya (−0.27) and Nigeria (−0.42). The time trend is significant in 49 countries, the highest coefficients being those corresponding to Kuwait (0.8274), Saudi Arabia (0.7463), Qatar (0.6784), UAE (0.6339), Iraq (0.6325), Mali (0.6218), Mauritania (0.5061) and Algeria (0.4739), while it is insignificant in five countries, namely Morocco, India, Pakistan, China and Paraguay.

Tables 3 and 4 have the same layout as Tables 1 and 2 but report the results under the assumption of autocorrelation in the error term modelled as in Bloomfield (1973). It can be seen from Table 3 that the time trend is now statistically insignificant in Tajikistan, Uzbekistan, Pakistan, China and Paraguay, in the latter three just as in the the previous case of white noise errors. Concerning the differencing parameter d, statistical evidence of a long memory pattern, i.e., $d > 0$, is now found in 19 countries, namely Tajikistan ($d = 0.84$), Uzbekistan (0.68), Tunisia, Kuwait and UAE (0.54), Saudi Arabia (0.49), Kazakhstan (0.48), Iraq (0.42), Chad and Qatar (0.41), Iran (0.40), Algeria (0.36), Afghanistan (0.34), Syria (0.30), Eritrea (0.24), Turkey (0.23), Pakistan and Egypt (0.22) and Sudan (0.17). Short memory or I(0) behaviour is found in 27 countries, namely China (0.30), Yemen (0.27), Morocco and Jordania (0.13), Mozambique and Argentina (0.08), Paraguay (0.06), USA (0.05), South Sudan (0.03), Niger

Table 3 Estimates of d under three deterministic specifications. Autocorrelated errors

North Africa			
Country	No terms	A constant	A constant and a linear trend
ALGERIA	0.73 (0.47, 1.06)	0.55 (0.40, 0.74)	**0.36 (0.13, 0.65)**
DJIBOUTI	0.28 (0.12, 0.51)	0.35 (0.17, 0.58)	**−0.21 (−0.73, 0.24)**
EGYPT	0.42 (0.28, 0.61)	0.47 (0.30, 0.66)	**0.22 (0.04, 0.50)**
LIBYA	0.19 (0.08, 0.37)	0.28 (0.11, 0.46)	**−0.52 (−1.08, −0.11)**
MOROCCO	0.39 (0.27, 0.60)	0.45 (0.32, 0.59)	**0.13 (−0.06, 0.40)**
TUNISIA	0.59 (0.35, 0.95)	0.55 (0.34, 0.93)	**0.54 (0.14, 0.94)**
Sub-Saharian Africa			
BENIN	0.28 (0.15, 0.44)	0.34 (0.18, 0.51)	**−0.42 (−0.75, −0.03)**
BURKINA FASO	0.35 (0.21, 0.54)	0.42 (0.27, 0.61)	**−0.32 (−0.71, 0.21)**
CAMEROON	0.29 (0.13, 0.46)	0.34 (0.18, 0.51)	**−0.09 (−0.38, 0.17)**
CHAD	0.58 (0.44, 0.75)	0.61 (0.48, 0.76)	**0.41 (0.20, 0.64)**
ERITREA	0.52 (0.40, 0.72)	0.57 (0.45, 0.74)	**0.24 (0.03, 0.57)**
ETHIOPIA	0.23 (0.12, 0.39)	0.36 (0.20, 0.53)	**−0.67 (−1.04, 0.11)**
GAMBIA	0.30 (0.18, 0.47)	0.35 (0.21, 0.51)	**−0.19 (−0.44, 0.12)**
GHANA	0.16 (−0.02, 0.42)	0.19 (−0.05, 0.45)	**−0.09 (−0.60, 0.29)**
MALI			
MALI	0.28 (0.19, 0.38)	0.42 (0.28, 0.55)	**−1.21 (−1.86, −0.58)**
MAURITANIA	0.25 (0.16, 0.37)	0.40 (0.25, 0.53)	**−0.54 (−0.95, −0.13)**
MOZAMBIQUE	0.12 (−0.15, 0.37)	0.12 (−0.12, 0.38)	**0.08 (−0.15, 0.34)**
NIGER	0.41 (0.30, 0.56)	0.48 (0.36, 0.62)	**−0.03 (−0.27, 0.25)**
NIGERIA	0.28 (0.17, 0.40)	0.35 (0.22, 0.49)	**−0.69 (−0.87, −0.39)**
SENEGAL	0.36 (0.23, 0.51)	0.43 (0.30, 0.57)	**−0.33 (−0.75, 0.17)**
SOUTH AFRICA	−0.05 (−0.24, 0.21)	−0.06 (−0.32, 0.26)	**−0.42 (−0.88, 0.05)**
SOMALIA	0.41 (0.24, 0.96)	0.51 (0.34, 0.97)	**−0.14 (−0.49, 0.98)**
SOUTH SUDAN	0.25 (0.07, 0.49)	0.28 (0.08, 0.49)	**0.03 (−0.22, 0.34)**
SUDAN	0.45 (0.33, 0.64)	0.51 (0.38, 0.68)	**0.17 (0.04, 0.49)**
TOGO	0.09 (−0.07, 0.32)	0.12 (−0.09, 0.39)	**−0.53 (−1.06, 0.04)**
Central Asia			
KAZAKHSTAN	0.54 (0.21, 0.85)	0.49 (0.20, 0.83)	**0.48 (0.16, 0.83)**
TAJIKISTAN	**0.84 (0.55, 1.13)**	0.84 (0.48, 1.13)	0.83 (0.57, 1.14)
UZBEKISTAN	**0.68 (0.25, 1.00)**	0.59 (0.18, 1.00)	0.68 (0.30, 1.01)
South Asia			
AFGHANISTAN	0.55 (0.37, 0.79)	0.52 (0.39, 0.68)	**0.34 (0.15, 0.56)**
BANGLADESH	0.11 (−0.17, 0.43)	0.07 (−0.12, 0.37)	**−0.24 (−0.51, 0.17)**
INDIA	−0.11 (−0.19, 0.35)	−0.48 (−0.80, −0.08)	**−0.54 (−0.82, −0.15)**
NEPAL	0.01 (−0.29, 0.40)	0.01 (−0.34, 0.31)	**−0.42 (−0.74, 0.09)**
PAKISTAN	0.70 (0.40, 0.99)	**0.22 (0.03, 0.49)**	0.18 (−0.01, 0.48)
West Asia and Middle East			
BAHRAIN	0.15 (−0.04, 0.47)	0.17 (−0.04, 0.47)	**−0.05 (−0.41, 0.41)**
IRAN	0.61 (0.45, 0.83)	0.59 (0.45, 0.75)	**0.40 (0.25, 0.63)**
IRAQ	0.60 (0.36, 1.03)	0.58 (0.44, 0.89)	**0.42 (0.11, 0.90)**
SYRIA	0.18 (0.02, 0.42)	0.21 (0.03, 0.46)	**−0.05 (−0.29, 0.32)**
JORDAN	0.28 (0.10, 0.54)	0.31 (0.12, 0.56)	**0.13 (−0.10, 0.47)**
KUWAIT	0.73 (0.38, 1.08)	0.62 (0.44, 1.07)	**0.54 (0.09, 1.06)**
OMAN	0.18 (0.12, 0.40)	0.40 (0.27, 0.59)	**−0.30 (−0.47, 0.02)**
QATAR	0.52 (0.37, 0.80)	0.57 (0.42, 0.78)	**0.41 (0.21, 0.71)**
SAUDI ARABIA	0.63 (0.50, 0.90)	0.70 (0.58, 0.90)	**0.49 (0.28, 0.83)**
SYRIA	0.42 (0.26, 0.64)	0.44 (0.29, 0.64)	**0.30 (0.11, 0.57)**
TURKEY	0.33 (0.17, 0.57)	0.37 (0.21, 0.58)	**0.23 (0.01, 0.56)**
U.A.E.	0.59 (0.43, 0.87)	0.65 (0.51, 0.88)	**0.54 (0.34, 0.84)**
YEMEN	0.53 (0.42, 0.71)	0.63 (0.51, 1.23)	**0.27 (−0.01, 0.77)**
East Asia and Pacific			
AUSTRALIA	0.03 (−0.08, 0.26)	0.06 (−0.18, 0.34)	**−0.24 (−0.60, 0.14)**
CHINA	0.35 (−0.01, 1.04)	**0.30 (−0.03, 0.71)**	0.35 (0.01, 0.69)

Table 3 (continued)

North Africa			
MYANMAR	−0.02 (−0.15, 0.17)	−0.03 (−0.22, 0.21)	**−1.03 (−1.69, −0.32)**
THAILAND	−0.11 (−0.28, 0.14)	−0.15 (−0.41, 0.17)	**−0.55 (−1.17, −0.08)**
America			
ARGENTINA	0.10 (−0.09, 0.64)	0.13 (−0.13, 0.51)	**0.08 (−0.29, 0.86)**
MEXICO	0.19 (0.06, 0.48)	0.28 (0.08, 0.52)	**−0.06 (−0.39, 0.33)**
PARAGUAY	0.06 (−0.25, 0.53)	**0.06 (−0.23, 0.48)**	0.10 (−0.20, 0.57)
U.S.A.	0.25 (0.07, 0.54)	0.30 (0.11, 0.50)	**0.05 (−0.29, 0.41)**

In bold the selected specification on the basis of the statistical significance of the deterministic components. The reported values are the estimates of d, and in brackets the corresponding 95% confidence intervals

Table 4 Estimated coefficients from the selected models. Autocorrelated errors

North Africa			
Country	diff. par. (95% band)	Intercept (t-value)	Time trend (t-value)
ALGERIA	0.36 (0.13, 0.65)	20.3542 (6.10)	0.4693 (6.04)
DJIBOUTI	−0.21 (−0.73, 0.24)	−0.7076 (−1.19)	0.2368 (15.80)
EGYPT	0.22 (0.04, 0.50)	0.4061 (0.43)	0.1069 (5.03)
LIBYA	−0.52 (−1.08, −0.11)	0.2828 (−1.08)	0.0681 (24.87)
MOROCCO	0.13 (−0.06, 0.40)	1.2932 (−0.06)	0.0849 (8.95)
TUNISIA	0.54 (0.14, 0.94)	0.1199 (0.05)	0.1442 (2.53)
Sub-Saharian Africa			
BENIN	−0.42 (−0.75, −0.03)	−0.3207 (−5.66)	0.0443 (28.22)
BURKINA FASO	−0.32 (−0.71, 0.21)	−0.7488 (−3.14)	0.1559 (24.69)
CAMEROON	−0.09 (−0.38, 0.17)	−0.1676 (−2.20)	0.0181 (9.80)
CHAD	0.41 (0.20, 0.64)	−1.6176 (−0.85)	0.2388 (5.22)
ERITREA	0.24 (0.03, 0.57)	−0.6227 (−1.03)	0.1176 (8.64)
ETHIOPIA	−0.67 (−1.04, 0.11)	0.7013 (42.74)	0.0409 (81.60)
GAMBIA	−0.19 (−0.44, 0.12)	−0.4760 (−4.06)	0.0361 (12.23)
GHANA MALI	−0.09 (−0.60, 0.29)	−0.0912 (−0.60)	0.0073 (5.78)
MALI	−1.21 (−1.86, −0.58)	15.2272 (446.99)	0.6133 (485.57)
MAURITANIA	−0.54 (−0.95, −0.13)	15.5827 (60.43)	0.5006 (66.88)
MOZAMBIQUE	0.08 (−0.15, 0.34)	0.0028 (0.12)	0.0009 (1.71)
NIGER	−0.03 (−0.27, 0.25)	−1.7392 (−1.80)	0.4081 (17.80)
NIGERIA	−0.69 (−0.87, −0.39)	−0.3105 (−13.76)	0.0384 (55.49)
SENEGAL	−0.33 (−0.75, 0.17)	0.0233 (1.24)	0.2259 (5.37)
SOUTH AFRICA	−0.42 (−0.88, 0.05)	−0.0044 (−2.26)	0.0003 (6.36)
SOMALIA	−0.14 (−0.49, 0.98)	0.0045 (00.25)	0.0063 (14.53)
SOUTH SUDAN	0.03 (−0.22, 0.34)	−0.8439 (−2.25)	0.0466 (5.35)
SUDAN	0.17 (0.04, 0.49)	0.2383 (0.19)	0.2875 (10.36)
TOGO	−0.53 (−1.06, 0.04)	−0.0658 (−5.00)	0.0055 (14.53)
Central Asia			
KAZAKHSTAN	0.48 (0.16, 0.83)	0.0183 (0.14)	0.0064 (1.87)
TAJIKISTAN	0.84 (0.55, 1.13)	------	------
UZBEKISTAN	0.68 (0.25, 1.00)	------	------
South Asia			
AFGHANISTAN	0.34 (0.15, 0.56)	3.2783 (3.19)	0.0940 (3.96)
BANGLADESH	−0.24 (−0.51, 0.17)	0.2914 (7.70)	−0.0049 (−5.08)
INDIA	−0.54 (−0.82, −0.15)	8.2815 (61.02)	0.0132 (3.36)
NEPAL	−0.42 (−0.74, 0.09)	0.2361 (17.65)	−0.0025 (−6.91)
PAKISTAN	0.22 (0.03, 0.49)	22.5716 (27.01)	------
West Asia and Middle East			
BAHRAIN	−0.05 (−0.41, 0.41)	−0.2843 (−0.28)	0.1259 (5.29)
IRAN	0.40 (0.25, 0.63)	7.1588 (6.21)	0.1621 (5.88)

Table 4 (continued)

North Africa			
IRAQ	0.42 (0.11, 0.90)	19.2862 (3.51)	0.6428 (4.81)
SYRIA	−0.05 (−0.29, 0.32)	−0.0119 (−0.98)	0.0009 (3.39)
JORDAN	0.13 (−0.10, 0.47)	−0.1355 (−0.46)	0.0192 (2.90)
KUWAIT	0.54 (0.09, 1.06)	48.2138 (5.18)	0.8714 (3.29)
OMAN	−0.30 (−0.47, 0.02)	26.4727 (46.62)	0.3088 (20.65)
QATAR	0.41 (0.21, 0.71)	23.2478 (3.21)	0.6844 (3.93)
SAUDI ARABIA	0.49 (0.28, 0.83)	14.0864 (2.82)	0.7323 (5.59)
SYRIA	0.30 (0.11, 0.57)	0.9216 (0.69)	0.0804 (2.67)
TURKEY	0.23 (0.01, 0.56)	0.0741 (1.47)	0.0021 (1.82)
U.A.E.	0.54 (0.34, 0.84)	32.3177 (3.57)	0.6182 (2.40)
YEMEN	0.27 (−0.01, 0.77)	1.1794 (1.23)	0.1962 (9.10)
East Asia and Pacific			
AUSTRALIA	−0.24 (−0.60, 0.14)	3.5276 (14.55)	0.0396 (6.36)
CHINA	0.30 (−0.03, 0.71)	0.1312 (2.65)	------
MYANMAR	−1.03 (−1.69, −0.32)	−0.0148 (7.01)	0.0037 (49.63)
THAILAND	−0.55 (−1.17, −0.08)	−0.0551 (−0.67)	0.0019 (8.08)
America			
ARGENTINA	0.08 (−0.29, 0.86)	0.0134 (0.26)	0.0039 (3.48)
MEXICO	−0.06 (−0.39, 0.33)	0.1226 (5.44)	0.0040 (7.51)
PARAGUAY	0.06 (−0.23, 0.48)	0.4202 (2.98)	------
U.S.A.	0.05 (−0.29, 0.41)	0.10004 (3.75)	0.0052 (8.41)

Column 2 reports the estimate of d and in brackets the corresponding 95% confidence intervals, whilst column 3 and 4 report the estimates of the intercept and of the coefficient on the time trend respectively as well as the corresponding t-values in brackets; --- indicates lack of statistical significance

(−0.3), Syria and Bahrain (−0.05), Mexico (−0.06), Cameron and Ghana (−0.09), Somalia (−0.14) Gambia (−0.19), Djibouti (−0.21), Bangladesh and Australia (−0.24), Oman (−0.30), Burkina Faso (−0.32), Senegal (−0.33), Nepal and South Africa (−0.42), Togo (−0.53), and Eritrea and Ethiopia (−0.67). Further, 8 countries exhibit anti-persistence ($d<0$), namely Benin (−0.42), Libya (−0.52), India and Mauritania (−0.54), Thailand (−0.55), Nigeria (−0.69), Myanmar (−1.09) and Mali (−1.21). Finally, the countries with the highest time trend coefficients are Kuwait (0.8714), Saudi Arabia (0.7323), Qatar (0.6844), Iraq (0.6428), U.A.E. (0.6182), Mali (0.6122), Mauritania (0.5006) and Algeria (0.4693). Tables 5 and 6 provide a summary of the results concerning the time trends and the degree of persistence respectively.

Table 6 Summary results. Persistence

No autocorrelation		With autocorrelation	
Highest d	Lowest d	Highest d	Lowest d
Tajkistan (0.48)	Nigeria (−0.42)	Tajkistan (0.84)	Mali (−1.21)
Qatar (0.46)	Myanmar (−0.29)	Uzbekistan (0.68)	Myanmar (−1.03)
Yemen (0.46)	Libya (−0.27)	Kuwait (0.53)	Nigeria (−0.69)
U.A.E. (0.43)	Thailand (−0.24)	U.A.E. (0.54)	Ethiopia (−0.67)
Saudi Arabia (0.37)	Togo (−0.17)	Tunisia (0.54)	Thailand (−0.55)
Chad (0.36)	South Africa (−0.15)	Saudi Arabia (0.49)	India (−0.54)
China (0.36)	Gambia (−0.14)	Kazakhstan (0.48)	Mauritania (−0.54)
Iran (0.34)	Nepal (−0.12)	Iraq (0.42)	Togo (−0.53)
Kuwait (0.34)	Syria (−0.12)	Qatar (0.41)	Libya (−0.52)
Sudan (0.33)	India (−0.11)	Chad (0.40)	Benin (−0.42)
Mali (0.31)	Oman (−0.10)	Iran (0.40)	Nepal (−0.42)
Iraq (0.31)		Algeria (0.36)	South Africa (−0.42)
		Afghanistan (0.34)	

Table 5 Summary results. Time trends

No autocorrelation		With autocorrelation	
Highest time trends	No time trends	Highest time trends	No time trends
Kuwait (0.8274)	Morocco	Kuwait (0.8714)	Tajikistan
Saudi Arabia (0.7463)	India	Saudi Arabia (0.7323)	Uzbekistan
Qatar (0.6784)	Pakistan	Qatar (0.6844)	Pakistan
U.A.E. (0.6339)	China	Iraq (0.6428)	China
Iraq (0.6325)	Paraguay	U.A.E. (0.6182)	Paraguay
Mali (0.6218)		Mali (0.6122)	
Mauritania (0.5061)		Mauritania (0.5006)	
Algeria (0.4739)		Algeria (0.4693)	

5 Conclusions

The number of hot days, namely those with temperatures above 35 °C, is often used as a measure of global warming and as the basis to design appropriate policies to tackle climate change. This paper uses fractional integration methods to obtain comprehensive evidence on how this variable has evolved in 54 countries from various regions of the world over the period from 1950 to 2022. The chosen modelling approach is most informative about the behaviour of the series as it provides evidence on the possible presence of time trends, on whether or not mean reversion occurs, and on the degree of persistence, with important implications for the design of effective climate policies. In brief, the findings indicate considerable heterogeneity among the countries studied.

More specifically, the results show that the Middle Eastern countries (in particular Kuwait, Saudi Arabia and Qatar) are those with the most pronounced upward trends. This result is in agreement with previous studies indicating that the Middle East, especially the Arabian Peninsula, is experiencing faster warming than the global average (Zittis et al. 2022; Masoudi et al. 2024).

Warming in this region is driven by a combination of global factors such as increased greenhouse gases (Malik et al. 2024) and local factors such as desertification, vegetation decrease and the urban heat island effect in densely populated cities (Adamo et al. 2022). Since this geographical area is characterised by arid and semi-arid climates, it is particularly vulnerable to small variations in temperature due to the limited capacity of the ecosystem to buffer climatic changes (Malik et al. 2024; Zittis et al. 2022).

Worrying positive trends are also found in the case of sub-Saharan Africa, where climatic conditions already severely limit water availability and agricultural productivity. In this region, global warming not only intensifies droughts, but also increases the frequency and intensity of heat waves, with direct effects on public health and food security (Ahmed 2020).

By contrast, there is less evidence of concerning trends in countries such as Morocco, China, India and Paraguay, which appear to be characterised by a more stable climate. This is likely to reflect local factors, such as effective environmental policies, higher levels of vegetation or natural climate variability, which counteract the effects of global warming. In particular, in India and China efforts to reduce emissions through climate policies and reforestation programmes could be contributing to this behaviour (Yu et al. 2020; Li et al. 2022).

As for persistence, the results based on white noise errors indicate that Tajikistan, Qatar, Yemen, UAE and Saudi Arabia are the countries where long-range dependence is most apparent. This could reflect reduced rainfall, increased greenhouse gas emissions and the retreat of resilient ecosystems. Under the assumption of autocorrelated errors an even higher degree of persistence is estimated in countries such as Tajikistan, Uzbekistan and Kuwait. In Central Asia this evidence could be linked to increasing aridity and altered atmospheric patterns resulting from both human activity and natural phenomena (Alahmad et al. 2022; Zong et al. 2020).

In other countries the estimates instead imply the presence of anti-persistence. These include Nigeria, Libya, Ethiopia, Mauritania, Myanmar, Thailand and India, with the coefficients being even bigger in absolute terms under the assumption of autocorrelated errors, for instance in Mali and Myanmar. The anti-persistence identified in these cases reflects climate patterns determined by extreme events counteracting each other over time and resulting in more pronounced and less predictable fluctuations. This feature may be associated with local factors such as massive deforestation, abrupt land-use changes, seasonal variability and socio-political instabilities, that limit the capacity of ecosystems and social systems to respond to climate change. In the case of Nigeria, for example, thermal fluctuations could be related to the impact of massive deforestation (Zaccheaus 2015), while in Myanmar and Libya, political and social instabilities have resulted in less effective climate change monitoring. In terms of climate change such patterns imply that these regions are highly vulnerable to sudden and variable weather changes. This phenomenon requires further analysis to develop adaptive strategies aimed at mitigating the risks inherent in this unusual thermal behaviour.

To sum up, the findings in this study indicate diverse climate patterns in different regions of the world, some of them, such as the Middle East and Sub-Saharan Africa, being characterised by pronounced upward trends and high persistence in the number of hot days, whilst in others there is less evidence of sustained warming. The observed differences reflect the interaction between the global phenomenon of climate change and local factors affecting warming. This evidence underscores the importance of adopting differentiated approaches to mitigate the effects of climate change, prioritising strategies that address both global factors and specific local dynamics.

A limitation of the present study is the use of a uniform absolute threshold of 35 °C to define a hot day in all countries analysed. While there is no universally accepted definition of this concept and that relative or locally adjusted thresholds would ideally be adopted, the choice of this threshold is justified for reasons of methodological comparability between countries and over time. Moreover, this threshold has support in the literature as an indicator of thermal health risk conditions in many regions (Raymond et al. 2020; Lu et al. 2023; Sun et al. 2018). However, we recognize that this choice may not adequately capture regional climatic diversity or differential impacts of extreme heat. Therefore, as a line of research, we propose to complement this analysis using other available thresholds (such as 40–42 °C) and explore relative definitions more sensitive to the local climate context which would allow for a more accurate characterization of thermal extremes and their implications. Work in this direction is now in progress.

Author contributions GMC proposed the original idea, and he participated in the interpretation of the results, conclusions and overall reading of the paper.LAGA obtained the dataset, wrote the codes and got the results. He also participated in the interpretation of the results, conclusions and writing.NCG wrote the introduction, the literature review and participated in the interpretation of the results and conclusions.

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Data availability Data are available from the authors upon request.

Declarations

Competing interests The authors declare no competing interests.

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