



Testing seasonal persistence of rainfall in arid and semi-arid african climatic zones using a seasonal fractional model

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Abstract

Arid and semi-arid regions of Africa are characterised by low mean annual rainfall with substantial temporal variability due to factors influencing climate in the region, coupled with hot temperatures in the Sahara region. This study therefore investigates seasonal persistence in the amount of rainfall in 17 African countries that are prone to aridity. For this purpose, we use a time series econometrics framework that is based on the concept of seasonal fractional integration, extending the seasonal unit root methods to the fractional case. Monthly data from January 1901 to December 2024 are used, and the results indicate fractional degrees of integration in the interval (0, 1) in all countries, with some of them showing a stationary pattern ($0 < d < 0.5$) while others showing nonstationarity ($d \geq 0.5$). The lowest degrees of persistence are found in several northern (Algeria, Tunisia) and eastern (Somalia, Kenya) countries, and a time trend is found to be significantly positive in a number of cases, being the highest for Ethiopia and Kenya. Results emanating from this study has important implications for drought and occasional flash floods management in the arid and semi-arid regions for ecosystems and human lives that depend majorly on rain-fed activities.

JEL Classification C22 · C02

1 Introduction

Arid regions are characterised by low mean annual rainfall with substantial temporal variability in precipitation patterns. In Africa, arid and semi-arid regions encompass the Sahara Desert in the north, the Sahel belt, the Namib and Kalahari deserts in the south, and smaller dryland areas in eastern Africa. Evaporation often exceeds precipitation in these regions, making them highly susceptible to desertification, soil degradation, recurrent drought, and water scarcity (UNCCD 2022). The Sahara Desert extends across much of northern Africa, covering large portions of Algeria, Libya, Egypt, Mali, Niger, Chad, and Sudan. Characterised by extremely low rainfall, high temperatures, and sparse vegetation, the Sahara is the world's largest hot desert. Semi-arid regions occur across the Sahel, extending from Mauritania in the west through Mali, Burkina Faso, Niger, northern Nigeria, Chad, and into Sudan and Eritrea in the east (UNEP 2011). In southern Africa, Namibia is dominated by the Namib Desert along its Atlantic coast, while about 70% of Botswana is covered by the Kalahari Desert. Other arid and semi-arid regions are found in the Horn of Africa and eastern Africa, particularly in Somalia, eastern

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and southern Ethiopia, and northern Kenya, where low and highly variable rainfall constrains agricultural production and increases vulnerability to drought (IPCC 2022).

African rainfall exhibits pronounced spatial and temporal variability due to multiple interacting atmospheric and oceanic processes. The strength and northward progression of the West African Monsoon controls the seasonality of rainfall majorly, while the seasonal movement of the Intertropical Convergence Zone (ITCZ) determines the onset, duration, and intensity of the rainy season (Nicholson 2018). Rainfall variability across eastern and southern Africa is strongly influenced by large-scale ocean–atmosphere interactions, particularly the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD), which modulate atmospheric circulation, moisture transport, and the frequency of droughts and floods (Reason et al. 2000; Black et al. 2003; Nicholson 2017). In North Africa, rainfall is largely influenced by the Mediterranean cyclones and winter westerly disturbances, while local topography, including the Ethiopian Highlands, East African Rift, and the Drakensberg Mountains, further modifies rainfall in the East African zones through orographic lifting and rain-shadow effects (Nicholson 2018). These climatic controls operate across a wide range of temporal scales and can introduce strong dependence on seasonality in rainfall, with differences in rainfall distribution based on regional variations in the relative influence and interaction of these large-scale climate drivers.

Seasonal rainfall persistence is the tendency for rainfall anomalies in a given season to depend on anomalies observed in subsequent seasons, years, quarters, or months. Time persistence reflects the influence of slowly varying large-scale climate drivers such as sea surface temperature, soil moisture, and atmospheric circulation patterns that enhance seasonal rainfall patterns. Statistically, this persistence is characterised based on the rate at which autocorrelations or temporal dependence reduce with increasing lag in a correlogram. In the ARFIMA modelling framework, this dependence is quantified by employing the fractional differencing parameter, d , such that when $0 < d < 0.5$, the rainfall series exhibits stationary long-range dependence (long memory), implying that correlations decay hyperbolically slowly rather than exponentially fast and that shocks to seasonal rainfall persist over a long period. With $d > 0.5$, the rainfall series becomes nonstationary with stronger persistence (Gil-Alana et al. 2019; Yaya and Vo 2020).

In arid and semi-arid regions, rainfall typically exhibits weak seasonal persistence due to the dominance of episodic and irregular precipitation events (Aryal et al. 2020; Quichimbo et al. 2023), therefore, access to historical rainfall time series is crucial, as they offer significant predictive insights for the regions under study. The high variability and

relative persistence will make hydrological modelling challenging in these environments; thus, a robust econometric approach is required, such as the framework proposed in this paper and based on seasonal unit roots and seasonally fractionally integrated processes.

By applying this methodology to rainfall in the arid and semi-arid African countries, the research uncovers objectively the degree of seasonal persistence and how precipitation dynamics evolve over time in these regions. The period analysed spanned for more than a century (1901 to 2024), which is long enough to study the climate of a geographic region. Specifically, the methodological contribution in this paper is in threefold. Firstly, it presents a rare long-term estimate of rainfall persistence in Africa using data on seasonal rainfall, covering the period from 1901 to 2024 and based on the World Bank Climate Change Knowledge Portal (CCKP). Secondly, unlike previous works on rainfall in Africa that considered annual or monthly rainfall for trend and autoregressive analysis, the present study employs an updated seasonal fractional integration framework to identify the persistence property of African rainfall. Thirdly, it considers arid and semi-arid climate regions of Africa in the analysis based on the nature of time series persistence of low and erratic rainfall expected in the regions.

2 Materials and methods

Country-level monthly rainfall amounts (mm) of the following 17 countries were analysed: Algeria, Botswana, Egypt, Ethiopia, Kenya, Libya, Morocco, Mali, Mauritania, Namibia, Niger, Sudan, Somalia, South Sudan, Chad, Tunisia, and South Africa. These are countries with arid, semi-arid or extensive arid and semi-arid lands (ASALS) according to the classification by UNEP (2011), which distinguishes countries from entirely drylands to significant dryland regions alongside more humid climatic zones. The rainfall data for these countries are the Climatic Research Unit Time Series (CRU TS) dataset of the World Bank Climate Change Knowledge Portal. The CRU TS dataset is a global $0.5^\circ \times 0.5^\circ$ gridded observational climate dataset developed by interpolating station-based monthly climate anomalies onto a regular grid, and it serves as the global historical observational dataset used by the World Bank (Harris et al. 2020; World Bank, 2021).

Each time period spans from January 1901 to December 2024, containing a total of 1488 monthly observations. Table 1 describes the monthly rainfall characteristics (in mm) across the 17 countries over the sample period (1,488 months). As can be seen, over the period 1901–2024, monthly rainfall exhibits substantial cross-country heterogeneity. Mean rainfall ranges from 1.8 mm in Egypt and

Table 1 Descriptive statistics on rainfall time series

Series	N months	Mean (mm)	SD (mm)	CV (%)	Skewness	Kurtosis
Algeria	1488	7.131	4.169	58.462	0.803	0.366
Botswana	1488	33.679	37.307	110.773	1.195	1.07
Chad	1488	29.657	40.221	135.619	1.571	1.805
Egypt	1488	1.806	1.943	107.566	1.935	4.475
Ethiopia	1488	70.545	48.362	68.554	0.343	-0.494
Kenya	1488	59.061	45.343	76.773	1.525	2.586
Libya	1488	3.361	3.212	95.559	1.311	1.483
Mali	1488	28.267	37.834	133.844	1.341	0.79
Mauritania	1488	9.65	14.295	148.132	1.763	2.402
Morocco	1488	27.574	24.042	87.19	1.108	1.068
Namibia	1488	23.712	29.952	126.312	1.661	2.777
Niger	1488	15.403	24.692	160.305	1.935	3.379
Somalia	1488	22.236	21.729	97.724	1.491	2.091
South Africa	1488	39.854	27.178	68.195	0.794	0.038
South Sudan	1488	82.75	67.743	81.865	0.257	-1.321
Sudan	1488	21.431	29.496	137.634	1.48	1.287
Tunisia	1488	22.471	18.523	82.429	1.126	1.385

3.4 mm in Libya to more than 70 mm in Ethiopia and 83 mm in South Sudan, reflecting the arid to semi-arid climate in the regions. Relative variability, measured by the coefficient of variation (CV), is often above 100% in many countries (e.g., Niger, Mauritania, Namibia), indicating strong variability from month to month, with intermittency and episodic heavy events, and is lowest in Algeria, South Africa, and Ethiopia. In addition, all the series are positively skewed, suggesting that rainfall in these countries presents many months with low rainfall and occasional heavy events.

As a preliminary check for seasonality, we conducted HEGY (Hylleberg et al. 1990) seasonal unit root tests of Beaulieu and Miron (1993) on the monthly dataset, and the

results are reported in Table 2. The results indicated rejections of non-seasonal and seasonal unit roots in the rainfall series of the 17 countries. Here, overdifferencing of seasonal and non-seasonal integration orders by the HEGY test, that is, $\{(1 - L^{12})^d\}$, with $d = 1\}$, might have led to spurious rejection of unit roots in the rainfall amount in arid and semi-arid regions of Africa. Thus, it is too restrictive to assume the unit differencing in $(1 - L^{12})^d$, with $d = 1$; as noted in Hassler and Wolters (1993).

Rejection of a unit root does not imply a short memory in a time series. The time series could still be fractionally integrated with slowly decaying autocorrelations and long

Table 2 HEGY unit root test

Series	t_1	t_2	$F_{3 \cap 4}$	$F_{5 \cap 6}$	$F_{7 \cap 8}$	$F_{9 \cap 10}$	$F_{11 \cap 12}$	$F_{1 \cap 12}$
Algeria	-9.80***	-10.46***	33.99***	79.67***	89.82***	97.81***	110.21***	91.26***
Botswana	-9.04***	-10.29***	7.27***	52.39***	121.61***	125.41***	111.07***	93.18***
Chad	-6.09***	-7.47***	0.67	2.63	8.40***	17.63***	35.43***	19.17***
Egypt	-8.84***	-10.02***	17.54***	68.41***	90.13***	99.33***	89.08***	76.97***
Ethiopia	-8.38***	-10.74***	3.32***	34.88***	38.99***	41.19***	88.62***	50.94***
Kenya	-7.48***	-10.85***	47.61***	13.79***	39.08***	56.70***	93.52***	62.73***
Libya	-10.12***	-10.21***	10.90***	74.75***	101.88***	106.34***	88.27***	84.70***
Mali	-5.69***	-7.92***	0.63	2.51	11.52***	37.34***	58.65***	27.95***
Mauritania	-6.18***	-8.19***	2.06	4.70***	14.67***	41.12***	68.20***	31.01***
Morocco	-9.69***	-10.52***	20.93***	69.00***	86.33***	105.63***	119.03***	85.76***
Namibia	-8.90***	-10.32***	11.69***	46.96***	97.13***	117.82***	116.71***	93.88***
Niger	-6.21***	-8.03***	1.40	3.76***	10.49***	24.19***	47.45***	24.01***
Somalia	-7.98***	-10.03***	38.81***	7.55***	75.38***	30.52***	86.51***	55.26
South Africa	-9.37***	-10.14***	12.77***	104.17***	117.11***	120.53***	109.03***	103.55***
South Sudan	-7.76***	-8.31***	1.10	40.06***	55.53***	80.33***	68.28***	54.02***
Sudan	-5.93***	-8.61***	1.13	4.03***	15.12***	32.45***	52.18***	28.32***
Tunisia	-9.99***	-11.51***	29.47***	70.66***	102.49***	109.33***	127.41***	93.88***

Note, the deterministic term is the constant, lag length is fixed to 0 in order to overcome the problem of determining it automatically based on the minimum information criteria. The computation of p-values is based on response surface regressions

seasonal memory as advocated in Hassler and Wolters (1993). Thus, a seasonal fractional model is the appropriate next step to quantify the degree of persistence of such a series.

2.1 The model

The first notions of fractional differencing and long memory in the context of seasonal data were proposed in Abrahams and Dempster (1979) and Jonas (1981), and it was later extended in a Bayesian framework by Carlin et al. (1985) and Carlin and Dempster (1989). These concepts, however, were barely employed in the analysis of observed data. Among the few who did so, Porter-Hudak (1990) applied a seasonally fractionally integrated model to quarterly US monetary data, and a few other applications include Silvapulle (1995), Ooms and Hassler (1997) and Gil-Alana (2002), Gil-Alana et al. (2019), Yaya and Vo (2020).

In the development of seasonal models for climatic series, Hamilton (1994) forms the basis, representing a climatic time series using the seasonal deterministic model with dummy variables, specified as:

$$x(t) = \alpha_0 + \sum_{i=1}^{s-1} \beta_i S_i(t) + u(t), \quad t = 1, 2, \dots, \quad (1)$$

in Hamilton (1994), where $x(t)$ refers to the observed data; $u(t)$ an *i.i.d.* process distributed with mean 0 and variance σ^2 ; $S_i(t)$ is a monthly seasonal series, such that $s=12$ in the case of a monthly series, that is, the number of periods per year; α_0 is the model intercept and β_i are the unknown seasonal coefficients. This model specification assumes that the seasonal pattern is repeated with constant amplitude and timing over time, implying a fixed deterministic form of seasonality rather than a stochastic one. This assumption seems unrealistic with the present data, and it is in fact, rejected in the paper with insignificant dummy coefficients in all series.

Under the stochastic autoregressive (AR)-based test, we define two simple classical seasonal specifications for $x(t)$. The first, which is the seasonal AR(1) model, is described by,

$$(1 - \rho_s L^s) x(t) = \epsilon(t), \quad t = 1, 2, \dots, \quad (2)$$

with $|\rho_s| < 1$ in the case of no seasonal unit root, as against a seasonal unit root with $\rho_s = 1$ (Hylleberg et al. 1990). In this context $\epsilon(t)$ is an uncorrelated (white noise) process. The other specification is the extension of the above to seasonal fractional integration, which emerged within the context of seasonal long memory models:

$$(1 - L^s)^d x(t) = u(t), \quad t = 1, 2, \dots, \quad (3)$$

where d can be any real number. If $d=1$, the model is equivalent to (2) with $\rho_s = 1$ and tests seasonal unit roots. For $0 < d < 0.5$, $x(t)$ displays a (seasonal) long memory property with slowly decaying autocorrelations having similar behaviour of spikes at every frequency $k=s$ lags. In this paper, we follow this latter approach, which has not been used very much in the time series literature, and is based on the fact that rainfall amounts from Arid regions are low and erratic over the seasonal cycle. Thus, in the empirical application carried out in the following section, we consider a model that, for the deterministic part, only contains an intercept and a (potential) linear time trend, i.e.,

$$y(t) = \alpha + \beta t + x(t), \quad t = 1, 2, \dots, \quad (4)$$

where $y(t)$ refers to the observed data; $x(t)$ is a fractional seasonal model of the form featuring in (3), with $u(t)$ displaying a short memory pattern that will adopt different forms, including the seasonal AR process in (2). The estimation is conducted via a particular version of the test of Robinson (1994), not much used in the literature, since we assume the presence of various poles or singularities in the spectrum according to the specification in (3) (Gil-Alana 1999).

Using the above approach, we test the null hypothesis:

$$H_o : d = d_o, \quad (5)$$

where d_o can be any real value, in a model given by:

$$y(t) = \alpha + \beta t + x(t), \quad (1 - L^s)^d x(t) = u(t) \quad (6)$$

and the test statistic is given by the following expression,

$$\hat{s} = \left(\frac{T}{\hat{A}} \right)^{1/2} \frac{\hat{a}}{\hat{\sigma}^2} \quad (7)$$

where T is the sample size, and $\hat{\sigma}^2$ is the variance of $\hat{u}_t$ defined as

$$\hat{u}_t = (1 - L^{12})^{d_o} y(t) - \hat{\alpha} (1 - L^{12})^{d_o} 1 - \hat{\beta} (1 - L^{12})^{d_o} t$$

with $\hat{\alpha}$ and $\hat{\beta}$ as the least squared estimates of α and β respectively. $\hat{A}$ is a real scalar value defined as:

$$\hat{A} = \frac{2}{\left(\sum \hat{\psi}(\lambda_j)^2 - \sum \hat{\psi}(\lambda_j) \hat{\epsilon}(\lambda_j)^T \left(\sum \hat{\epsilon}(\lambda_j) \hat{\epsilon}(\lambda_j)^T \right)^{-1} \sum \hat{\epsilon}(\lambda_j) \hat{\psi}(\lambda_j) \right)}$$

where $\psi(\lambda_j)$ is defined in Robinson (1994) as $\psi(\lambda_j) = \Re \left[\frac{\partial}{\partial d} \log(1 - e^{12i\lambda})^d \right]$, implying that $\psi(\lambda_j) = \sum_{m=1}^7 \psi_m(\lambda_j)$, and

$$\psi_1(\lambda_j) = \log \left| 2 \sin \frac{\lambda_j}{2} \right|$$

$$\psi_2(\lambda_j) = \log \left(2 \cos \frac{\lambda_j}{2} \right)$$

$$\psi_3(\lambda_j) = \log |2 \cos \lambda_j|$$

$$\psi_4(\lambda_j) = \log |2 (\cos \lambda_j - \cos(2\pi/3))|$$

$$\psi_5(\lambda_j) = \log |2 (\cos \lambda_j - \cos(\pi/3))|$$

$$\psi_6(\lambda_j) = \log |2 (\cos \lambda_j - \cos(5\pi/6))|$$

and

$$\psi_7(\lambda_j) = \log |2 (\cos \lambda_j - \cos(\pi/6))|$$

Table 3 Estimates of d. White noise errors

Country	No terms	An intercept	A linear time trend
Algeria	0.23 (0.14, 0.30)	0.25 (0.22, 0.28)	0.27 (0.24, 0.30)
Botswana	0.36 (0.33, 0.39)	0.36 (0.33, 0.38)	0.36 (0.33, 0.39)
Chad	0.68 (0.65, 0.72)	0.66 (0.63, 0.70)	0.66 (0.63, 0.70)
Egypt	0.33 (0.30, 0.36)	0.32 (0.29, 0.35)	0.32 (0.30, 0.35)
Ethiopia	0.52 (0.49, 0.56)	0.49 (0.46, 0.52)	0.49 (0.47, 0.52)
Kenya	-0.27 (-0.36, -0.18)	0.17 (0.08, 0.24)	0.27 (0.23, 0.31)
Libya	0.54 (0.51, 0.57)	0.38 (0.36, 0.42)	0.39 (0.36, 0.42)
Mali	0.70 (0.66, 0.74)	0.67 (0.64, 0.71)	0.67 (0.64, 0.71)
Mauritania	0.55 (0.52, 0.58)	0.54 (0.51, 0.57)	0.54 (0.51, 0.57)
Morocco	0.32 (0.28, 0.36)	0.32 (0.28, 0.35)	0.32 (0.30, 0.36)
Namibia	0.40 (0.38, 0.43)	0.40 (0.37, 0.43)	0.40 (0.38, 0.43)
Niger	0.57 (0.54, 0.60)	0.56 (0.53, 0.59)	0.56 (0.53, 0.59)
Somalia	-0.08 (-0.22, 0.23)	0.21 (0.16, 0.27)	0.25 (0.21, 0.29)
South Africa	0.40 (0.36, 0.43)	0.38 (0.36, 0.41)	0.39 (0.37, 0.42)
South Sudan	0.65 (0.61, 0.68)	0.60 (0.57, 0.63)	0.60 (0.58, 0.63)
Sudan	0.62 (0.59, 0.65)	0.60 (0.58, 0.64)	0.61 (0.58, 0.64)
Tunisia	0.25 (0.22, 0.29)	0.25 (0.23, 0.29)	0.27 (0.25, 0.30)

The values are the estimates of the seasonal differencing parameter d, with the 95% bands in parenthesis. In bold, the chosen deterministic model for each country

Moreover, $\hat{\epsilon}(\lambda_j) = \frac{\partial}{\partial \tau} \log g(\lambda_j; \tau)$, evaluated at $\hat{\tau} = \arg \min_{\tau} \hat{\sigma}^2(\tau)$ with g being the part of the spectral density function of u(t), removing the constant term $\left(\frac{\sigma^2}{2\pi}\right)$. Thus, if u(t) is a white noise process, g=1, and for an AR(p) process, $g = \left|1 - \sum_{j=1}^p \tau_j e^{i\lambda_j}\right|^{-2}$, with $\tau_1, \tau_2, \dots, \tau_p$ as the AR coefficients. Finally, $\hat{a} = -\frac{2\pi}{T} \sum_j^* \psi(\lambda_j) g(\lambda_j; \hat{\tau})^{-1} I(\lambda_j)$, where $I(\lambda_j)$ is the periodogram of $\hat{u}(t)$ evaluated at $\lambda_j = \frac{2\pi j}{T}$. The sums on * indicate all frequencies which are away from poles or singularities in the spectrum.¹ A full description of this procedure and its code in Fortran is available in Gil-Alana (1998).

A simple adaptation in Robinson (1994) and Gil-Alana (1999) shows that the test statistics $\hat{s}$ follows an asymptotic standard normal distribution, i.e.,

$$\hat{s} \rightarrow_{T \rightarrow \infty} N(0, 1) \text{ as } T \rightarrow \infty \quad (8)$$

The fractional seasonal model described above is more general and caters for the overdifferencing issue often encountered with the HEGY seasonal unit root tests of monthly and quarterly datasets.

3 Empirical results

Table 3 displays the estimates of d in the model given by Eq. (6) under the assumption that u(t) is an uncorrelated (white noise) process. Thus, all the time dependence is captured throughout the seasonal differencing parameter d. Note that in this context, the test statistics $\hat{s}$ in (7) substantially simplifies since $g \equiv 1$ and consequently $\hat{\epsilon}(\lambda_j) = 0$, and thus $\hat{A}$ simply becomes $\frac{2}{T} \sum_j^* \psi(\lambda_j)^2$.

As is standard in the unit roots literature (Bhargava 1986; Schmidt and Phillips 1992), we consider in Table 3 the cases of (i) no deterministic terms (results reported in column 2); (ii) with an intercept (column 3), and with an intercept and a linear time trend (column 4). The significant model for each series is marked in bold in the table. It can be seen that a time trend is required in 10 out of the 17 countries examined.

Table 4 focuses on the estimated coefficients of the selected models for each series. It can be observed that the estimates of d lie in the interval (0, 1) in all cases, supporting the hypothesis of fractional integration and the mean reversing effects of shocks; however, the estimates of d

¹ Note that based on the functional forms of $\psi_i(\lambda_j)$ for $i=1, 2, 3, 4, 5, 6$ and 7, these specifications tend to infinite for $j=T/12, 5T/12, T/6, T/4, T/3, T/2$ and $j>T/2$.

substantially vary across countries; thus, the lowest values correspond to countries such as Somalia ($d=0.25$), Algeria, Tunisia and Kenya (0.27) and Morocco and Egypt (0.32); for these countries, along with Botswana (0.36), Libya and South Africa (0.39) and Namibia (0.40), all the values in the confidence intervals are lower than 0.50 supporting the hypothesis of stationarity; on the other extreme, the highest degrees of seasonal persistence are found in the cases of Mauritania (0.54), Niger (0.56), South Sudan and Sudan ($d=0.60$), Chad (0.66) and Mali (0.67), where we cannot reject the hypothesis of nonstationary series. Ethiopia (with $d=0.49$) is located around the stationarity/nonstationarity bound. This latter set of countries with higher persistence experiences rainfall that is concentrated within a single monsoonal wet season governed by the northward and southward migration of the ITCZ and the West African Monsoon (WAM), and rainfall events tend to occur in coherent seasonal sequences while prolonged dry seasons and relatively low intra-seasonal variability enhance temporal persistence in these semi-arid regions (Nicholson 2018). In contrast, Somalia, Kenya, Algeria and Tunisia display lower persistence due to their complex and heterogeneous climatic mechanisms. Kenya and Somalia experience multiple rainfall regimes, including the “long rains” and “short rains,” resulting from the seasonal migration of the ITCZ, with strong modulation by the Indian Ocean Dipole (IOD), ENSO, and regional topography. These interacting drivers

increase interannual and intra-seasonal rainfall variability, thereby reducing persistence. Likewise, rainfall in Algeria and Tunisia is primarily associated with Mediterranean cyclones and mid-latitude weather systems, which produce episodic and irregular precipitation rather than sustained seasonal rainfall. The greater spatial heterogeneity of rainfall-generating mechanisms in these countries therefore, leads to weaker long-memory characteristics compared with the monsoon-dominated Sahelian region (Lionello and Scarascia 2018; IPCC 2021).

Looking at the time trend coefficients in Table 3, they are statistically significant in 10 out of the 17 countries examined, and the highest coefficients are observed in the cases of Ethiopia (0.0169), and Kenya (0.0285) as given in Table 4. This indicates increments of 0.2028 and 0.3420 mm per year in the respective countries.

Table 5 extends the results to allow for weak time dependence; however, instead of imposing the standard Autoregressive Moving Average (ARMA)-class of models for the disturbances $u(t)$ in (6), we report the results based on a non-parametric specification based on Bloomfield (1973). This model is non-parametric in the sense that it is only implicitly defined in terms of the spectral density function of $u(t)$, which is given by.

$$f(\lambda; \tau) = \frac{\sigma^2}{2\pi} \exp\left(2 \sum_{j=1}^m \tau_j \cos(\lambda \tau_j)\right)$$

and the log version of which approximates the spectrum of an ARMA process with far fewer parameters; this method produces autocorrelations decaying exponentially fast as in the AR case and it is stationary across all range of values τ_j . Another computational advantage of the model of Bloomfield is that $\hat{e}(\lambda_j)$ in the test statistic is now relatively simple as its l^{th} element becomes $2\cos(\lambda_j l)$. In our application and for simplicity, we select $m=1$. Employing values of m higher than 1 produced almost identical results in terms of the estimation of the differencing parameter d .

We observe in Table 5 that the estimates of d are again in the interval (0, 1), lying between 0.10 in Kenya and 0.57 in Mali. Stationarity is found in the same ten countries as with white noise errors, along with Ethiopia, while nonstationarity is now found only in South Sudan (0.54), Chad (0.56) and Mali (0.57). The time trend is now significant in all countries except three (Egypt, Mali and Mauritania), and the highest coefficients again correspond to the same three countries as in Table 4, that is, Kenya (0.0364) and Ethiopia (0.0184), implying annual increments of 0.4368 mm and 0.2208 mm, respectively.

As a final approach, we transformed all the rainfall data to quarterly using a three-month interval sampling by assuming the first monthly data point for the quarterly

Table 4 Estimated coefficients of the selected models. White noise errors

Country	d (95% interval)	α , Intercept (tv)	β , Time trend (tv) , Time trend (tv)
Algeria	0.27 (0.24, 0.30)	6.3544 (13.78)	0.0016 (3.60)
Botswana	0.36 (0.33, 0.39)	28.0468 (5.48)	0.0097 (1.98)
Chad	0.66 (0.63, 0.70)	27.9022 (8.65)	0.0058 (1.04)
Egypt	0.32 (0.29, 0.35)	1.6963 (7.62)	0.0003 (1.39)
Ethiopia	0.49 (0.47, 0.52)	65.4763 (12.21)	0.0169 (2.72)
Kenya	0.27 (0.23, 0.31)	38.4852 (9.65)	0.0285 (7.37)
Libya	0.39 (0.36, 0.42)	3.0953 (7.81)	0.0006 (1.66)
Mali	0.67 (0.64, 0.71)	27.3446 (9.14)	0.0047 (0.88)
Mauritania	0.54 (0.51, 0.57)	9.5256 (7.12)	0.0016 (0.94)
Morocco	0.32 (0.30, 0.36)	24.2678 (8.46)	0.0053 (1.89)
Namibia	0.40 (0.38, 0.43)	19.4940 (5.47)	0.0061 (1.67)
Niger	0.56 (0.53, 0.59)	12.7340 (5.58)	0.0045 (1.49)
Somalia	0.25 (0.21, 0.29)	17.9014 (11.10)	0.0081 (5.23)
South Africa	0.39 (0.37, 0.42)	33.4752 (9.83)	0.0103 (2.94)
South Sudan	0.60 (0.57, 0.63)	80.4454 (13.19)	0.0132 (1.49)
Sudan	0.60 (0.58, 0.64)	18.5862 (7.37)	0.0044 (1.17)
Tunisia	0.27 (0.25, 0.30)	18.7391 (9.47)	0.0065 (3.41)

Column 2 shows the estimates of d and 95% bands; columns 3 and 4 show respectively the values for the intercept and the time trend coefficients, with t -values in parenthesis. In bold, significant coefficients at the 5% level. T -values above 1.645 indicate statistical significance

Table 5 Estimated coefficients of the selected models. Bloomfield errors

Country	d (95% interval)	α , Intercept (tv)	β , Time trend (tv), Time trend (tv)	Bloomfield
Algeria	0.21 (0.18, 0.24)	5.9577 (15.87)	0.0020 (5.57)	0.174
Botswana	0.33 (0.30, 0.35)	27.2881 (5.86)	0.0105 (2.27)	0.117
Chad	0.56 (0.53, 0.59)	27.2574 (10.15)	0.0064 (1.80)	0.334
Egypt	0.31 (0.28, 0.33)	1.6773 (7.76)	0.0003 (1.52)	0.056
Ethiopia	0.44 (0.40, 0.46)	63.3663 (13.37)	0.0184 (3.60)	0.344
Kenya	0.10 (0.04, 0.17)	30.3495 (12.31)	0.0364 (15.10)	0.409
Libya	0.34 (0.31, 0.36)	3.0034 (8.87)	0.0007 (2.28)	0.176
Mali	0.57 (0.55, 0.60)	26.7673 (10.56)	0.0052 (1.50)	0.286
Mauritania	0.48 (0.45, 0.51)	9.3717 (7.98)	0.0017 (1.29)	0.170
Morocco	0.28 (0.25, 0.31)	23.1274 (9.22)	0.0065 (2.66)	0.144
Namibia	0.32 (0.30, 0.34)	17.9821 (6.62)	0.0077 (2.89)	0.289
Niger	0.48 (0.46, 0.51)	12.3364 (6.45)	0.0048 (2.21)	0.258
Somalia	0.13 (0.06, 0.19)	15.8049 (13.36)	0.0101 (8.83)	0.289
South Africa	0.32 (0.30, 0.35)	31.0641 (11.37)	0.0125 (4.66)	0.224
South Sudan	0.54 (0.51, 0.56)	79.5511 (14.63)	0.0145 (2.11)	0.207
Sudan	0.52 (0.49, 0.54)	0.2999 (18.24)	0.0050 (1.95)	0.302
Tunisia	0.24 (0.21, 0.26)	18.1816 (10.22)	0.0071 (4.15)	0.126

Column 2 shows the estimates of d and 95% bands; columns 3 and 4 show respectively the values for the intercept and the time trend coefficients, with t-values in parentheses. In bold, significant coefficients at the 5% level. T-values above 1.645 indicate statistical significance

value, that is, we recorded January, April, July and October rainfall amounts for quarterly records Q1, Q2, Q3, and Q4, correspondingly, for all months through the sampled years, to obtain the new quarterly rainfall time series. This transformation still allowed us to retain the seasonality in the rainfall time series, as it is practised in applied econometrics. Since rainfall is a cumulative variable, one can also obtain a quarterly variable by summing up rainfall amounts in every three months to make up a quarter, i.e. January – March as Q1, April – June as Q2, July – September as Q3, and October – December as Q4, using a three-month interval sampling, to obtain a quarterly sum series for each country. This sum can further be averaged over 3 samples

(three months summed together) to obtain a quarterly average series for each country.

Based on the three-month interval sampling transformation, we then assume that the model for this time series is the same as before, but now $u(t)$ follows a quarterly seasonal AR(1) process of the form:

$$(1 - \rho_4 L^4) u(t) = \epsilon(t), \quad t = 1, 2, \dots, \quad (9)$$

where $\epsilon(t)$ is now a white noise process.

The results are presented in Table 6. Once again, we find all the estimates of d to be above 0 and below 1, though they are now slightly higher than in the previous cases. Thus, only six countries display statistical evidence of stationarity (Somalia, Algeria, Kenya, Tunisia, Egypt and Morocco), while nonstationarity is found in a group of nine countries (Libya, Namibia, Ethiopia, Mauritania, South Sudan, Sudan, Niger, Mali and Chad). The lowest degrees of persistence correspond to Northern and Eastern countries such as Somalia (0.33), Algeria and Kenya (0.35) and Tunisia (0.39), while the highest values of d are found in Niger (0.80), Mali (0.84) and Chad (0.89). The time trend is now significant in eight countries, and the highest values occur again in Kenya and Ethiopia.

Further, by replacing the three-month interval sampling values with those based on the sum of the three months in a quarter and the average values produced almost identical results, and these are reported in the Appendix in Table 8.

4 Discussion

Based on the estimated seasonal fractional differencing parameters reported across Tables 4 and 5, for monthly data with white noise and Bloomfield disturbances, respectively, and Table 6 for quarterly data, we have the following summary that is reported in Table 7.

The following six countries present statistical evidence of stationarity across the three model specifications: Somalia, Algeria, Kenya, Tunisia, Egypt and Morocco. In addition, Namibia, South Africa, Botswana and Libya also show this pattern with uncorrelated errors and also Ethiopia if the model of Bloomfield is considered. This result implies that rainfall deviations from the mean are corrected relatively quickly in these countries. On the other extreme, South Sudan, Chad and Mali are the only three countries with statistical evidence of nonstationarity in the three models, though values of d in the range (0.5–0.8) are also observed in other countries like Mauritania, Niger, and Sudan. These countries exhibit moderate to strong persistence, implying that rainfall anomalies are highly enduring and revert to the mean level slowly. Thus, rainfall shocks such as droughts or

Table 6 Estimated coefficients of the selected models using a three-month interval sampling. Seasonal errors

Country	d (95% interval)	α , Intercept (tv)	β , Time trend (tv), Time trend (tv)	Seasonal AR
Algeria	0.35 (0.30, 0.41)	6.9128 (11.94)	0.0010 (1.86)	-0.205
Botswana	0.46 (0.43, 0.50)	30.3356 (4.69)	0.0075 (2.05)	-0.285
Chad	0.89 (0.83, 0.98)	28.3889 (7.84)	0.0056 (0.37)	-0.439
Egypt	0.41 (0.37, 0.45)	1.8656 (6.61)	0.0002 (0.55)	-0.227
Ethiopia	0.63 (0.59, 0.68)	69.6677 (10.71)	0.0141 (1.97)	-0.346
Kenya	0.35 (0.21, 0.49)	42.4598 (8.58)	0.0252 (5.10)	-0.165
Libya	0.55 (0.51, 0.60)	3.2791 (6.03)	0.0004 (0.69)	-0.381
Mali	0.84 (0.79, 0.92)	27.7882 (8.42)	0.0048 (0.44)	-0.359
Mauritania	0.66 (0.62, 0.71)	9.7225 (6.31)	0.0014 (0.53)	-0.304
Morocco	0.42 (0.37, 0.47)	27.1417 (7.26)	0.0026 (0.67)	-0.230
Namibia	0.57 (0.53, 0.62)	2.1650 (4.50)	0.0037 (0.57)	-0.429
Niger	0.80 (0.74, 0.88)	1.3293 (4.76)	0.0046 (0.58)	-0.466
Somalia	0.33 (0.18, 0.44)	1.9468 (9.74)	0.0068 (3.47)	-0.089
South Africa	0.52 (0.48, 0.57)	37.4056 (8.49)	0.0068 (2.26)	-0.348
South Sudan	0.73 (0.69, 0.78)	80.8174 (11.87)	0.0113 (2.76)	-0.316
Sudan	0.77 (0.72, 0.83)	18.697 (6.66)	0.0037 (0.52)	-0.387
Tunisia	0.39 (0.35, 0.44)	20.951 (7.62)	0.0043 (1.53)	-0.307

Column 2 shows the estimates of d and 95% bands; columns 3 and 4 show respectively the values for the intercept and the time trend coefficients, with t -values in parenthesis. In bold, significant coefficients at the 5% level. T -values above 1.645 indicate statistical significance

wet periods tend to have long-lasting effects in these semi-arid/arid regions. In sum, semi-arid and arid African regions display heterogeneous climatic persistence with some areas experiencing rapid mean-reverting rainfall patterns, while others exhibit slowly decaying dependence, reflecting differing levels of hydroclimatic resilience to shocks.

In Fig. 1, we present maps of Africa showing the distribution of persistence of rainfall with time trends based on Bloomfield and quarterly seasonal errors. In the two maps in the upper panel, countries with values of d above 0.5 have significant rainfall time trend values of 0.005 to 0.100. Rainfall is also expected to trend up in the southern African region

Table 7 Summary results on persistence

i) White noise disturbances		
Stationarity ($d < 0.50$)	$d \approx 0.50$	Nonstationarity ($d \geq 0.50$)
Somalia (0.25)	Ethiopia (0.49)	Mauritania (0.54)
Kenya, Tunisia, Algeria (0.27)		Niger (0.56)
Egypt, Morocco (0.32)		South Sudan (0.60)
Botswana (0.36)		Sudan (0.60)
Libya, South Africa (0.39)		Chad (0.66)
Namibia (0.40)		Mali (0.67)
ii) Bloomfield disturbances		
Stationarity ($d < 0.50$)	$d \approx 0.50$	Nonstationarity ($d \geq 0.50$)
Kenya (0.10)	Mauritania, Niger (0.48)	South Sudan (0.54)
Somalia (0.13)	Sudan (0.52)	Chad (0.56)
Algeria (0.21)		Mali (0.57)
Tunisia (0.24)		
Morocco (0.28)		
Egypt (0.31)		
Namibia, South Africa (0.32)		
Botswana (0.33)		
Libya (0.34)		
Ethiopia (0.44)		
iii) Seasonal AR disturbances		
Stationarity ($d < 0.50$)	$d \approx 0.50$	Nonstationarity ($d \geq 0.50$)
Somalia (0.33)	Botswana (0.46)	Libya (0.55)
Algeria, Kenya (0.35)	South Africa (0.52)	Namibia (0.57)
Tunisia (0.39)		Ethiopia (0.63)
Egypt (0.41)		Mauritania (0.66)
Morocco (0.42)		South Sudan (0.73)
		Sudan (0.77)
		Niger (0.80)
		Mali (0.84)
		Chad (0.89)

The first column reports the countries where the estimates of d are significantly below 0.50, implying stationarity. The second column displays the countries with values in the boundary between stationarity and nonstationarity, while those in column 3 indicate countries with a statistically significant nonstationary behaviour ($d \geq 0.50$)

and some countries in the north, based on this estimation approach. Basing our estimation on seasonal errors, there are many more countries with $d > 0.5$, and other countries in the upper north and at the southern end with $d > 0.35$. Substantial spatial heterogeneity in rainfall persistence is therefore observed across the arid and semi-arid regions of Africa. The concentration of persistent rainfall patterns in parts of northern and southern Africa further indicates that climatic shocks may dissipate more slowly in these areas, and the findings underscore varying levels of hydroclimatic resilience across African regions (IPCC 2021).

Finally, the linear nature of the trend imposed in Eq. (6) can be replaced by alternative non-linear trends, including,

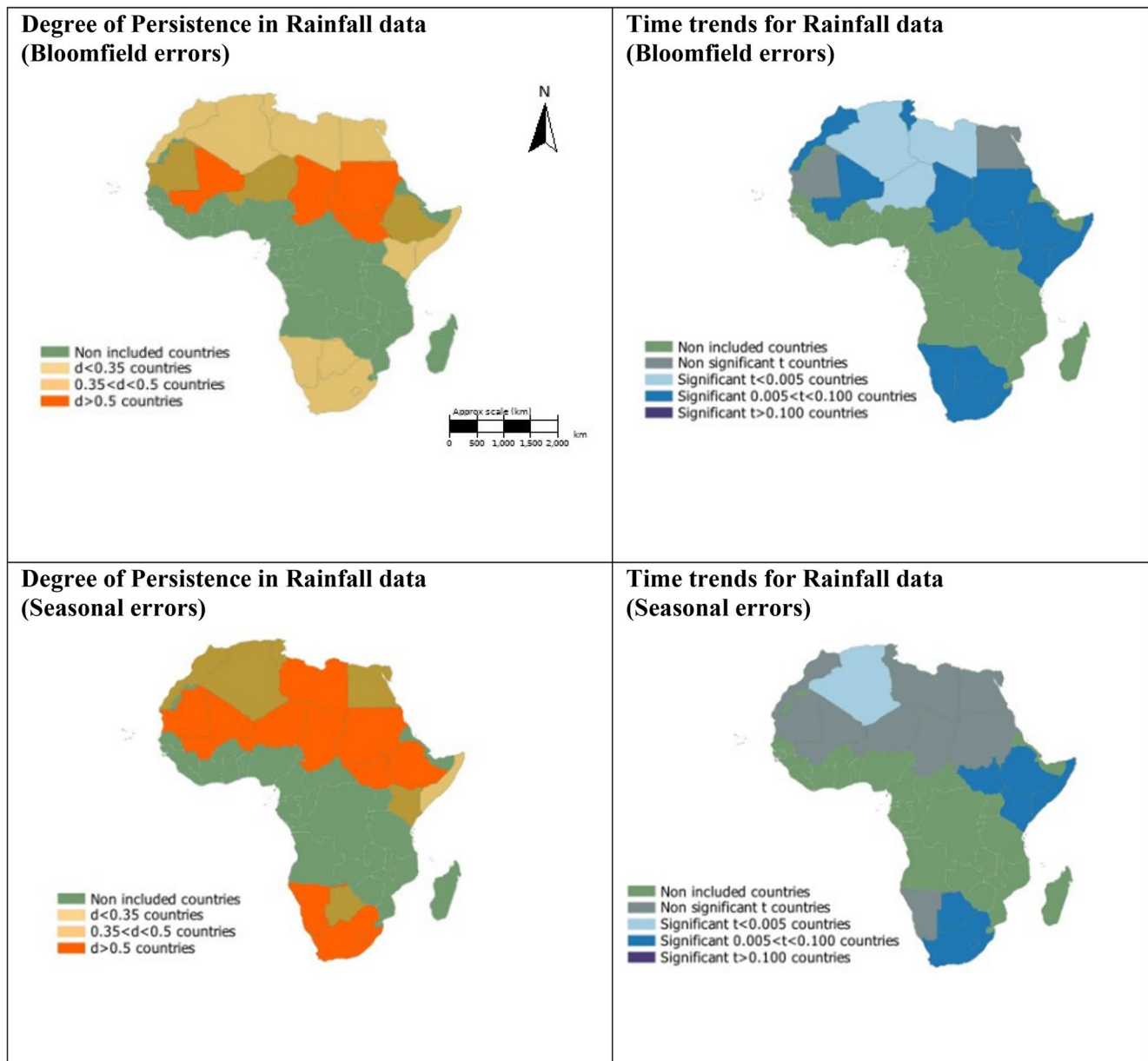


Fig. 1 Map of Africa showing the geographic distribution of rainfall persistence and time trends. Shapefile source: <https://www.naturalearthdata.com>

for example, the use of Chebyshev polynomials in time (as in Cuestas and Gil-Alana 2016), Fourier functions (Gil-Alana and Yaya 2021) or neural networks (Yaya et al. 2021). On the other hand, a natural extension of the present work might be to investigate if the seasonal differencing parameter remains equal across all frequencies in the spectrum. This requires a more complex specification for the functional form of the testing procedure, though its development was already reported for the quarterly case in Gil-Alana and Robinson (2001). In addition, the presence of breaks, still in this context of seasonal data, is another issue that should be investigated in our dataset and that might be creating

spurious evidence of (seasonal) long memory behaviour. In this context, the non-linear structures mentioned above might be alternative specifications that avoid the abrupt changes produced by breaks. Work in these directions for the monthly data will be conducted in future papers.

5 Conclusion

In this study, we propose a flexible long-memory approach for handling monthly (and quarterly) time-series data, specifically rainfall amounts (mm) in arid regions of Africa. We

investigate the degree of (seasonal) persistence and the existence of significant linear trends in the data for the following 17 countries: Algeria, Botswana, Egypt, Ethiopia, Kenya, Libya, Morocco, Mali, Mauritania, Namibia, Niger, Sudan, Somalia, South Sudan, Chad, Tunisia, and South Africa. Our results indicate that all orders of integration are in the interval (0, 1), supporting the hypothesis of seasonal persistence or seasonal fractional integration. More specifically, the lowest levels of integration are observed in several northern (Algeria, Tunisia) and eastern (Somalia, Kenya) countries, and a time trend is significantly positive in several cases, with the highest values for Ethiopia and Kenya. Countries with higher seasonal persistence may therefore require different drought-monitoring and agricultural-planning strategies than countries where rainfall anomalies revert more quickly.

A limitation of this study is the use of country-level average rainfall, which may mask substantial sub-national spatial variability in rainfall persistence. This is particularly relevant for climatically heterogeneous countries such as Kenya, Ethiopia, South Africa, and Sudan, where distinct regional rainfall regimes may not be adequately represented by national averages. Consequently, the findings should be interpreted as reflecting broad national-scale patterns rather than localised rainfall dynamics. We therefore also consider as future research monthly rainfall totals, monthly anomalies relative to the 1991–2020 climate, standardised precipitation anomalies, and log-transformed rainfall series and compare our findings.

Appendix

Table 8 Estimated coefficients of the differencing parameter with alternative datasets: summing and averaging

Country	Summing	Averaging
Algeria	0.34 (0.22, 0.53)	0.31 (0.18, 0.48)
Botswana	0.43 (0.34, 0.59)	0.40 (0.31, 0.53)
Chad	0.96 (0.84, 1.03)	0.92 (0.80, 0.99)
Egypt	0.42 (0.26, 0.57)	0.40 (0.31, 0.49)
Ethiopia	0.63 (0.48, 0.75)	0.61 (0.50, 0.72)
Kenya	0.37 (0.28, 0.58)	0.32 (0.22, 0.51)
Libya	0.61 (0.53, 0.71)	0.59 (0.50, 0.67)
Mali	0.86 (0.73, 0.99)	0.84 (0.71, 0.95)
Mauritania	0.72 (0.44, 0.76)	0.67 (0.42, 0.74)
Morocco	0.35 (0.20, 0.53)	0.33 (0.17, 0.48)
Namibia	0.60 (0.47, 0.66)	0.59 (0.44, 0.65)
Niger	0.77 (0.65, 0.93)	0.77 (0.62, 0.90)
Somalia	0.44 (0.23, 0.54)	0.38 (0.19, 0.49)
South Africa	0.56 (0.45, 0.67)	0.54 (0.43, 0.62)
South Sudan	0.78 (0.76, 0.90)	0.76 (0.66, 0.89)
Sudan	0.81 (0.73, 0.83)	0.79 (0.68, 0.81)
Tunisia	0.41 (0.30, 0.58)	0.42 (0.31, 0.54)

Author contributions L.A.G.A. conducted the empirical application and interpretation of results. O.Y. proposed the original data and data collection along with interpretation of results. R.G. made the figures, collected data and wrote the conclusions; P.O. wrote the introduction and review along with data description.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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