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Trends in temperatures in Sub-Saharan Africa. Evidence of global warming☆

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ABSTRACT

Climate change has become a serious environmental matter of global concern. This paper attempts to verify if there is climatic change in Sub-Saharan Africa with the help of monthly station data from January 1901 to December 2020 on the mean temperatures of 48 countries of Sub-Saharan Africa. To do this, we employ fractional integration to account for the data's probable long memory feature. However, because other statistical features such as linear trends and seasonality might also be present in the data, we propose a broad framework that treats these three characteristics (long-range dependence, time trends, and seasonality) in a unified treatment. We first note that long memory is an observed feature in the data and using the original data, the time trends are found to be significant in Southern and Eastern countries, with higher coefficients being observed when the post-War II data are employed. When looking at the anomalies with respect to selected periods, long memory is found in all cases, and a higher number of trends are detected. Thus, 41 countries show significant time trends, with the values being higher again in the post WW2 sample, suggesting that industrialization might have contributed to global warming. The results also indicate some degree of heterogeneity across the African countries.

1. Introduction

Global warming has become a serious matter of concern to all and sundry with respect to both the environment in the world today and to that of the future. According to IPCC (2018), global warming produced by human activity is expected to be around 1.0 °C higher than in pre-industrial periods, with a possible range between 0.8 °C and 1.2 °C. If current trends continue, the warming would reach 1.5 °C between 2030 and 2052. The report noted that some regions are experiencing warming that is greater than the global annual average. Ray (2021) stated that, Sub-Saharan Africa is predicted to see greater warming than the rest of the world. This is in line with the opinion of Shepard (2019) who stated that the Sub-Saharan region is expected to experience a temperature rise above that of the rise in the global mean temperature. He stressed that African regions within a 15° radius of the equator are expected to experience hotter nights and frequent and protracted heat waves.

Nevertheless, these are all projections, though based on the present and historical records. This is the reason why this study aims to ascertain if there is global warming in Sub-Saharan Africa by checking for significant trends in Sub-Saharan Africa employing historical data on mean temperature in the region.

Though there are many modelling frameworks when dealing with temperatures, including among others, Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), structural models, etc., we use in this article, a long memory class of models denominated, fractionally integrated. This is not new since previous research has used fractional integration to assess temperature time series (Baillie and Chung, 2002; Gil-Alana, 2003, 2005, 2008a,b; Mills, 2007; Rea et al., 2011; Choudhary et al., 2016; Gil-Alana and Sauci, 2019a,b; Vera-Valdes, 2021; etc.). This paper, therefore, aims, with the aid of fractional integration, to examine the monthly data on temperatures in Sub Saharan Africa to see if there is global warming by testing for linear time trends, persistence and seasonality. Thus, the originality of this work focuses on the methodology used that, though not new, has not been employed so far in the analysis of Sub-Saharan African climatological data. This methodology is more flexible and general than the standard methods that use exclusively ARMA or ARIMA models for the

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Table 1
Descriptive statistics for the whole sample for mean temperature (original data).

COUNTRY	MEAN	SD	MEDIAN	MIN	MAX	RANGE
ANGOLA	21.56	1.76	22.42	17.11	24.35	7.24
BENIN	27.58	1.73	27.21	23.56	32.60	9.04
BOTSWANA	21.61	4.43	23.09	12.04	28.21	16.17
BURKINA FASO	28.21	2.37	27.86	22.17	33.92	11.75
BURUNDI	20.13	0.76	20.12	18.02	22.59	4.57
CABO VERDE	22.97	1.83	22.82	18.82	26.62	7.80
CAMEROON	24.68	1.12	24.36	22.58	27.85	5.27
CENTRAL AFRICAN REP.	25.01	1.26	24.60	21.81	28.35	6.54
CHAD	26.86	3.42	27.80	18.56	32.71	14.15
COMOROS	24.68	1.12	24.36	22.58	27.85	5.27
CONGO (DR)	24.11	0.59	24.19	22.22	25.68	3.46
CONGO REP.	24.63	0.84	24.64	22.17	26.75	4.58
COTE D'IVOIRE	26.42	1.28	26.19	23.72	30.28	6.56
EQUATORIAL GUINEA	24.31	0.80	24.37	21.96	26.60	4.64
ERITREA	26.29	2.38	26.80	20.28	31.14	10.86
ESWATINI	20.07	2.99	20.51	12.91	25.90	12.99
ETHOPIA	22.55	1.12	22.53	18.70	26.27	7.57
GABON	25.12	1.05	25.28	21.99	27.33	5.34
GAMBIA(THE)	27.42	1.80	27.56	22.26	31.31	9.05
GHANA	27.32	1.45	27.09	24.17	31.07	6.90
GUINEA	25.75	1.53	25.34	22.69	30.07	7.38
GUINEA BISSAU	26.92	1.63	26.82	22.83	31.13	8.30
KENYA	24.39	1.24	24.50	20.66	27.96	7.30
LESOTHO	11.91	4.09	12.66	3.35	19.21	15.86
LIBERIA	25.45	0.93	25.48	22.98	28.24	5.26
MADAGASCAR	22.48	2.07	23.06	17.95	26.10	8.15
MALAWI	22.05	2.34	22.73	16.68	26.55	9.87
MALI	28.32	4.10	29.72	18.99	34.81	15.82
MAURITANIA	27.82	4.70	28.94	18.27	34.50	16.23
MAURITUS	23.19	2.03	23.32	19.37	27.11	7.74
MOZAMBIQUE	23.85	2.45	24.69	18.34	27.77	9.43
NAMIBIA	20.14	3.63	21.16	12.77	26.06	13.29
NIGER	27.43	4.71	29.20	15.84	34.66	18.82
NIGERIA	26.94	1.80	26.61	21.67	31.61	9.94
RWANDA	18.82	0.64	18.84	17.04	20.70	3.66
SAO TOME &PRINCIPE	22.96	1.16	23.20	20.00	25.20	5.20
SENEGAL	28.11	2.11	28.21	22.48	32.76	10.28
SEYCHELLES	27.07	0.85	27.06	24.83	29.40	4.57
SIERRA LEONE	26.22	1.10	26.05	23.63	29.44	5.81
SOMALIA	26.87	1.16	27.06	23.73	29.28	5.55
SOUTH AFRICA	17.62	4.35	18.13	8.96	24.88	15.92
SOUTH SUDAN	26.98	1.52	26.68	23.45	31.76	8.31
SUDAN	27.01	3.77	28.38	17.45	33.18	15.73
TANZANIA	22.25	1.32	22.52	18.58	24.83	6.25
TOGO	27.03	1.56	26.84	23.32	31.61	8.29
UGANDA	22.53	1.03	22.51	19.63	26.04	6.41
ZAMBIA	21.77	2.57	22.66	15.63	26.68	11.05
ZIMBABWE	21.23	3.28	22.37	13.66	26.42	12.76

description of the data if they are stationary or nonstationary respectively. In the former case, the order of integration is 0 while in the latter, it is 1. Allowing for fractional integration we can consider, for example, situations where the series are nonstationary but display reversion to the mean if the order of integration is higher than 0.5 but smaller than 1.

The results reported in the paper can be anticipated as follows: fractional degrees of integration are found in all the original temperature data, and significant time trends are observed in the cases of Lesotho, South Africa and Eswatini (in Southern Africa), and in South Sudan, Rwanda and Burundi (in East Africa). For the anomalies, long memory (i.e., fractional integration) is also found in all cases and time trends are now significant in all except in seven countries. Nevertheless, we also notice a degree of heterogeneity in the results about global warming in the Sub-Saharan region.

The rest of the article is structured as follows: In Section 2, we look at the contextual settings and a short literature review; Section 3 briefly explains the methodology, which relies on fractional integration; Section 4 explains the dataset; Section 5 reports the empirical results, while Section 6 contains the conclusions of the paper.

2. Contextual setting and a short literature review

Global warming is evident in the persistent rise in temperatures in the globe. The term "global warming" refers to an increase in global temperatures mostly caused by rising greenhouse gas concentrations in the atmosphere. Consider the solar radiation that warms the Earth's surface and the thermal radiation that is radiated out to space to understand the basic concept of global warming. These two radiation streams must, on average, be in equilibrium. The greenhouse effect occurs when greenhouse gases absorb thermal radiation released by the Earth's surface and prevents them from passing though. The greenhouse effect occurs when infrared radiation is prevented from passing through (absorbed by) the greenhouses gases, but visible radiation passes through. The basic radiation balance is disrupted if the levels of greenhouse gases generated by human activities rises. An increase in the Earth's surface temperature can help to restore the equilibrium. (Houghton, 2005).

Over the last century, the global mean surface temperature has grown by 0.6 ± 0.2 °C, and by 2100, the temperature increase might

Table 2
Estimated time trend coefficients imposing in Eq. (1) that d = 0.

	Total sample			Data starting at 1946m1		
	alpha	beta	Seas.	Alpha	beta	Seas.
ANGOLA	21.2924 (229.99)	**0.00037 (3.34)**	0.970	21.3455 (183.00)	**0.00064 (2.86)**	0.964
BENIN	27.3007 (299.84)	**0.00038 (3.50)**	0.897	27.0900 (238.23)	**0.00112 (5.15)**	0.915
BOTSWANA	20.9982 (90.11)	**0.00086 (3.05)**	0.978	21.1825 (72.34)	**0.00136 (2.41)**	0.976
BURKINA F.	27.6744 (223.51)	**0.00075 (5.04)**	0.914	27.8008 (179.26)	**0.00124 (4.14)**	0.922
BURUNDI	19.5213 (551.57)	**0.00084 (19.76)**	0.689	19.8695 (468.12)	**0.00107 (13.06)**	0.665
CABO VERDE	22.7512 (236.14)	**0.00031 (2.67)**	0.938	22.6855 (192.17)	**0.00073 (3.25)**	0.938
CAMEROON	24.5077 (415.14)	**0.00023 (3.23)**	0.920	24.5507 (326.24)	**0.00036 (2.52)**	0.906
C. AF. REP.	24.7601 (372.36)	**0.00034 (4.32)**	0.910	24.7714 (285.49)	**0.00066 (3.95)**	0.887
CHAD	26.4384 (147.22)	**0.00058 (2.69)**	0.972	26.1441 (11.354)	**0.00170 (3.83)**	0.963
COMOROS	24.5097 (415.14)	**0.00023 _(3.23)**	0.920	24.5507 (326.24)	**0.00036 (2.52)**	0.906
CONGO (DR)	23.8747 (787.35)	**0.00032 (8.92)**	0.856	23.8646 (607.85)	**0.00067 (8.92)**	0.807
CONGO REP.	24.4121 (558.33)	**0.00030 (5.81)**	0.870	24.4632 (429.39)	**0.00051 (4.67)**	0.849
C. D'IVOIRE	26.1677 (391.32)	**0.00036 (4.42)**	0.909	26.1311 (306.05)	**0.00078 (4.80)**	0.899
EQU. GUINEA	24.1180 (580.80)	**0.00027 (5.44)**	0.845	24.0693 (318.65)	**0.00060 (4.15)**	0.580
ERITREA	25.7822 (206.93)	**0.00070 (4.72)**	0.922	25.5119 (162.18)	**0.00194 (6.41)**	0.918
ESWATINI	19.2200 (123.50)	**0.00118 (6.30)**	0.947	19.7091 (100.15)	**0.00144 (3.81)**	0.941
ETHOPIA	22.1358 (382.39)	**0.00057 (8.28)**	0.845	22.0678 (298.71)	**0.00129 (9.10)**	0.835
GABON	24.8818 (452.04)	**0.00033 (4.94)**	0.911	25.0043 (352.25)	**0.00042 (3.10)**	0.907
GAMBIA(THE)	27.0339 (287.63)	**0.00054 (4.77)**	0.902	26.8564 (224.81)	**0.00142 (6.21))**	0.894
GHANA	27.0039 (354.89)	**0.00043 (4.73)**	0.902	26.9100 (280.59)	**0.00102 (5.55)**	0.916
GUINEA	25.4849 (316.59)	**0.00036 (3.78)**	0.919	2533.50 (244.17)	**0.00104 (5.16)**	0.917
GUINEA BIS	26.5481 (311.96)	**0.00051 (4.98)**	0.909	26.3937 (241.84)	**0.00133 (6.33)**	0.907
KENYA	23.5272 (394.97)	**0.00119 (16.73)**	0.823	24.1914 (343.23)	**0.00118 (8.71)**	0.859
LESOTHO	10.9591 (51.24)	**0.00132 (5.15)**	0.970	11.6027 (42.88)	**0.00143 (2.74)**	0.966
LIBERIA	25.3466 (517.07)	**0.00013 (2.33)**	0.849	25.1206 (420.94)	**0.00072 (6.31)**	0.837
MADAGASCAR	22.4821 (412.79)	–	0.953	21.9275 (62.98)	**0.00093 (3.59)**	0.969
MALAWI	21.6794 (176.54)	**0.00051 (3.46)**	0.951	21.6523 (41.23)	**0.00108 (3.66)**	0.949
MALI	27.7405 (128.75)	**0.00080 (3.10)**	0.974	27.9297 (103.77)	**0.00124 (2.40)**	0.973
MAURITANIA	27.2821 (110.44)	**0.00074 (2.49)**	0.983	27.3045 (87.80)	**0.00143 (2.39)**	0.979
MAURITUS	22.7897 (214.23)	**0.0055 (4.33)**	0.978	22.6269 (166.96)	**0.00143 (5.48)**	0.965
MOZAMBIQUE	23.4360 (182.09)	**0.00057 (3.73)**	0.956	23.4973 (146.09)	**0.00105 (3.38)**	0.956
NAMIBIA	19.7501 (103.50)	**0.00054 (2.36)**	0.984	19.7645 (81.97)	**0.00105 (2.27)**	0.983
NIGER	27.4271 (221.01)	–	0.971	26.7576 (84.79)	**0.00148 (2.44)**	0.964
NIGERIA	26.7471 (281.68)	**0.00026 (2.34)**	0.904	26.4542 (221.59)	**0.00104 (4.53)**	0.899
RWANDA	18.1738 (66.27)	**0.00090 (27.47)**	0.476	18.5663 (600.08)	**0.00110 (18.51)**	0.401
SAO TOME	22.7628 (373.64)	**0.00027 (3.79)**	0.925	22.8329 (293.49)	**0.00042 (2.80)**	0.924
SENEGAL	27.7115 (250.80)	**0.00055 (4.17)**	0.924	27.5272 (195.63)	**0.00147 (5.42)**	0.917
SEYCHELLES	26.5545 (637.23)	**0.00071 (14.34)**	0.793	26.7762 (520.69)	**0.00107 (10.87)**	0.805
SIERRA LEONE	26.0373 (449.85)	**0.00025 (3.64)**	0.869	25.8016 (355.11)	**0.00097 (6.96)**	0.875
SOMALIA	26.6396 (438.36)	**0.00032 (4.38)**	0.907	26.6916 (349.99)	**0.00052 (3.56)**	0.918
S. AFRICA	16.8035 (73.65)	**0.0113 (4.12)**	0.978	17.2148 (59.73)	**0.00148 (2.67)**	0.976
SOUTH SUDAN	26.3280 (339.74)	**0.0090 (9.69)**	0.854	26.1135 (259.41)	**0.00222 (11.47)**	0.843
SUDAN	26.4055 (133.36)	**0.00084 (3.55)**	0.945	25.9686 (103.08)	**0.00249 (5.14)**	0.944
TANZANIA	21.5350 (324.91)	**0.00099 (12.50)**	0.903	22.0569 (270.43)	**0.00104 (6.64)**	0.907
TOGO	26.7689 (327.37)	**0.00036 (3.75)**	0.894	26.5760 (258.62)	**0.00107 (5.42)**	0.916
UGANDA	21.6055 (467.66)	**0.00128 (23.06)**	0.731	22.1350 (404.16)	**0.00161 (15.32)**	0.734
ZAMBIA	21.3767 (158.38)	**0.00054 (3.33)**	0.949	21.3135 (126.03)	**0.00120 (3.71)**	0.949
ZIMBABWE	20.7240 (120.23)	**0.00070 (3.38)**	0.951	20.7803 (96.74)	**0.00131 (3.17)**	0.954

The values in bold are significant time trend coefficients. In parenthesis, the associated t-values.

range from 1.4 to 5.8 °C (IPCC, 2007). Africa, where temperature rises are the most pronounced, has been rated as one of the world's most vulnerable regions to climate change impacts. (IPCC, 2014; Niang et al., 2014). There are many predictions that temperatures are expected to rise faster in Africa, especially in the drier parts of the continent, than in other parts of the world in the 21st century (Climate and Development Knowledge Network (CDKN), 2014).

Many papers have looked at trends in mean temperatures over time (Ghil and Vautard, 1991; Woodward and Gray, 1993; Hasselmann, 1993; Schlesinger and Ramankutty, 1994; North and Kim, 1995; North et al., 1995; Vogelsang and Franses, 2005; Kaufmann and Stern, 2002; Kaufmann et al., 2010, 2013), as well as global patterns of temperature change (Santer et al., 1995; Hegerl et al., 1996, 1997; Jones and Hegerl, 1998, and so on). Hansen and Lebedeff (1988), Nicholls et al. (1996), Jones et al. (1997) indicated that global mean annual surface temperatures have increased by 0.3°–0.6 °C over the last 150 years. In most of these papers, the unobservable random error is found to be integrated of order 0 or stationary without a trend. Nevertheless, Stern and Kaufmann (2000) and Kaufmann et al. (2006) showed that unit roots (or integration of order 1, I(1)) exist in global surface temperature. Thus, it seems to be a controversy in the literature about which is the number of differences to be taken in the data, i.e., 0 if we suppose temperatures are stationary, or 1 if they are not and they possess unit roots. It is in this context where a new framework emerges based on the idea of fractional integration.

Long memory models were originally used in the analysis of temperature data by Bloomfield (1992) and Bloomfield and Nychka, 1992. To get adequate confidence intervals, the authors observed that long memory should be included in trend estimations for temperature series. To estimate the long memory parameter, Baillie and Chung (2002) and Mills (2007) utilize fractional differentiation within parametric models, whereas Gil-Alana (2005) and Mangat and Reschenhofer (2020) employ

Table 3
Comparisons of time trends across samples.

Country	1901m1 – 2020m12	1946m1 – 2020m12	% change
ANGOLA	0.00037 (3.34)	0.00064 (2.86)	+72.97%
BENIN	0.00038 (3.50)	0.00112 (5.15)	+194.74% 194.74
BOTSWANA	0.00086 (3.05)	0.00136 (2.41)	+58.14%
BURKINA F.	0.00075 (5.04)	0.00124 (4.14)	+65.33%
BURUNDI	0.00084 (19.76)	0.00107 (13.06)	+27.38%
CABO VERDE	0.00031 (2.67)	0.00073 (3.25)	+135.48%
CAMEROON	0.00023 (3.23)	0.00036 (2.52)	+56.52%
C. AF. REP.	0.00034 (4.32)	0.00066 (3.95)	+94.11%
CHAD	0.00058 (2.69)	0.00170 (3.83)	+193.10%
COMOROS	0.00023 (3.23)	0.00036 (2.52)	+56.52%
CONGO (DR)	0.00032 (8.92)	0.00067 (8.92)	+109.38%
CONGO REP.	0.00030 (5.81)	0.00051 (4.67)	+70.00%
C. D'IVOIRE	0.00036 (4.42)	0.00078 (4.80)	+116.67%
EQU. GUINEA	0.00027 (5.44)	0.00060 (4.15)	+122.22%
ERITREA	0.00070 (4.72)	0.00194 (6.41)	+177.14%
ESWATINI	0.00118 (6.30)	0.00144 (3.81)	+22.03%
ETHOPIA	0.00057 (8.28)	0.00129 (9.10)	+126.32%
GABON	0.00033 (4.94)	0.00042 (3.10)	+27.27%
GAMBIA(THE)	0.00054 (4.77)	0.00142 (6.21))	+162.96%
GHANA	0.00043 (4.73)	0.00102 (5.55)	+137.21%
GUINEA	0.00036 (3.78)	0.00104 (5.16)	+188.89%
GUINEA BIS	0.00051 (4.98)	0.00133 (6.33)	+160.78%
KENYA	0.00119 (16.73)	0.00118 (8.71)	−0.84%
LESOTHO	0.00132 (5.15)	0.00143 (2.74)	+8.33%
LIBERIA	0.00013 (2.33)	0.00072 (6.31)	+453.85%
MADAGASCAR	–	0.00093 (3.59)	–
MALAWI	0.00051 (3.46)	0.00108 (3.66)	+111.76%
MALI	0.00080 (3.10)	0.00124 (2.40)	+55.00%
MAURITANIA	0.00074 (2.49)	0.00143 (2.39)	+93.24%
MAURITUS	0.0055 (4.33)	0.00143 (5.48)	−74.00%
MOZAMBIQUE	0.00057 (3.73)	0.00105 (3.38)	+84.21%
NAMIBIA	0.00054 (2.36)	0.00105 (2.27)	+94.44%
NIGER	–	0.00148 (2.44)	–
NIGERIA	0.00026 (2.34)	0.00104 (4.53)	+300.00%
RWANDA	0.00090 (27.47)	0.00110 (18.51)	+22.22%
SAO TOME	0.00027 (3.79)	0.00042 (2.80)	+55.56%
SENEGAL	0.00055 (4.17)	0.00147 (5.42)	+167.27%
SEYCHELLES	0.00071 (14.34)	0.00107 (10.87)	+50.70%
SIERRA LEONE	0.00025 (3.64)	0.00097 (6.96)	+288.00%
SOMALIA	0.00032 (4.38)	0.00052 (3.56)	+62.50%
S. AFRICA	0.0113 (4.12)	0.00148 (2.67)	−86.90%
SOUTH SUDAN	0.0090 (9.69)	0.00222 (11.47)	−75.33%
SUDAN	0.00084 (3.55)	0.00249 (5.14)	+196.43%
TANZANIA	0.00099 (12.50)	0.00104 (6.64)	+5.05%
TOGO	0.00036 (3.75)	0.00107 (5.42)	+197.22%
UGANDA	0.00128 (23.06)	0.00161 (15.32)	+25.78%
ZAMBIA	0.00054 (3.33)	0.00120 (3.71)	+122.22%
ZIMBABWE	0.00070 (3.38)	0.00131 (3.17)	+87.14%

The values in parenthesis are the associated t-values. — means lack of significancy.

frequency domain semiparametric estimators. They all came to the same conclusion: temperature data displays a long memory pattern. They do, however, differ in terms of memory capacity. Given that a considerable degree of memory suggests a nonstationary process or even a process that does not revert to the mean, the distinction is important.

Other papers that employ long memory in temperatures are Gil-Alana (2003), which used fractional integration to examine Central England Temperatures (CET), concluding that recent temperature increases have averaged 0.23 °C every 100 years. Also using fractional integration but with segmented time trends, Gil-Alana (2008a) shows that the northern, southern, and global temperature anomaly series are fractionally integrated, and that the three series reveals increase in warming effects after the breaks. Further, Gil-Alana (2008b) used a non-parametric approach to model integration and shows that the same three series (global, northern and southern temperatures) are fractionally integrated around the order of 0.5. Gil-Alana and Sauci (2019a) investigated time trends coefficients in temperatures of 48 states of the United States of America, finding an increase in temperature anomalies for all except ten states, which is greater than what was discovered using other conventional methods. In another study Gil-Alana and Sauci (2019b) also found long memory in temperature data and increasing warming trends across Europe.

There are several studies investigating temperature trends in Sub-Saharan Africa. Kruger and Shongwe (2004), Kruger and Sekele (2012) and Kruger and Nxumalo (2016) presented evidence of increased warming trends in South Africa. New et al. (2006) examined trends in daily climate extremes over Southern and Western Africa and found that there is a repeating pattern of temperature extremes that is associated to rising temperatures. Muthoni (2020) studied the extent and importance of spatial-temporal trends in rainfall, maximum (Tmax), and lowest (Tmin) temperatures for West Africa over a 37-year period. Positive and negative trends of changing magnitude were observed in the three variables. Neumann et al. (2007) found that temperature time series in the Volta basin, West Africa exhibited highly significant positive trends. King'uyu, Ogallo and Anyamba (2000) discovered a considerable increase in night-time temperatures over Eastern Africa. Coastal areas and

Table 4
Estimated coefficients in the model given by Eq. (1). Whole data set.

COUNTRY	D (95% BAND)	Intercept	Time trend	Seasonality
ANGOLA	0.28 (0.22, 0.33)	21.5633 (81.64)	–	0.966
BENIN	0.32 (0.27, 0.38)	27.5685 (83.68)	–	0.881
BOTSWANA	0.26 (0.21, 0.31)	21.6489 (38.10)	–	0.972
BURKINA FASO	0.28 (0.23, 0.34)	28.1221 (76.49)	–	0.907
BURUNDI	0.35 (0.30, 0.40)	19.7665 (20.11)	0.00065 (126.67)	0.684
CABO VERDE	0.32 (0.27, 0.38)	22.9002 (69.93)	–	0.919
CAMEROON	0.40 (0.35, 0.45)	24.5834 (74.98)		0.913
CENTRAL AF. REP.	0.29 (0.24, 0.34)	25.0053 (125.57)	–	0.910
CHAD	0.20 (0.15, 0.26)	26.8399 (86.42)	–	0.967
COMOROS	0.40 (0.35, 0.45)	24.5834 (74.98)	–	0.913
CONGO (DR)	0.43 (0.38, 0.48)	24.1159 (120.06)	–	0.860
CONGO REP.	0.48 (0.43, 0.54)	24.5992 (72.95)	–	0.858
COTE D'IVOIRE	0.35 (0.30, 0.40)	26.4791 (93.09)	–	0.897
EQUATORIAL GUINEA	0.52 (0.47, 0.58)	24.2536 (66.48)	–	0.829
ERITREA	0.28 (0.23, 0.33)	26.2796 (76.97)	–	0.901
ESWATINI	0.22 (0.18, 0.28)	19.3211 (41.15)	0.00112 (2.07)	0.935
ETHOPIA	0.42 (0.37, 0.48)	22.5088 (65.64)	–	0.823
GABON	0.53 (0.47, 0.58)	25.1338 (49.24)	–	0.907
GAMBIA(THE)	0.33 (0.28, 0.39)	27.4091 (7505)	–	0.891
GHANA	0.37 (0.31, 0.43)	27.3164 (76.50)	–	0.885
GUINEA	0.31 (0.26, 0.36)	25.8242 (93.17)	–	0.909
GUINEA BISSAU	0.33 (0.28, 0.38)	26.9330 (79.43)	–	0.904
KENYA	0.50 (0.45, 0.56)	24.5151 (51.41)	–	0.800
LESOTHO	0.17 (0.12, 0.22)	10.9875 (21.76)	0.00132 (2.25)	0.964
LIBERIA	0.39 (0.33, 0.45)	25.6660 (101.97)	–	0.818
MADAGASCAR	0.27 (0.23, 0.33)	22.6108 (81.04)	–	0.941
MALAWI	0.28 (0.23, 0.33)	22.0549 (64.25)	–	0.941
MALI	0.26 (0.21, 0.31)	28.1902 (53.00)	–	0.968
MAURITANIA	0.29 (0.24, 0.35)	27.6476 (38.85)	–	0.978
MAURITUS	0.53 (0.48, 0.59)	23.9402 (27.76)	–	0.970
MOZAMBIQUE	0.26 (0.22, 0.32)	23.8763 (75.75)	–	0.945
NAMIBIA	0.16 (0.11, 0.21)	20.1534 (78.78)	–	0.982
NIGER	0.22 (0.17, 0.28)	27.3714 (56.71)	–	0.965
NIGERIA	0.28 (0.23, 0.34)	26.9140 (96.64)	–	0.894
RWANDA	0.34 (0.30, 0.39)	18.4332 (125.98)	0.00069 (3.90)	0.407
SAO TOME & PRINCIPE	0.51 (0.45, 0.57)	23.0166 (46.48)	–	0.907
SENEGAL	0.33 (0.28, 0.39)	28.0748 (65.82)	–	0.914
SEYCHELLES	0.49 (0.44, 0.55)	26.7599 (80.71)	–	0.774
SIERRA LEONE	0.32 (0.27, 0.37)	26.3380 (124.70)	–	0.853
SOMALIA	0.50 (0.44, 0.54)	26.5270 (54.34)	–	0.901
SOUTH AFRICA	0.17 (0.12, 0.22)	16.8412 (31.24)	0.00112 (1.80)	0.974
SOUTH SUDAN	0.28 (0.23, 0.34)	26.5638 (84.93)	0.00071 (1.99)	0.821
SUDAN	0.23 (0.17, 0.29)	26.9979 (66.10)	–	0.933
TANZANIA	0.44 (0.39, 0.50)	22.2807 (52.50)	–	0.889
TOGO	0.36 (0.30, 0.42)	27.0566 (75.14)	–	0.871
UGANDA	0.46 (0.40, 0.52)	22.6313 (73.94)	–	0.635
ZAMBIA	0.26 (0.21, 0.31)	21.7817 (63.94)	–	0.941
ZIMBABWE	0.24 (0.20, 0.30)	21.2642 (56.28)	–	0.940

— means lack of significancy.

those near large bodies of water showed substantial reverse trends, particularly north of 5°S.

There are also works on temperature trends in Sub-Saharan Africa, with fractional integration. Gil-Alana et al. (2019) by using linear trends, seasonality, and long-range dependence, examined temperatures in western, eastern, and southern regions (Botswana, Ethiopia, Ghana, Nigeria, Uganda, and South Africa), finding that in most circumstances, time trends were required to explain climate features. They also found that temperatures have long memory and structural breaks for Ethiopia, Ghana, and Uganda. In a similar vein, Carcel and Gil-Alana (2015) looked at temperatures in South Africa, Kenya, and Côte d'Ivoire They showed that only Kenya has experienced a significant temperature increase in the last 30 years.

3. Methodology

Long memory is defined in the frequency domain as a process whose spectral density function is unbounded at one or more frequencies in the spectrum. That is, denoting $f(\lambda)$ as the spectral density function, which is basically the Fourier transform of the autocovariances $\gamma(u) = E[x_t - Ex_t](Ex_{t+u}-Ex_t)]$ of a stationary process, i.e.,

$$f(\lambda) = \frac{1}{2\Pi} \sum_{u=-\infty}^{\infty} \gamma(u) e^{i\lambda u},$$

the process is long memory if:

$$f(\lambda) \quad \to \infty, for \quad any \quad \lambda \in [0, \pi).$$

There are many models in practice that satisfy this property, and one very simple and common within time series analysts is the one based on the concept of fractional integration.

A process x_t, $t = 0, \pm 1, \ldots$ is said to be fractionally integrated or integrated of order d and denoted by I(d) if it can be expressed as

$$(1-B)^d x_t = u_t, t = 0, \pm 1, \ldots,$$

where d can be any real value, u_t is short memory or I(0), and thus

Table 5
Estimated coefficients in the model given by Eq. (1). Data starting from January 1946.

COUNTRY	NO TERMS	INTERCEPT	TIME TREND	SEASONAL
ANGOLA	0.32 (0.26, 0.39)	21.6591 (59.68)	–	0.960
BENIN	0.29 (0.22, 0.36)	27.6082 (96.18)	–	0.902
BOTSWANA	0.26 (0.19, 0.33)	21.8713 (34.56)	–	0.971
BURKINA FASO	0.23 (0.17, 0.30)	28.3351 (92.50)	–	0.916
BURUNDI	0.34 (0.27, 0.41)	19.9335 (93.13)	0.00096 (2.33)	0.680
CABO VERDE	0.39 (0.32, 0.47)	22.7420 (47.19)	–	0.918
CAMEROON	0.37 (0.32, 0.44)	24.8144 (82.35)	–	0.896
CENTRAL AF. REP.	0.27 (0.22, 0.34)	25.0992 (123.24)	–	0.870
CHAD	0.20 (0.14, 0.27)	26.8450 (73.70)	–	0.956
COMOROS	0.37 (0.32, 0.44)	24.8144 (82.35)	–	0.896
CONGO (DR)	0.44 (0.38, 0.50)	24.2298 (107.47)	–	0.814
CONGO REP.	0.48 (0.42, 0.55)	24.9639 (70.21)	–	0.834
COTE D'IVOIRE	0.36 (0.29, 0.42)	26.5033 (85.23)	–	0.887
EQUATORIAL GUINEA	0.50 (0.44, 0.58)	24.7518 (70.56)	–	0.821
ERITREA	0.28 (0.22, 0.35)	25.4415 (45.96)	0.00200 (1.93)	0.898
ESWATINI	0.21 (0.15, 0.28)	20.3946 (62.74)	–	0.928
ETHOPIA	0.41 (0.36, 0.48)	22.4827 (63.95)	–	0.816
GABON	0.53 (0.46, 0.60)	25.6645 (48.83)	–	0.901
GAMBIA(THE)	0.38 (0.31, 0.45)	27.2415 (52.72)	–	0.886
GHANA	0.36 (0.29, 0.43)	27.4006 (75.47)	–	0.903
GUINEA	0.32 (0.26, 0.39)	25.7885 (78.54)	–	0.908
GUINEA BISSAU	0.38 (0.31, 0.44)	26.8168 (58.08)	–	0.906
KENYA	0.48 (0.42, 0.55)	24.7395 (56.15)	–	0.845
LESOTHO	0.17 (0.11, 0.23)	12.2734 (34.38)	–	0.959
LIBERIA	0.40 (0.33, 0.47)	25.4908 (92.81)	–	0.816
MADAGASCAR	0.44 (0.37, 0.50)	22.7153 (33.85)	–	0.958
MALAWI	0.27 (0.21, 0.34)	22.1507 (62.04)	–	0.939
MALI	0.21 (0.15, 0.27)	28.4358 (67.03)	–	0.968
MAURITANIA	0.28 (0.22, 0.35)	27.7459 (37.25)	–	0.973
MAURITUS	0.54 (0.47, 0.62)	23.9789 (26.38)	–	0.953
MOZAMBIQUE	0.25 (0.19, 0.32)	24.0000 (72.55)	–	0.946
NAMIBIA	0.18 (0.12, 0.25)	20.2671 (60.42)	–	0.980
NIGER	0.20 (0.13, 0.28)	27.3565 (55.08)	–	0.956
NIGERIA	0.26 (0.20, 0.33)	26.9096 (97.39)	–	0.888
RWANDA	0.30 (0.24, 0.37)	18.6319 (143.72)	0.00099 (4.06)	0.398
SAO TOME & PRINCIPE	0.48 (0.41, 0.56)	23.4557 (50.75)	–	0.904
SENEGAL	0.37 (0.30, 0.44)	27.9573 (51.13)	–	0.910
SEYCHELLES	0.56 (0.50, 0.62)	26.7671 (64.55)	–	0.813
SIERRA LEONE	0.35 (0.29, 0.42)	26.2350 (101.71)	–	0.867
SOMALIA	0.40 (0.34, 0.46)	26.7770 (76.57)	–	0.909
SOUTH AFRICA	0.18 (0.12, 0.24)	17.9174 (44.75)	–	0.971
SOUTH SUDAN	0.27 (0.21, 0.33)	26.2814 (75.05)	0.00187 (2.87)	0.817
SUDAN	0.20 (0.13, 0.27)	25.9439 (40.70)	0.00247 (2.09)	0.933
TANZANIA	0.46 (0.39, 0.52)	22.5406 (49.95)	–	0.894
TOGO	0.33 (0.27, 0.40)	27.0998 (82.04)	–	0.900
UGANDA	0.43 (0.36, 0.52)	22.8089 (82.71)	–	0.655
ZAMBIA	0.27 (0.21, 0.34)	21.8586 (54.64)	–	0.941
ZIMBABWE	0.22 (0.16, 0.29)	21.3969 (56.69)	–	0.945

— means lack of significancy.

characterized because the spectral density function is positive and bounded at all frequencies in the spectrum, i.e.,

$$0 \; < \; f(\lambda) \; < \infty, for \quad \lambda \in [0, \pi).$$

In this context, x_t displays the property of long memory if d is positive since its spectral density function tends to infinity as λ approaches zero, i.e.,

$$f(\lambda) \quad \to \infty, as \quad \lambda \quad \to \quad 0^{+}.$$

We use in this work fractional integration to take into account the potential long memory feature on the data. However, noting that other statistical properties such as linear trends and seasonality are also present in the data, we consider a very general framework that takes into account these three features (long range dependence, time trends and seasonality) in a unified treatment. The model under consideration is the following one,

$$y_t = \alpha + \beta t + x_t, (1 - B)^d x_t = u_t, \mathrm{u}_t = \rho u_{t-12} \varepsilon_t \tag{1}$$

where y_t refers to the observed data; α and β are unknown coefficients, namely the intercept (constant) and the linear time trend coefficient; B indicates the backshift operator such that $Bx_t = x_{t-1}$; x_t stands for the regression errors, assumed to be integrated of order d or I(d), meaning that u_t is integrated of order 0 (I(0)); moreover, given the seasonal nature inherent to the data, a seasonal (monthly) AR(1) process is assumed for the I(0) disturbances u_t, where ρ is the seasonality indicator, and ε_t is a white noise process.

We estimate the parameters in the model by using the Whittle function in the frequency domain as in Dahlhaus (1989). For this purpose, we implement a simple version of the tests of Robinson (1994) widely used in the empirical literature on fractional integration. It tests the null hypothesis:

$$H_o : d = d_o, \tag{2}$$

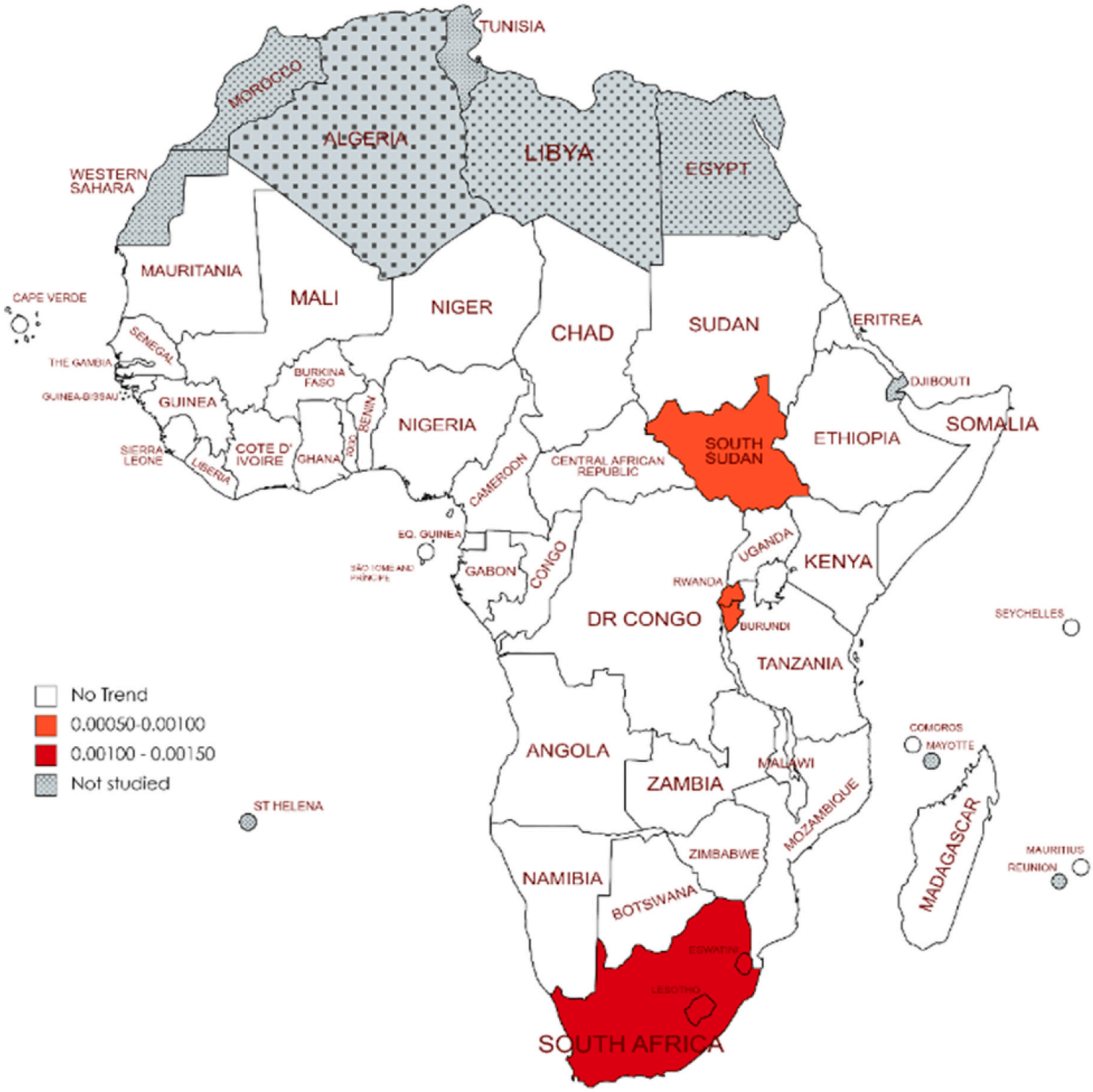

Fig. 1. Time trends for mean temperatures based on Table 4.

in the model given by Eq. (1) where d_o can be any real value. The test statistic, denoted by R, is based on the Lagrange Multiplier (LM) principle and thus, it relies on (2), where the first two equations in (1) can be written as

$$yd(t) = \alpha 1d(t) + \beta\, td(t) + u(t), \tag{3}$$

where $yd(t) = (1-L)^{do} y(t);\quad 1d(t) = (1-L)^{do} 1, \textit{and } td(t) = (1-L)^{do} t$. The functional form can be found in any of the numerous empirical applications using these tests (see, e.g., Gil-Alana and Robinson, 1997). Its limiting distribution is standard Normal, and the method is the most efficient one in the Pitman sense against local departures from the null (see, Robinson, 1994). Using alternative estimation methods produced essentially the same type of results. In particular, we try both parametric (Sowell, 1992) and semiparametric (Robinson, 1995; Shimotsu and Phillips, 2006) methods and though quantitatively we observe some slight differences, qualitatively we get very similar results to those reported in the manuscript.

4. Data

The data employed in this study are observed monthly historical data from January 1901 to December 2020 for 48 countries of Sub-Saharan Africa, obtained from the Climate Change Knowledge Portal (CCKP) of the World Bank Group (https://climateknowledgeportal.worldbank.org/).

The CCKP obtained the dataset from Climatic Research Unit (CRU) of the University of East Anglia (UEA). The most extensively used observational climate dataset is CRU TS (Climatic Research Unit gridded Time Series). Over all land domains except Antarctica, data is displayed on a 0.5° latitude by 0.5° longitude grid. It is calculated by interpolating monthly climate anomalies from a large network of weather station readings. The CRU TS version 4.05 gridded dataset is based on empirical data and contains quality-controlled temperature and rainfall readings from thousands of weather stations throughout the world, as well as secondary products such as monthly climatologies and long-term historical climatologies (Harris et al., 2020).

Table 1 displays the descriptive statistics for the data on mean

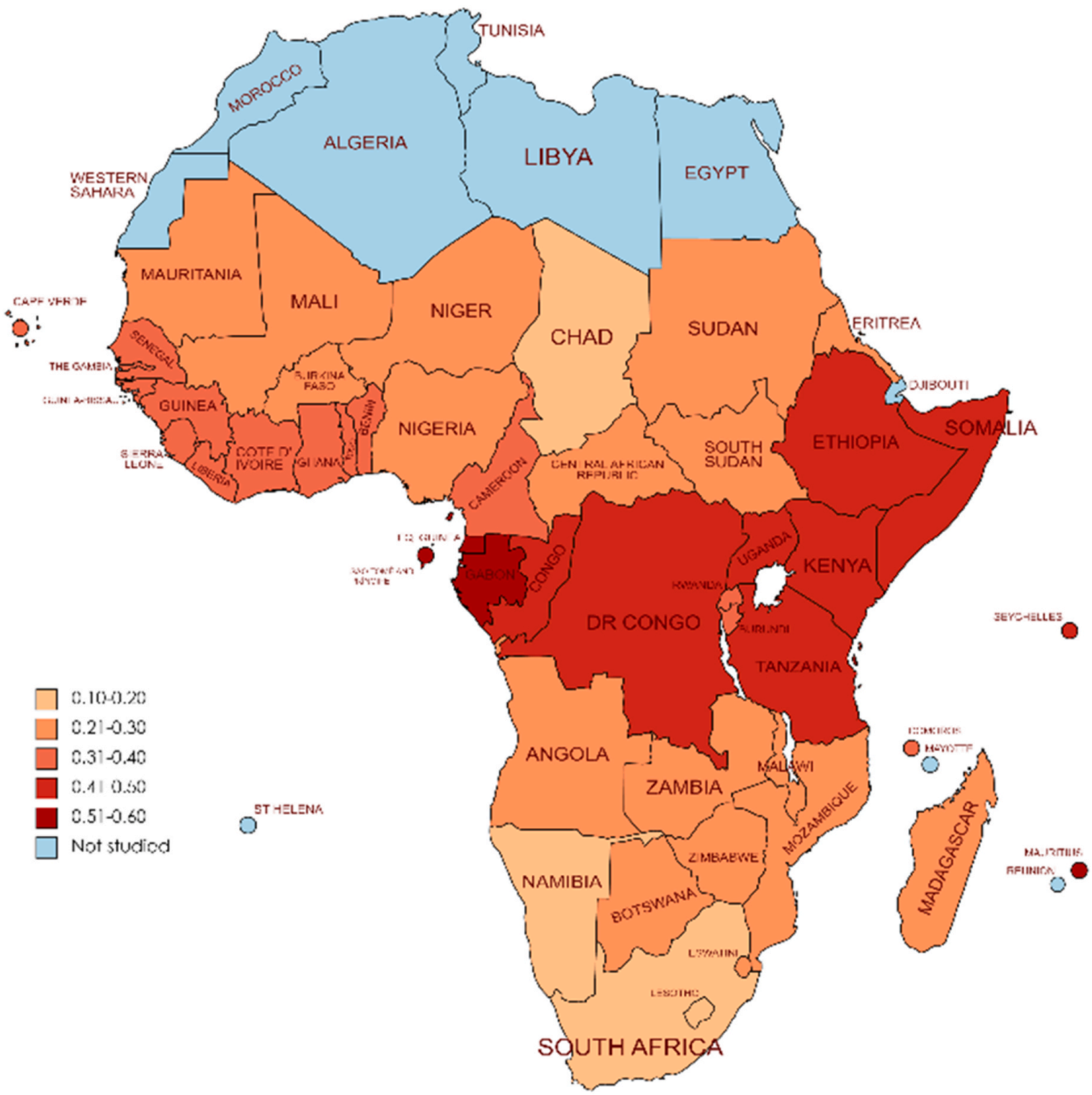

Fig. 2. Estimates of the degree of persistence (d) for mean temperature based on Table 4.

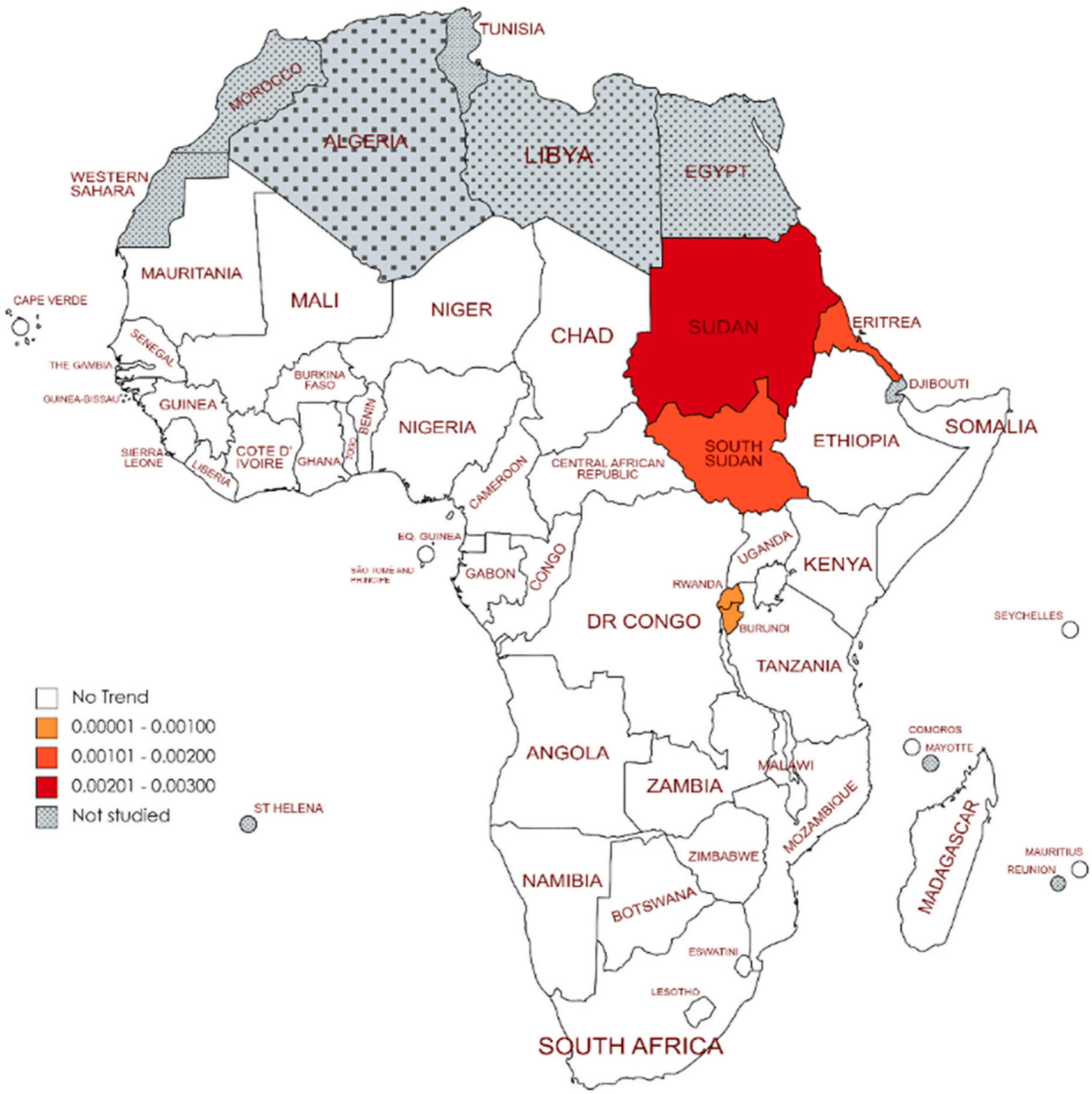

Fig. 3. Time trends for mean temperatures based on Table 5.

temperatures of Sub-Saharan African (SSA) countries from January 1901 to December 2020. The data shows that the countries with the highest mean for the mean temperature data are Mali (28.32 °C), Burkina Faso (28.21 °C) and Senegal (28.11 °C), all of them in West Africa. The country with the lowest mean is Lesotho (11.91 °C) with the closest being South Africa (17.62 °C); both in Southern Africa. Congo (DR) (0.59) has the lowest standard deviation which means data for temperatures are clustered around the mean, while Niger (4.71) has the highest standard deviation indicating that the data are more spread out. The countries with the lowest minimum mean temperatures are Lesotho (3.35 °C) and South Africa (8.96 °C); while the highest minimum of mean temperatures is Seychelles (24.83 °C). The countries with the highest maximum of mean temperatures are Mali (34.81 °C), Niger (34.66 °C) and Mauritania (34.50 °C), while Lesotho (19.21 °C) has the lowest maximum of mean temperatures in SSA. Niger (18.82 °C) has the widest range of mean temperatures in SSA, while Rwanda (3.66 °C) has the narrowest range of mean temperatures in SSA.

As a preliminary step and prior to our empirical calculations, we first estimate the parameters in Equation (1) under the assumption that the detrended series, x_t is integrated of order 0 and based on the seasonal nature of the data, a seasonal AR(1) process such as the one in the last equality in Equation (1) is used to describe that behavior. In other words, we suppose temperatures are short memory, not displaying high levels of dependence. Table 2 displays the estimated coefficients in the model, i.e., the intercept (α in Eq. (1)), the time trend coefficient (β) along with the seasonal parameter (ρ), firstly, using the whole sample size (1901m1 – 2020m12) and then using data starting after World War II (i.e., 1946m1 – 2020m12).

Looking first at the results for the whole dataset, we observe that the time trend is statistically significantly positive in all cases, the only exceptions being Madagascar and Niger. If we use post-WWII data, the time trend is significant in all cases, also observing an increase in the magnitude of the coefficient in all countries. According to these results, temperatures have been increasing with the passing of time in almost all countries, and the increase is higher with post WWII data (Table 3). Nevertheless, as we show in the following section, these results will be invalidated since they are based on the incorrect assumption that the series are short memory (d = 0), and this hypothesis will be decisively

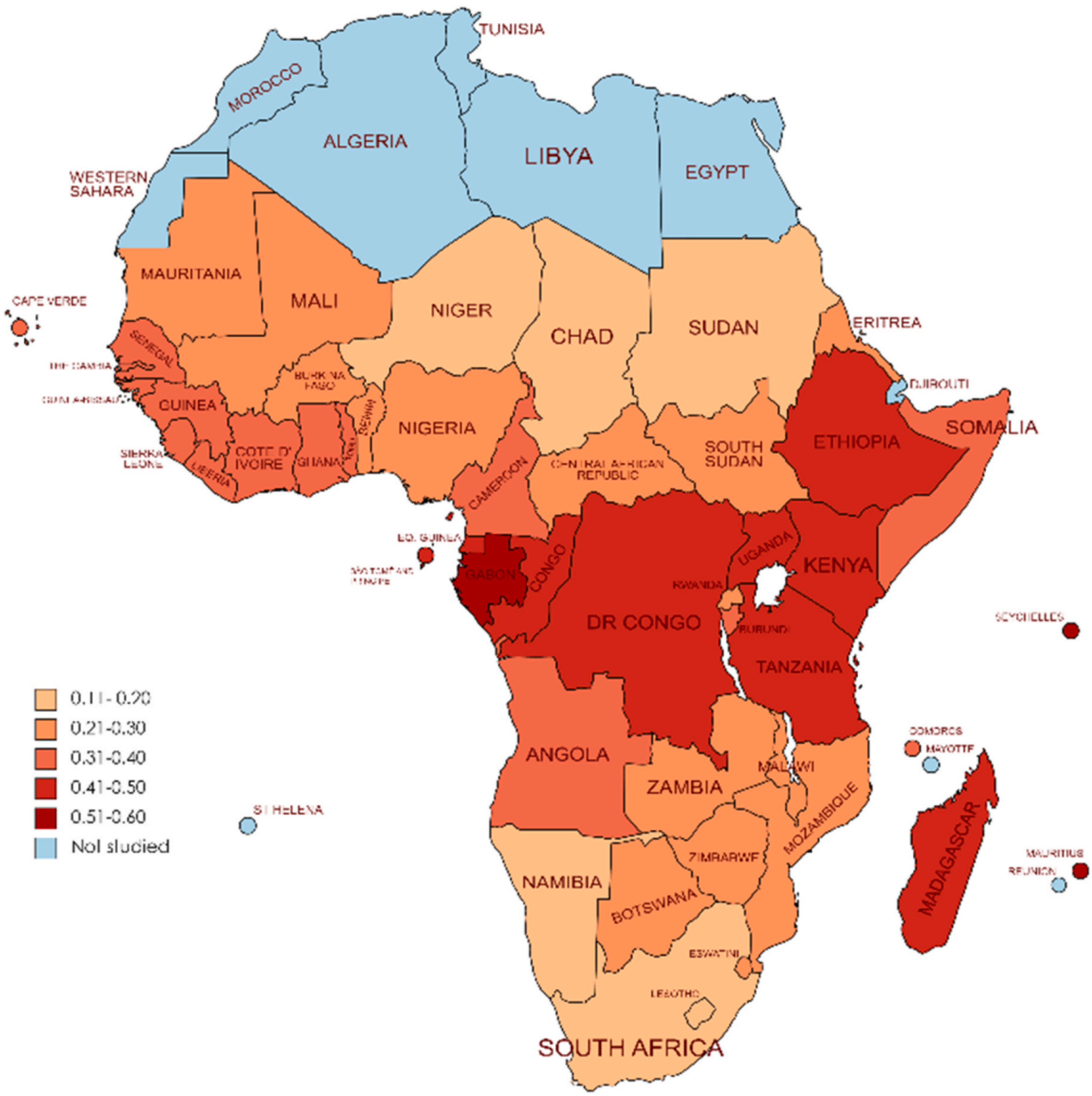

Fig. 4. Estimates of the degree of persistence (d) for mean temperature based on Table 5.

rejected in favor of long memory (d > 0) in all countries in the sample in the empirical application carried out in the following section.

5. Empirical results

As we have said in previous sections, the data under investigation might display long memory. Thus, based on the large body of evidence of positive values of d in climatological data (Gil-Alana, 2003, 2005; etc.) in what follows we estimate the parameters displayed in Eq. (1) including thus the differencing (or long memory) parameter d in that equation. We display first the results based on the original data (Section 5a). In Section 5b, we focus on the anomalies with respect to 1910 January to 1945 December for countries in the northern hemisphere, and to 1930 December for countries in the southern hemisphere (Jones et al., 2006).

5.1. Original data

We first perform the results for the whole sample size and estimate d in Equation (1) under three potential scenarios with respect to the first equality in (1). First, we make the assumption that $\alpha = \beta = 0$, i.e., $y_t = x_t$ and therefore there are no deterministic terms; then, we suppose that only $\beta = 0$ (i.e., the model incorporates only the intercept); and finally, we estimate the model with both the constant and the linear trend. In this latter case, if the two coefficients are statistically significant, we choose the model with both terms, and if only the intercept is statistically significant, we choose the model with an intercept. The results in terms of the estimated coefficients are reported in Table 4.

We see in Table 4 that the time trend is statistically significant only in a few groups of countries: Lesotho (with an estimated trend of 0.00168), South Africa and Eswatini (β = 0.00112), South Sudan (0.00071), Rwanda (0.00069) and Burundi (0.00065), all Southern and Eastern countries. In all the other cases, the trend is insignificant and only an intercept is required to describe the deterministic part. On the other hand, the seasonal component is important in all cases, with the seasonal AR parameter being close to 1 in the majority of the cases, the lowest values corresponding to Rwanda (0.407), Uganda (0.655) and Burundi (0.684). These results are in sharp contrast to those reported in Table 2 and based on the standard assumption that x_t in Eq. (1) is I(0). In fact, this (short memory) hypothesis is decisively rejected in all countries

Table 6
Descriptive statistics for the whole sample for the temperature anomalies with respect to 1910m1 – 1930m12/1945m12.

COUNTRY	MEAN	SD	MEDIAN	MIN	MAX	RANGE
ANGOLA	0.18	0.40	0.11	−1.19	1.64	2.83
BENIN	−0.01	0.68	−0.07	−2.78	2.40	5.18
BOTSWANA	0.35	0.81	0.32	−2.22	2.78	5.01
BURKINA FASO	0.23	0.85	0.23	−3.41	2.94	6.35
BURUNDI	0.48	0.56	0.48	−1.17	2.21	3.38
CABO VERDE	0.07	0.52	0.02	−1.95	2.39	4.34
CAMEROON	0.04	0.36	0.01	−1.41	1.29	2.70
CENTRAL AFRICAN REP.	0.08	0.45	0.03	−2.68	2.07	4.75
CHAD	0.06	0.69	0.02	−2.55	2.21	4.76
COMOROS	0.44	1.15	0.74	−2.74	2.74	5.48
CONGO (DR)	0.12	0.29	0.05	−0.73	1.19	1.92
CONGO REP.	0.15	0.37	0.05	−1.31	1.45	2.77
COTE D'IVOIRE	0.12	0.47	0.10	−1.91	2.04	3.96
EQUATORIAL GUINEA	0.08	0.36	−0.01	−1.47	1.42	2.89
ERITREA	0.18	0.83	0.18	−2.84	3.53	6.37
ESWATINI	0.62	0.87	0.57	−2.07	3.38	5.45
ETHOPIA	0.18	0.57	0.15	−2.15	2.92	5.07
GABON	0.17	0.38	0.08	−1.55	1.45	2.99
GAMBIA(THE)	0.15	0.69	0.11	−2.15	3.30	5.45
GHANA	0.07	0.57	0.05	−2.29	2.02	4.31
GUINEA	0.13	0.54	0.10	−1.73	2.39	4.12
GUINEA BISSAU	0.15	0.62	0.12	−1.74	3.22	4.96
KENYA	0.61	0.77	0.72	−2.42	2.65	5.07
LESOTHO	0.66	0.93	0.61	−2.13	3.50	5.63
LIBERIA	0.05	0.44	0.05	−1.55	1.61	3.17
MADAGASCAR	−0.36	0.65	−0.33	−2.51	1.28	3.78
MALAWI	0.06	0.62	0.05	−1.64	1.97	3.62
MALI	0.28	0.82	0.30	−3.07	3.24	6.31
MAURITANIA	0.22	0.73	0.18	−2.16	3.40	5.56
MAURITUS	0.13	0.46	0.00	−1.02	1.77	2.79
MOZAMBIQUE	0.17	0.62	0.17	−1.92	2.26	4.18
NAMIBIA	0.20	0.54	0.12	−1.48	2.19	3.67
NIGER	−0.06	0.89	−0.09	−3.47	3.09	6.57
NIGERIA	−0.08	0.65	−0.11	−3.14	2.28	5.42
RWANDA	0.53	0.58	0.55	−1.14	2.23	3.37
SAO TOME &PRINCIPE	0.08	0.37	0.01	−1.85	1.65	3.5
SENEGAL	0.14	0.71	0.11	−2.12	3.33	5.45
SEYCHELLES	0.16	0.52	0.17	−1.30	1.71	3.00
SIERRA LEONE	0.08	0.50	0.07	−1.75	1.86	3.61
SOMALIA	0.08	0.43	0.07	−1.36	1.91	3.27
SOUTH AFRICA	0.50	0.83	0.43	−1.92	3.33	5.26
SOUTH SUDAN	0.25	0.81	0.19	−2.67	3.59	6.26
SUDAN	0.12	1.06	0.14	−4.15	4.09	8.24
TANZANIA	0.61	0.62	0.65	−1.28	2.24	3.51
TOGO	0.01	0.64	−0.04	−2.41	2.25	4.65
UGANDA	0.63	0.78	0.66	−1.74	3.00	4.74
ZAMBIA	0.14	0.68	0.10	−1.70	2.53	4.23
ZIMBABWE	0.25	0.85	0.24	−2.34	3.14	5.48

based on the confidence intervals reported for the value of d across Table 4. We observe that the values of d are significantly positive in all cases, ranging from 0.16 in Lesotho and Namibia, and 0.17 in South Africa to values higher than 0.5 in Equatorial Guinea (0.52) and Gabon and Mauritius (with an estimated value of d of 0.53). Thus, all series are highly persistent with shocks having long lasting effects.

We next repeat the analysis but using only data starting after World War II, i.e., the first observation corresponding to January 1946. Results are reported in Table 5. We first observe that the time trend appears to be significant in five countries: Sudan ($\beta = 0.00247$), Eritrea (0.00200), South Sudan (0.00187), Rwanda (0.00099) and Burundi (0.00090). Thus, the highest increase in temperatures seems to occur now in the Eastern countries. Seasonality is important in almost all countries, the lowest coefficients corresponding to Rwanda (0.398), Uganda (0.655) and Burundi (0.680), and long memory is statistically significant in all cases, the values of d ranging from 0.17 (Lesotho) and 0.18 (Namibia) to 0.54 (Mauritius) and 0.56 (Seychelles). See Figs. 1–4 for an illustration of the geographical representation of both the degree of persistence and the time trend coefficients.

5.2. Anomalies

In this subsection we repeat the analysis, but this time based on the anomalies. Most studies work with temperature anomalies rather than absolute (mean) temperatures because temperature anomalies provide a frame of reference that enables more meaningful comparisons between places and more precise computations of temperature trends. They also depict climate variability across wider areas more accurately than absolute temperatures do. Therefore, in this study, we also examine temperature anomalies for the countries in the Sub-Saharan Africa.

To calculate the anomalies, we try to find a reference point, i.e., a period of stable temperatures. According to Jones et al. (2006): "*there are several notable differences between the series: a steady period of warming is seen for the northern hemisphere from about 1910 through the mid-1940s. For the southern hemisphere there is less warming observed from 1910 through 1930, with sudden and rapid warming from 1930 through mid-1940s. The northern hemisphere records show gradual cooling from the mid-1940s through the mid-1970s, followed by rather steady temperature increases thereafter. The southern hemisphere shows an abrupt shift to cooler*

Table 7
Estimated coefficients in the model given by Eq. (1). Whole data set. Anomalies with respect to 1910m1 – 1930m12/1945m12.

COUNTRY	d (95% band)	Intercept	Time trend	Seasonality
ANGOLA	0.29 (0.25, 0.34)	−0.05933 (−1.68)	0.00034 (3.41)	0.268
BENIN	0.34 (0.30, 0.38)	−0.29906 (−1.72)	0.00047 (2.25)	0.107
BOTSWANA	0.30 (0.25, 0.35)	−0.19110 (−1.69)	0.00083 (3.97)	0.085
BURKINA FASO	0.31 (0.27, 0.36)	−0.35713 (−1.79)	0.00083 (3.51)	0.113
BURUNDI	0.37 (0.33, 0.40)	0.01483 (2.11)	0.00063 (3.73)	0.079
CABO VERDE	0.35 (0.30, 0.40)	0.08935 (1.99)	–	0.111
CAMEROON	0.39 (0.35, 0.43)	−0.24913 (−2.15)	0.00038 (2.60)	0.020
CENTRAL AF. REP.	0.30 (0.27, 0.34)	−0.18234 (−1.81)	0.00040 (3.37)	0.083
CHAD	0.29 (0.25, 0.32)	−0.28837 (−1.99)	0.00056 (3.29)	0.024
COMOROS	0.40 (0.35, 0.45)	0.24612 (2.71)	–	0.906
CONGO (DR)	0.41 (0.38, 0.46)	−0.12088 (−1.88)	0.00043 (2.23)	0.094
CONGO REP.	0.45 (0.41, 0.50)	−0.03486 (−2.40)	0.00029 (2.58)	0.079
COTE D'IVOIRE	0.35 (0.32, 0.39)	−0.00411 (−2.33)	0.00034 (2.26)	0.060
EQUATORIAL GUINEA	0.46 (0.42, 0.51)	−0.26534 (−1.86)	0.00046 (2.23)	0.068
ERITREA	0.32 (0.28, 0.36)	−0.08873 (−1.84)	0.00056 (2.37)	0.093
ESWATINI	0.25 (0.22, 0.29)	−0.18824 (−1.92))	0.00118 (7.18)	0.041
ETHOPIA	0.46 (0.38, 0.49)	−0.01044 (−1.85)	0.00045 (1.71)	0.136
GABON	0.49 (0.44, 0.54)	−0.19626 (−2.24)	0.00051 (2.06)	0.095
GAMBIA(THE)	0.36 (0.31, 0.40)	−0.00684 (−2.03)	0.00044 (1.78)	0.109
GHANA	0.37 (0.33, 0.42)	−0.22598 (−1.69)	0.00050 (2.48)	0.080
GUINEA	0.35 (0.31, 0.40)	−0.07138 (−1.97)	–	0.114
GUINEA BISSAU	0.36 (0.32, 0.41)	−0.01738 (−1.98)	0.00041 (1.91)	0.118
KENYA	0.51 (0.47, 0.55)	−0.34965 (−1.99)	0.00084 (2.01)	0.047
LESOTHO	0.21 (0.17, 0.25)	−0.31716 (−2.60)	0.00137 (9.74)	0.053
LIBERIA	0.39 (0.35, 0.44)	0.22655 (1.79)	–	0.099
MADAGASCAR	0.32 (0.27, 0.37)	−0.14534 (−1.88)	–	0.053
MALAWI	0.30 (0.26, 0.35)	−0.26777 (−1.91)	0.00051 (3.09)	0.102
MALI	0.30 (0.25, 0.35)	−0.27852 (−1.91)	0.00080 (3.70)	0.142
MAURITANIA	0.30 (0.26, 0.35)	−0.20198 (−2.23)	0.00067 (3.47)	0.069
MAURITUS	0.52 (0.48, 0.58)	−0.05853 (−1.37)	0.00057 (2.15)	−0.0002
MOZAMBIQUE	0.29 (0.25, 0.34)	−0.19400 (−1.97)	0.00057 (3.72)	0.077
NAMIBIA	0.23 (0.20, 0.27)	−0.17711 (−2.07)	0.00054 (5.53)	0.042
NIGER	0.27 (0.23, 0.32)	−0.35423 (−1.89)	0.00044 (2.01)	0.052
NIGERIA	0.32 (0.28, 0.36)	−0.32089 (−1.94)	0.00036 (1.81)	0.082
RWANDA	0.38 (0.34, 0.42)	−0.19034 (−1.85)	0.00066 (3.74)	0.077
SAO TOME & PRINCIPE	0.45 (0.41, 0.50)	−0.24759 (−1.75)	0.00044 (2.21)	0.056
SENEGAL	0.35 (0.30, 0.40)	−0.04855 (−2.24)	0.00046 (1.92)	0.110
SEYCHELLES	0.45 (0.42, 0.50)	−0.43398 (−2.87)	0.00084 (3.74)	0.058
SIERRA LEONE	0.36 (0.32, 0.41)	0.22765 (2.46)	–	0.120
SOMALIA	0.47 (0.42, 0.52)	0.03675 (1.94)	–	0.181
SOUTH AFRICA	0.22 (0.18, 0.26)	−0.33165 (−2.87)	0.00118 (8.89)	0.060
SOUTH SUDAN	0.34 (0.31, 0.38)	−0.14625 (−1.78)	0.00073 (3.23)	0.098
SUDAN	0.29 (0.25, 0.33)	−0.26765 (−1.77)	0.00070 (2.64)	0.048
TANZANIA	0.46 (0.42, 0.50)	−0.28029 (−2.52)	0.00074 (2.78)	0.047
TOGO	0.37 (0.33, 0.41)	−0.22290 (−1.98)	0.00042 (1.81)	0.114
UGANDA	0.47 (0.43, 0.51)	−0.30290 (−1.95)	0.00087 (2.67)	0.023
ZAMBIA	0.30 (0.26, 0.34)	−0.15746 (−2.00)	0.00047 (2.57)	0.084
ZIMBABWE	0.28 (0,23, 0.32)	−0.15114 (−1.84)	0.00065 (3.07)	0.085

— means lack of significancy.

temperatures after 1945, quite variable temperatures until the mid-1960s, followed by a gradual increase over the remainder of the record.". Therefore, we use 1910 to 1945, and 1910 to 1930 for our reference points for Sub-Saharan African countries in the northern and southern hemispheres respectively when calculating for temperature anomalies.

The following countries are situated fully or majorly in the northern hemisphere; Benin, Burkina Faso, Cameroon, Cabo Verde, Central African Republic, Chad, Cote D'Ivoire, Equatorial Guinea, Eritrea, Ethiopia, The Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Liberia, Mali, Mauritania, Niger, Nigeria, Sao Tome & Principe, Senegal, Sierra Leone, Somalia, South Sudan, Sudan, Togo, and Uganda, while the countries of.

Angola, Botswana, Burundi, Comoros, Congo (Democratic Republic), Congo Republic, Eswatini, Gabon, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Rwanda, Seychelles, South Africa, Tanzania, Zambia, and Zimbabwe, are fully or majorly situated in the southern hemisphere.

The descriptive statistics of the anomalies for SSA countries (displayed in Table 6) reveal the following: Lesotho (0.66 °C) had the highest mean value while Madagascar (−0.36 °C) had the lowest mean value, i.e., Lesotho, on average, experienced more warming, while Madagascar experienced more cooling on average. Comoros (1.15 °C) had the highest standard deviation while Congo DR (0.29 °C) had the lowest. Niger (−3.47 °C) had the lowest minimum of the anomalies, while Congo DR (−0.73 °C) had the highest minimum of the anomalies, i.e., that of all countries that are cooler than the reference value, Niger had the coolest period while Congo DR had the least cool period from the reference value. Sudan (4.09 °C) had the highest maximum of the anomalies, while Congo DR (1.19 °C) had the lowest maximum of the anomalies, i.e., Sudan had the warmest period from the reference value, while Congo DR had the least warm period from the reference value. Sudan (8.24 °C) had the widest range of the anomalies, while Congo DR (1.92 °C) had the narrowest range, i.e., Sudan had a widest departure from her reference value, while Congo DR had the narrowest departure from her reference value.

Table 7 displays the estimated coefficients using the whole sample

Table 8
Estimated coefficients in the model given by Eq. (1). Data starting at January 1946. Anomalies with respect to 1910m1 – 1930m12/1945m12.

COUNTRY	d (95% band)	Intercept	Time trend	Seasonality
ANGOLA	0.32 (0.26, 0.39)	0.04776 (2.39)	0.00049 (2.13)	0.318
BENIN	0.29 (0.25, 0.34)	−0.38331 (−2.63)	0.00102 (3.77)	0.110
BOTSWANA	0.30 (0.24, 0.36)	0.08612 (2.42)	0.00115 (2.99)	0.127
BURKINA FASO	0.24 (0.18, 0.30)	−0.11087 (−1.72)	0.00115 (4.07)	0.123
BURUNDI	0.31 (0.27, 0.37)	0.27773 (2.56)	0.00097 (4.92)	0.032
CABO VERDE	0.40 (0.34, 0.47)	−0.11147 (−1.66)	0.00060 (1.97)	0.169
CAMEROON	0.38 (0.34, 0.43)	0.15632 (2.01)	–	−0.029
CENTRAL AF. REP.	0.29 (0.27, 0.34)	−0.06900 (−1.69) 564982.56)-	0.00059 (2.56)	0.079
CHAD	0.23 (0.25, 0.32)	−0.56490 (−4.00)	0.00154 (5.91)	0.098
COMOROS	0.38 (0.35, 0.45)	0.49532 (2.19)	–	0.891
CONGO (DR)	0.41 (0.36, 0.48)	0.06294 (1.58)	0.00044 (5.91)	0.064
CONGO REP.	0.45 (0.40, 0.51)	0.34109 (2.10)	–	0.102
COTE D'IVOIRE	0.33 (0.28, 0.38)	−0.10224 (−1.76)	0.00047 (2.99)	0.257
EQUATORIAL GUINEA	0.45 (0.40, 0.50)	0.27896 (2.03)	–	0.092
ERITREA	0.28 (0.23, 0.34)	−0.51645 (−2.78)	0.00179 (5.16)	0.094
ESWATINI	0.23 (0.19, 0.29)	0.32971 (2.10)	0.00139 (4.80)	0.072
ETHOPIA	0.39 (0.34, 0.45)	−0.15142 (−1.81)	0.00110 (2.93)	0.137
GABON	0.49 (0.44, 0.56)	0.38475 (2.10)	–	0.114
GAMBIA(THE)	0.37 (0.30, 0.44)	−0.26897 (−2.16)	0.00128 (2.79)	0.146
GHANA	0.34 (0.29, 0.39)	−0.20525 (−2.43)	0.00092 (3.25)	0.096
GUINEA	0.33 (0.27, 0.39)	−0.17359 (−2.19)	0.00095 (3.20)	0.146
GUINEA BISSAU	0.38 (0.32, 0.44)	−0.23461 (−2.13)	0.00122 (2.93)	0.163
KENYA	0.45 (0.39, 0.51)	0.56132 (2.93)	0.00109 (2.56)	0.110
LESOTHO	0.20 (0.14, 0.25)	0.38412 (2.65)	0.00142 (5.32)	0.085
LIBERIA	0.36 (0.31, 0.42)	−0.16010 (−2.19)	0.00063 (2.38)	0.125
MADAGASCAR	0.43 (0.37, 0.50)	−0.43961 (−1.91)	–	0.631
MALAWI	0.29 (0.23, 0.35)	−0.21695 (2.41)	0.00091 (3.19)	0.157
MALI	0.24 (0.20, 0.31)	−0.00335 (−1.88)	0.00108 (3.64)	0.167
MAURITANIA	0.29 (0.23, 0.35)	−0.15851 (−1.82)	0.00122 (2.33)	0.084
MAURITUS	0.51 (0.45, 0.57)	−0.13331 (−1.68)	0.00120 (2.12)	−0.033
MOZAMBIQUE	0.25 (0.20, 0.34)	−0.08821 (−1.61)	0.00095 (3.54)	0.140
NAMIBIA	0.23 (0.19, 0.28)	−0.07717 (−1.75)	0.00090 (4.78)	0.049
NIGER	0.21 (0.15, 0.27)	−0.63631 (−3.83)	0.00131 (4.27)	0.013
NIGERIA	0.26 (0.21, 0.32)	−0.47223 (−3.37)	0.00092 (3.55)	0.050
RWANDA	0.32 (0.27, 0.37)	0.34222 (3.04)	0.00099 (4.62)	0.046
SAO TOME & PRINCIPE	0.44 (0.38, 0.50)	0.28465 (2.00)	–	0.082
SENEGAL	0.37 (0.30, 0.43)	−0.27911 (−2.15)	0.00129 (2.69)	0.147
SEYCHELLES	0.51 (0.45, 0.57)	−0.3221 (−1.77)	0.00136 (2.91)	0.122
SIERRA LEONE	0.35 (0.30, 0.41)	−0.20090 (−2.40)	0.00085 (3.04)	0.157
SOMALIA	0.38 (0.32, 0.44)	−0.01641 (−2.12)	0.00044 (1.64)	0.199
SOUTH AFRICA	0.21 (0.15, 0.26)	0.15501 (2.14)	0.00144 (5.79)	0.093
SOUTH SUDAN	0.31 (0.26, 0.37)	−0.48104 (−2.52)	0.00194 (5.40)	0.104
SUDAN	0.22 (0.17, 0.29)	−0.83533 (−4.50)	0.00230 (6.72)	0.040
TANZANIA	0.42 (0.37, 0.49)	0.54301 (3.42)	0.00092 (2.75)	0.037
TOGO	0.34 (0.30, 0.40)	−0.29139 (−1.78)	0.00095 (3.01)	0.149
UGANDA	0.39 (0.34, 0.45)	0.40142 (2.34)	0.00139 (4.00)	0.038
ZAMBIA	0.30 (0.25, 0.36)	−0.15662 (−1.89)	0.00093 (2.83)	0.128
ZIMBABWE	0.27 (0.21, 0.33)	−0.07824 (−2.41)	0.00114 (3.25)	0.150

— means lack of significancy.

Table 9
Summary results in terms of persistence.

d – Estimation			
Highest values		Lowest values	
Whole sample	+1946	Whole sample	+1946
MAURITIUS (0.52)	SEYCHELLES (0.51)	LESOTHO (0.21)	LESOTHO (0.20)
KENYA (0.51)	MAURITIUS (0.51)	SOUTH AFRICA (0.22)	SOUTH AFRICA (0.21)
GABON (0.49)	GABON (0.49)	NAMIBIA (0.23)	NIGER (0.21)
SOMALIA (0.47)	KENYA (0.45)	ESWATINI (0.25)	SUDAN (0.22)
UGANDA (0.47)	EQ. GUINEA (0.45)	NIGER (0.27)	ESWATINI (0.23)
TANZANIA (0.46)	CONGO REP. (0.45)	ZIMBABWE (0.28)	NAMIBIA (0.23)
ETHIOPIA (0.46)	SAO TOME (0.44)	MOZAMBIQUE (0.29)	MOZAMBIQUE (0.25)

size while Table 8 focuses on the post-WW2 data. Starting with the whole dataset, the first noticeable feature is that the time trend is now required in 41 out of the 48 countries examined. That is, there are only seven countries that show evidence of no trends. These countries are Cabo Verde, Comoros, Guinea, Liberia, Madagascar, Sierra Leone and Somalia. On the other hand, the highest coefficients for the time trend are observed in Eswatini, Lesotho and South Africa (all Southern African countries), and followed by Uganda, Kenya, and Seychelles (Eastern Africa). Looking at the degree of integration of the series, we see that all of them are in the interval (0, 1) implying long memory and fractional

Table 10
Summary results in terms of time trends.

β_1 – Estimation			
Time trends		No time trends	
Whole sample	+1946	Whole sample	+1946
ESWATINI (0.00118)	SUDAN (0.00230)	CABO VERDE	CAMEROON
LESOTHO (0.00137)	S. SUDAN (0.00194)	COMOROS	COMOROS
S. AFRICA (0.00118)	ERITREA (0.00179)	GUINEA	CONGO REP.
UGANDA (0.00087)	CHAD (0.00154)	LIBERIA	EQ. GUINEA
KENYA (0.00084)	S. AFRICA (0.00144)	MADAGASCAR	GABON
SEYCHELLES (0.00084)	LESOTHO (0.00144)	SIERRA LEONE	MADAGASCAR
		SOMALIA	SAO TOME

integration and the highest values refer to Mauritius (d = 0.52), followed by Kenya (0.51), Gabon (0.49), Somalia and Uganda (0.47) and Tanzania and Ethiopia (0.46). On the other extreme, the lowest values of d correspond to Lesotho (d = 0.21), South Africa (0.22), Namibia (0.23), Eswatini (0.25) all of them being Southern African countries. Thus, there seems to be a clear geographical correlation in relation with both the degree of persistence and the time trend coefficients. Tables 9 and 10 report summary statistics dealing with these two issues for both the whole data and the sample starting at 1946.

Table 8 reports the results for the data starting after World War II. We

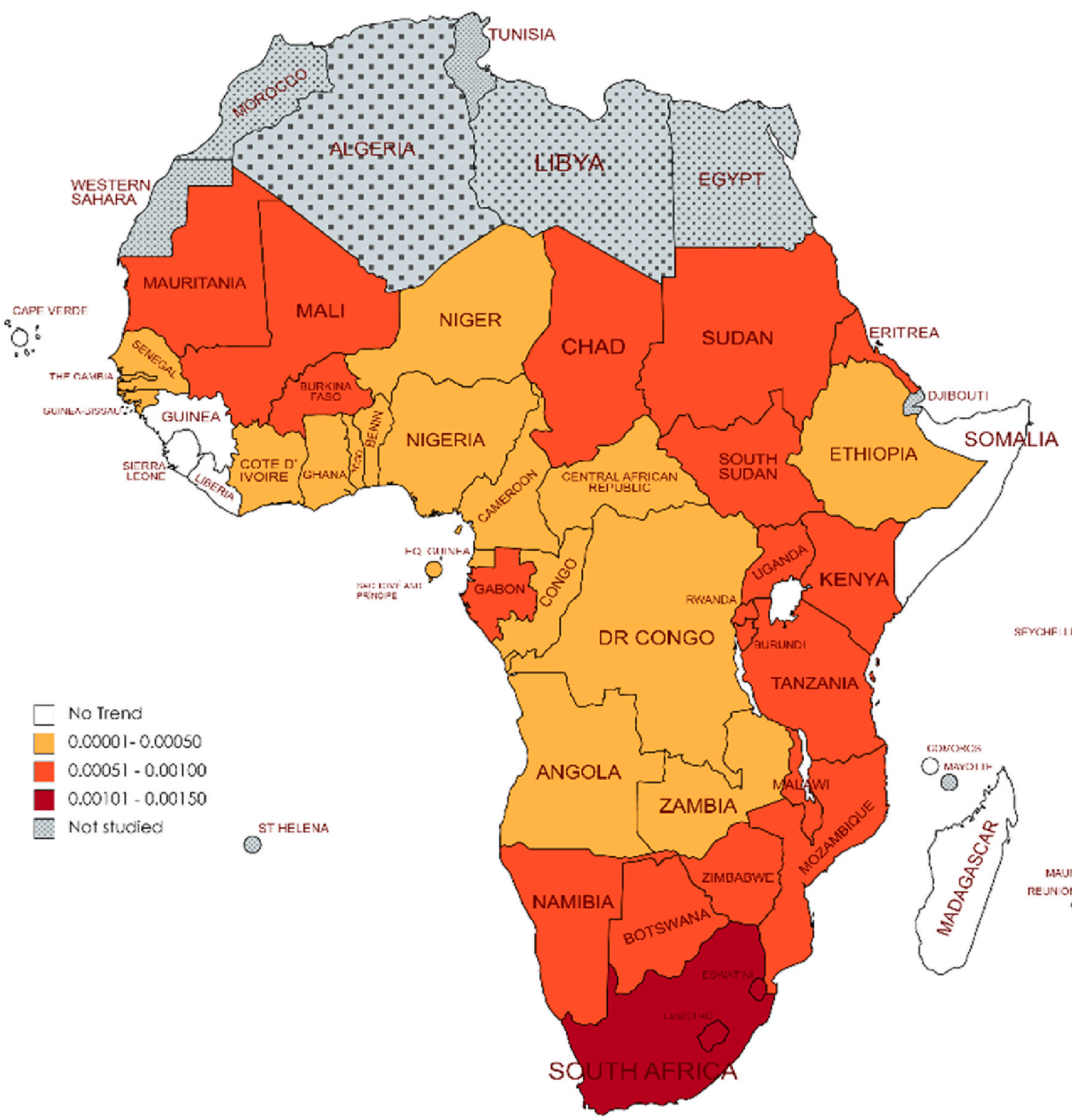

Fig. 5. Time trends for temperature anomalies based on Table 7.

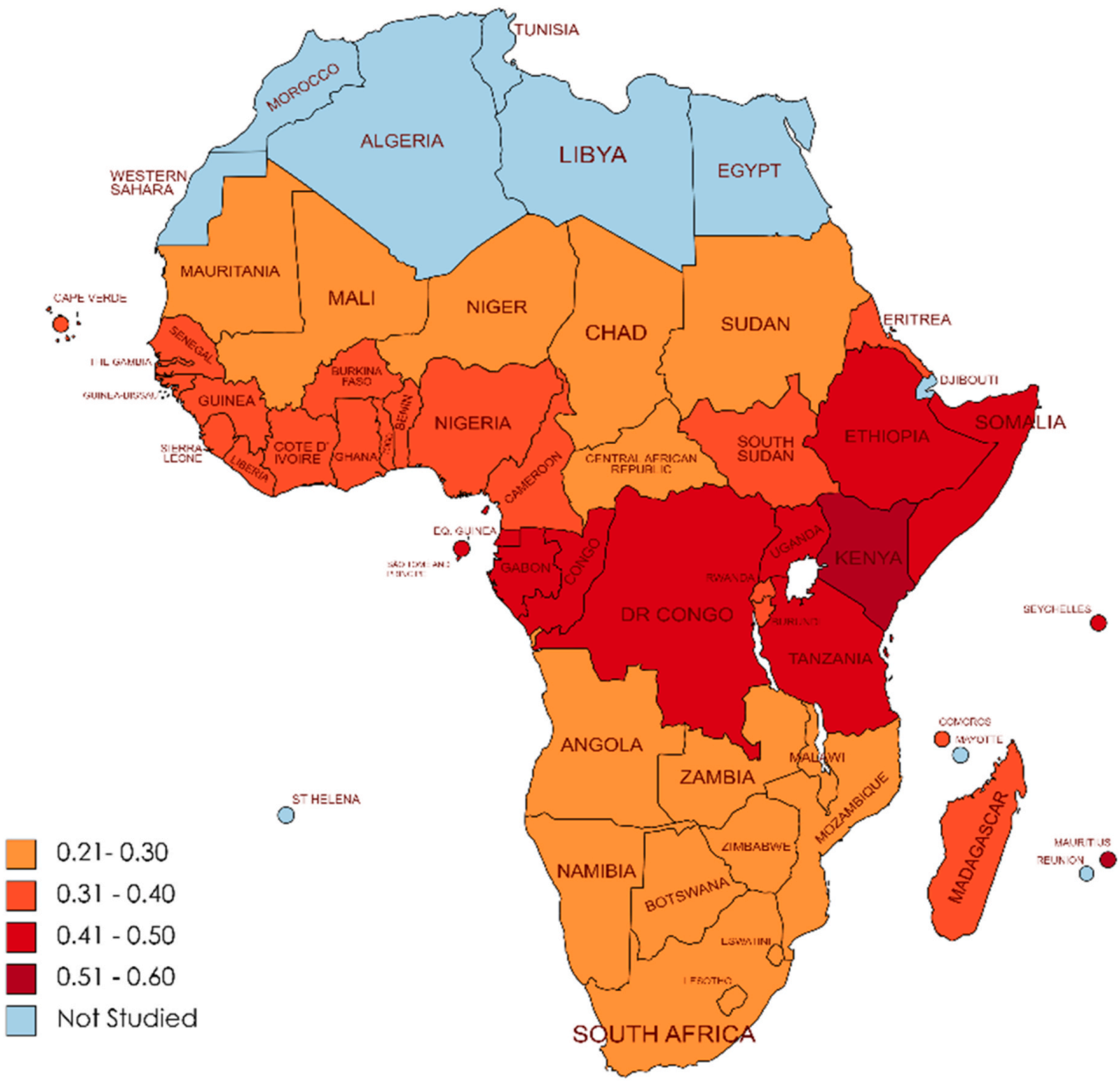

Fig. 6. Estimates of the degree of persistence (d) for temperature anomalies based on Table 7.

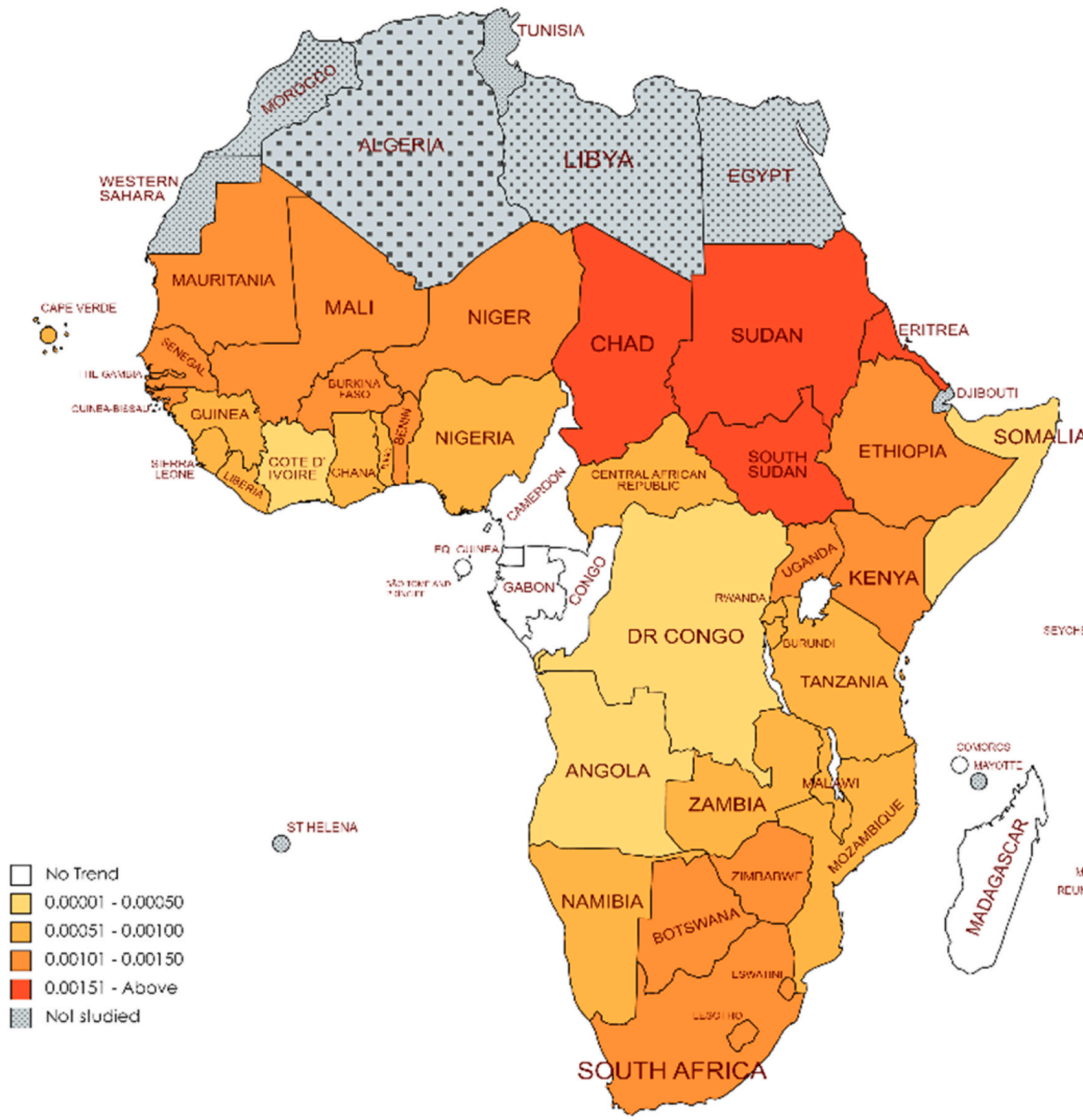

Fig. 7. Time trends for temperature anomalies based on Table 8.

observe that the time trend coefficient is now statistically significant again in 41 countries (non-significant trends are now found in Cameroon, Comoros, Congo Rep., Equatorial Guinea, Gabon, Madagascar and Sao Tome) and the highest coefficients take place in Sudan, South Sudan, Eritrea, Chad, South Africa and Lesotho. Also, higher values are observed than when the whole sample size was examined (see Table 10). With respect to the degree of persistence, the highest d-estimates are obtained for Nigeria (d = 0.56), Seychelles and Mauritius (0.51), Gabon (0.49), and Kenya, Equatorial Guinea and Congo Rep. (with d = 0.45), while the lowest ones refer once more to some Southern countries such as Lesotho (d = 0.20) and South Africa (0.21). Graphical representations of both components (persistence and time trends) in the anomalies are displayed in the Appendix across Figs. 5–8.

6. Conclusions

In this paper we have examined the time series properties of the temperature and temperature anomalies in Sub-Saharan Africa, looking at the data for the 48 countries that form this area. For this purpose, we have used techniques based on fractional integration.

Based on the assumption of short memory in the temperatures (though later invalidated by our long memory tests), we observe that the time trend is statistically significantly positive in all cases, except for Madagascar and Niger, while all, without exception, are significant following the use of post-WWII data, with an increase also being observed in the magnitude of the coefficient in all countries. According to these results, temperatures have been increasing over time in almost all countries, and the increase is higher when post WWII data were used.

Testing for long memory, our results validate this hypothesis. Examining first the original data (mean temperatures) and using the whole sample, we find that the time trend coefficient is statistically significant only for Lesotho, South Africa and Eswatini (which are in Southern Africa), and South Sudan, Rwanda and Burundi (in East Africa), while in the post WWII sample, the time trend is statistically significant in Sudan, Eritrea, South Sudan, Rwanda and Burundi. There is seasonality as well as persistence (long memory) for all countries in both the whole sample and the post-WWII sample.

Using temperature anomalies, long memory is again detected in all countries, and employing again first the whole sample size, we find that all except seven countries (Cabo Verde, Comoros, Guinea, Liberia, Madagascar, Sierra Leone and Somalia) have significant time trends. A

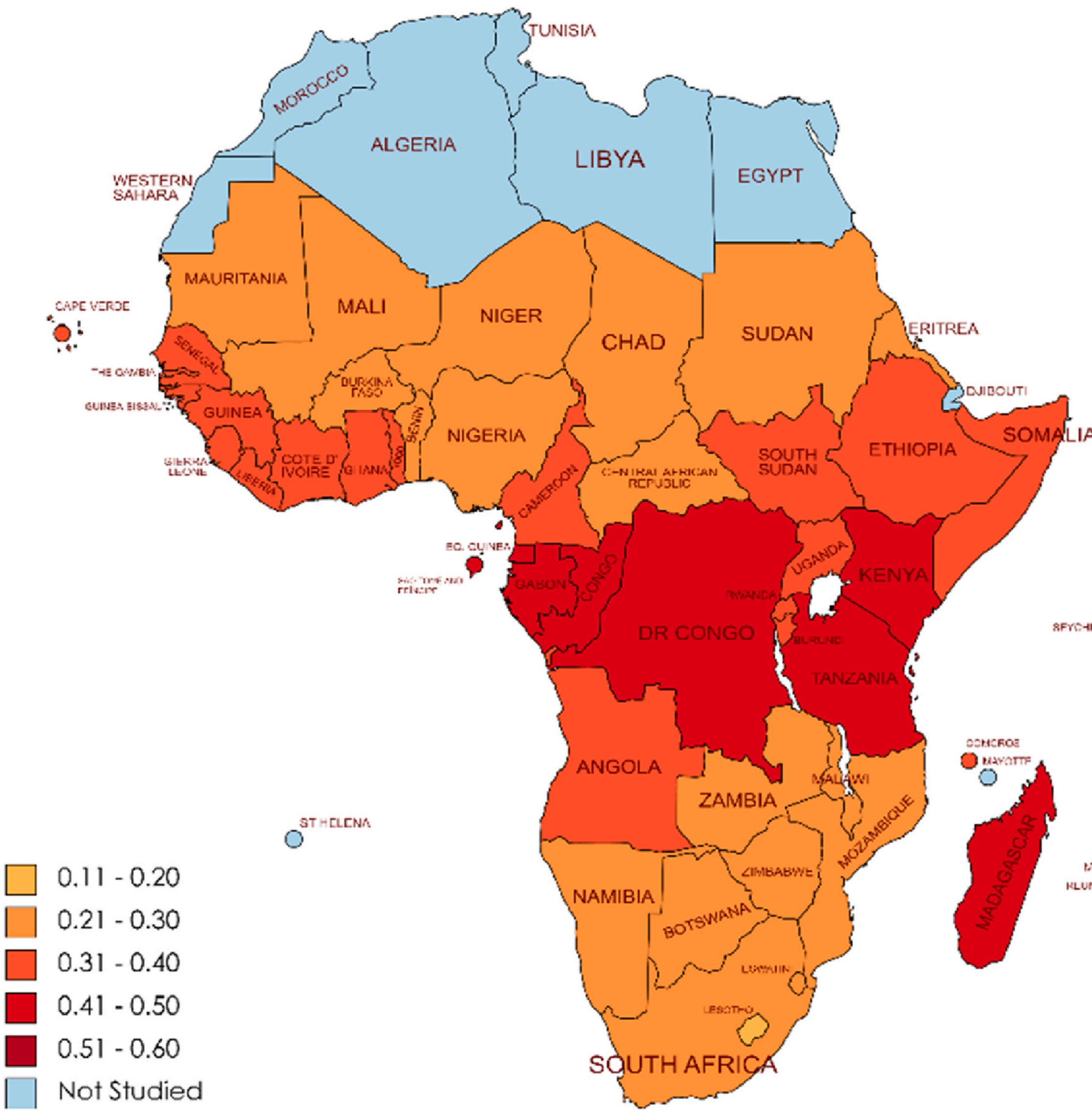

Fig. 8. Estimates of the degree of persistence (d) for temperature anomalies based on Table 8.

similar scenario plays out in the post-WW2 sample with non-significant trends being found in Cameroon, Comoros, Congo Rep., Equatorial Guinea, Gabon, Madagascar and Sao Tome. The values of the time trend experience a significant increase in the post-WWII sample, suggesting that industrialization has contributed to global warming. Thus, the results for both the whole sample period and the post-WWII sample period show that global warming is evident across the majority of Sub-Saharan countries. We observe some heterogeneity in global warming across Sub-Saharan Africa.

Due to the persistence (long memory) of global warming in SSA and the evident impact of global warming vis-à-vis climate change on economic activity (which has been corroborated in many studies, e.g., Deschênes and Michael, 2007; Barrios, Bertinelli and Strobl, 2010; Dell et al., 2009, 2012, 2014; Ward and Shively, 2012; Burke et al., 2015; Cáceres and Malone, 2015; Letta and Tol, 2018; Tol, 2018, 2020), there is a need for stronger climate/environmental policies (more adaptation than mitigation policies as some effects are irreversible and SSA countries are not major polluters) on the part of countries of Sub-Sahara Africa. Nevertheless, due to the heterogeneity of global warming across Sub-Saharan Africa, all countries must enact specific climate cum environmental policies as it affects them in different ways across countries.

Our results are consistent with many other articles that also find long memory in climatological time series (Vyushin and Kushner, 2009; Rypdal and Rypdal, 2014; Yuan et al. 2014a, 2014b, 2022; Gil-Alana et al., 2022). However, there are issues that have not been treated in this work like the potential presence of structural breaks in the data. This is relevant, noting that some authors argue that long memory might be an artificial artifact generated by the presence of breaks unaccounted in the data. In that respect, the use of non-linear I(d) frameworks may be alternative approaches to those used in this work. In addition, and based on the monthly nature of the data, seasonal (monthly) long memory structures like those suggested in Gil-Alana (1999), or more recently, in Bisognin and Lopes (2009) and Del Barrio Castro and Rachinger (2021) can be examined.

CRediT authorship contribution statement

Samuel Chibuzor Umeh: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation. **Luis A. Gil-Alana:** Validation, Supervision, Software, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

There is no conflict of interest with the publication of the present manuscript.

Data availability

Data will be made available on request.

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