Review Article

Climate Warming: Is There Evidence in Africa?

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We have examined the temperature time series across several locations in Africa. In particular, we focus on three countries, South Africa, Kenya, and Côte d'Ivoire, examining the monthly averaged temperatures from three weather stations at different locations in each country. We examine the presence of deterministic trends in the series in order to check if the hypothesis of warming trends for these countries holds; however, instead of using conventional approaches based on stationary $I(0)$ errors, we allow for fractional integration, which seems to be a more plausible approach in this context. Our results indicate that temperatures have only significantly increased during the last 30 years for the case of Kenya.

1. Introduction

In this paper we analyze the statistical properties of several monthly temperature time series data in Africa. In particular, we are interested in investigating two features in the data. First, the degree of persistence across time and second the potential presence of a warming effect. Seasonality is another aspect that will be taken into account in the present work. Three countries are investigated: South Africa, Côte d'Ivoire, and Kenya, and three series, located far distant one from each other, are investigated for each country. Thus, for South Africa, we look at data obtained in Durban, Pretoria, and Cape Town. For Côte d'Ivoire we examine the data at Bondoukou, Abidjan, and Gagnoa, and finally in Kenya we look at temperature observations in Kisumu, Mombasa, and Nairobi.

One feature that is commonly observed in many climatological time series is the degree of persistence. This means that the observations are highly dependent and this dependency has been commonly modelled in the climatological community by means of a simple autoregressive order one (AR(1)) process, due fundamentally to its relation with the stochastic first-order differential equation. Other authors have employed other more elaborated models, extending the AR(1) structure to the general Autoregressive Moving Average (ARMA) model, and other recent approaches use the concept of long-run dependence or long memory to

model high dependence among the data. In this paper we will employ this latter approach (fractional integration) that includes all the standard (ARMA) models as particular cases of interest. The literature on long memory processes in the context of climate time series is quite extensive. Thus, for example, Percival et al. [1] examine some short and long memory processes for the winter averaged sea level pressure time series for the Aleutian low and the Sitka (Alaska) winter air temperature records. In that paper, the authors argue that fractional differencing models can be viable alternatives to traditional ARMA approaches. Similar long-range dependent results are obtained for global mean temperatures [2], daily Italian rainfall amounts [3], and wind power variations from 1961 to 1978 over Ireland [4]. In another recent work, Stephenson et al. [5] show that, for the North Atlantic Oscillation (NAO), a long-range fractionally integrated noise provides a better fit than do other models like stationary red noise or a nonstationary random walk.

On the other hand, the statistical analysis of temperature time series has not yet provided conclusive evidence about the climatic warming effect. The most common used indicator of climate change is the surface air temperature and there is a vast amount of papers examining the trends in global and regional mean temperatures over time [6–10] and in global patterns of temperature change ([11–13], Hegerl et al. (1997), etc.). Most of these papers conclude that global mean annual surface temperatures have increased between 0.3° and 0.6°C

during the last 150 years [14–16]. Focusing on Africa, there are several papers investigating temperatures and climatological data in countries such as South Africa [17, 18], Kenya [19], and other countries [20].

When looking at the significance of a deterministic trend in time series data, a standard approach has been used to assume a linear trend model of the form

$$y_t = \beta_0 + \beta_1 t + x_t, \quad t = 1, 2, \dots, \quad (1)$$

where y_t represents observations on the time series y at time t and x_t is the deviation term. The parameter β_1 measures the average change in y_t per time period. Thus, long-run warming may be occurring if β_1 is positive, in which case there is an increasing trend in temperature. Testing the null hypothesis of

$$H_0 : \beta_1 = 0, \quad (2)$$

in (2), the warming effect will correspond to the one sided alternative: $H_a : \beta_1 > 0$. However, a crucial point here is to determine the structure of the deviation term. Thus, for example, if it follows an AR(1) process we can use the Prais and Winsten [21] transformation in order to obtain a t statistic, which converges in distribution to an $N(0, 1)$ random variable. However, as noted by Park and Mitchell [22] and Woodward and Gray [23], significant size distortions appear in the test statistic when the AR coefficient is close to 1. Following the long memory literature on climatological data, we allow the error term to be fractionally integrated or $I(d)$. In this context we need to consistently estimate the fractional differencing parameter d along with the unknown coefficients in (4). Otherwise, the estimates of the time trend coefficients are liable to be inconsistent.

The outline of this paper is as follows. Section 2 contains a brief review of the literature on climate warming focusing mainly on those articles using techniques based on long-range dependence. Section 3 describes the methodology. Section 4 is devoted to the empirical results, while Section 5 contains some concluding comments.

2. A Review of the Literature

A lot of research has been conducted in the last two decades in the field of warming climate, both at a world and local scales. Two decades ago it was argued that the upward drift over the past century could easily be a cyclical upswing of the type that has occurred many times in the past [24]. In upcoming years, climate change will be more severe and challenging, and, as a result, it will fetch the attention of the whole world. In this scenario, different policy options and techniques have evolved to cope with the climatic changes and their effects on society, economy, and nature, giving especial importance to the concept of adaptation as one of the best possible solutions to the problem [25]. Focusing on climate change in Africa, many authors have investigated its impact on agriculture in sub-Saharan countries, showing that countries are influenced not only by regional climate change, but also by climate-induced changes in competitiveness [26], in agricultural production, with results showing that climate, measured

as changes in country-wide rainfall and temperature, has been a major determinant of agricultural production in sub-Saharan Africa [27] and providing advances in rainfall forecasting methodologies in countries such as Zimbabwe [28]. More recently, relevant studies have been undertaken proving that the climate of southern Africa has undergone a significant warming which may accelerate from $+0.01^\circ\text{C}/\text{year}$ to $+0.02^\circ\text{C}/\text{year}$ [29].

Fractional integration and long memory techniques have been also applied in the field of global warming. Thus, applications of $I(d)$ models in meteorological time series data are very common. Part of the debate over climate change centers on the possibility that the changes observed over the past century are natural. This raises the question of how large a change could be expected as a result of natural variability. If the climate measurement of interest is modelled as a stationary (or related) Gaussian time series, this question can be answered in terms of the way in which the change is estimated or by the spectrum of the time series [2]. Furthermore, a time series version of the multivariate adaptive regression splines (MARS) algorithm, TSMARS, has proven valuable in its use to obtain univariate adaptive spline threshold autoregressive models that capture many of the physical characteristics of the temperatures and are useful for short- and long-term prediction (Lewis and Selvam, 1997). Long-term persistence and multifractality of precipitation and river runoff records have also been investigated [30].

The most common used indicator of climate change is the surface air temperature. There is a vast amount of papers examining the trends in global and regional mean temperatures over time [6–10] and in global patterns of temperature change [11–13] (Hegerl et al., 1997). Most of these papers conclude that global mean annual surface temperatures have increased between 0.3°C and 0.6°C during the last 150 years (Hansen and Lebedeff, 1987) [15, 16]. These papers focus on the majority of cases in the $I(0)/I(1)$ specifications; however, recent empirical evidence suggests that temperatures may be well described in terms of fractionally integrated processes [31–34]. Evidence of increasing trends in temperatures using fractional integration has been found across many locations in the world, including Alaska [1], Spain [35], India, the Antarctic Peninsula [36], and the UK [31, 37].

3. Methodology

As earlier mentioned, we are interested in testing for warming trends in the temperatures and for this purpose we consider a model with a linear deterministic time trend along with a fractionally integrated or $I(d)$ process for the detrended series. In other words, our specified model is

$$y_t = \beta_0 + \beta_1 t + x_t; \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (3)$$

where y_t is the observed time series (in our case the monthly average temperatures at different locations in Africa); β_0 and β_1 are the coefficients corresponding, respectively, to the intercept and the linear time trend, and the regressions errors

TABLE 1: Monthly means for each series.

Month	South Africa				Côte d'Ivoire			Kenya	
	DURB	PRET	CAPE	BOND	GAGN	ABID	KISU	MOMB	NAIR
JAN	24.38	22.91	21.04	27.14	26.77	26.89	24.07	26.90	19.79
FEB	24.96	22.76	21.18	28.60	27.32	27.79	23.96	27.46	20.40
MAR	24.05	21.38	19.67	28.84	27.32	28.01	23.56	27.87	20.51
APR	22.17	18.49	17.32	27.84	27.05	28.01	22.81	27.35	19.61
MAY	19.84	15.25	14.94	27.06	26.27	27.53	22.34	26.43	18.66
JUN	17.46	12.22	13.05	25.66	25.37	26.20	22.03	25.81	12.59
JUL	17.14	12.32	12.41	24.41	24.76	24.97	22.09	24.88	17.04
AUG	18.32	15.16	12.83	24.15	24.72	24.34	22.40	24.62	17.43
SEP	19.62	19.26	14.22	24.71	25.41	24.68	22.86	24.86	18.49
OCT	20.36	21.07	16.30	25.55	25.89	26.30	23.18	25.21	19.57
NOV	21.83	21.70	18.22	26.44	26.13	27.31	23.36	25.93	19.06
DEC	23.47	22.43	20.23	26.05	26.15	27.14	23.61	26.54	19.18

DURB: Durban, PRET: Pretoria, CAPE: Cape Town, BOND: Bondoukou, GAGN: Gagnoa, ABID: Abidjan, KISU: Kisumu, MOMB: Mombasa, and NAIR: Nairobi.

x_t are supposed to be $I(d)$ as defined by the second equation in (3), where d can be any real number and u_t is $I(0)$ defined as a covariance stationary process with a spectral density function that is positive and finite. This basically means that u_t is short memory, implying that if it is autocorrelated, it is of a “weak” form as described by stationary AR(MA) processes.

We estimate the parameters in the model given by (3) throughout the Whittle function (the Whittle function is an approximation to the likelihood function, which is quite convenient in the present context; see [38].) in the frequency domain [39] and we also employ a testing procedure developed by Robinson [40]. This method allows us to test the null hypothesis:

$$H_o : d = d_o, \quad (4)$$

in (3) for any real value d_o . Moreover, it has several advantages compared with other approaches: first, it allows us to test any real value d_o , encompassing thus stationary ($d_o < 0.5$) and nonstationary ($d_o \geq 0.5$) hypotheses; second, the limit distribution is standard normal, and this limiting behavior holds independently of the type of deterministic terms included in the model and of the way of modeling the $I(0)$ error term u_t . Moreover, it does not require Gaussianity and it is supposed to be robust against other complex representations for the error term.

4. Data and Empirical Results

We look at monthly temperatures from the online website TuTiempo.net, with data obtained from the World Meteorological Organization (WMO, https://www.wmo.int/pages/index_es.html). It gathers precise meteorological data since 1973 from many locations across the world. We computed the average monthly temperature values of the following African cities: Durban, Pretoria, and Cape Town in South Africa; Bondoukou, Abidjan, and Gagnoa in Côte d'Ivoire; and Kisumu, Mombasa, and Nairobi in Kenya. We have

decided to analyze these cities since we wanted to show results corresponding to three different geographical locations within Africa, in which the effects of global warming could be happening differently and have severe effects. We think that the three chosen countries represent the main sub-Saharan regions, namely, western Africa, southern Africa, and eastern Africa and it is thus our aim to see if climate warming is taking place at the same level in these regions. The choice of the cities was purely based on the availability of data.

We present in the appendix a brief description of the weather stations from which the temperatures have been collected. The exact names of the source together with their coordinates (latitude, longitude, and altitude) are given there (we have arbitrarily chosen these locations for each country, though each of them corresponds to a different meteorological area within each country).

Figure 1 displays the plots of the original series. We see a strong seasonal pattern in all cases, which is a feature that must also be taken into account when modelling trends. First, we consider a model of the form given by (3), with seasonal AR disturbances. For this latter feature, we consider a simple (monthly) AR(1) process of the following form:

$$u_t = \theta u_{t-12} + \varepsilon_t, \quad t = 1, 2, \dots, \quad (5)$$

assuming that ε_t is a white noise process. Thus, under null hypothesis (4), the model becomes

$$y_t = \beta_0 + \beta_1 t + x_t; \quad (6)$$

$$(1 - L)^{d_o} x_t = u_t, \quad u_t = \rho u_{t-12} + \varepsilon_t.$$

Table 1 displays the estimates of d along with the 95% confidence band of the nonrejection values of d using Robinson's [40] approach for the three standard cases of no regressions (i.e., $\beta_0 = \beta_1 = 0$ a priori in (6)), an intercept (β_0 unknown and $\beta_1 = 0$ a priori), and an intercept with a linear trend (β_0 and β_1 unknown). We marked in bold in the tables

FIGURE 1: Original time series.

the significant models in terms of the deterministic terms, and we observe that the time trend is statistically insignificant in all cases. If we focus on the estimated coefficients of the selected models, displayed in Table 2, we observe that the estimated values of d are constrained between 0 and 1 in all cases, implying fractional integration, with values ranging between 0.151 (Cape Town) and 0.555 (Mombasa). On the other hand, the seasonal AR coefficient is high in all cases, in particular for the South African data.

The lack of significant trends in the results presented above might be a consequence of the seasonality that is

implicit in the data, especially noting that the AR coefficients are very large in some cases and that seasonality might have not been adequately captured throughout the AR model in (5). Thus, seasonality can be obscuring and distorting the evidence of trends. Based on this, we decided to remove the seasonality by means of subtracting in each observation its corresponding averaged monthly mean value. The monthly averaged values for each series are presented in Table 3.

It can be seen that the highest value corresponds to March in Bondoukou (28.84°C), while the lowest value is 12.22°C corresponding to June in Pretoria.

TABLE 2: Estimates of d in the original data using a long memory model with seasonal AR disturbances.

	No regressors	An intercept	A linear time trend
(a) South Africa			
DURBAN	0.896 (0.802, 1.011)	0.244 (0.162, 0.346)	0.244 (0.161, 0.347)
PRETORIA	0.676 (0.594, 0.773)	0.225 (0.142, 0.327)	0.225 (0.142, 0.329)
CAPE TOWN	0.726 (0.634, 0.835)	0.151 (0.077, 0.242)	0.153 (0.07, 0.246)
(b) Côte d'Ivoire			
BONDOUKOU	0.941 (0.861, 1.037)	0.318 (0.241, 0.417)	0.319 (0.242, 0.418)
GAGNOA	0.893 (0.824, 0.976)	0.295 (0.216, 0.407)	0.293 (0.204, 0.405)
ABIDJAN	0.916 (0.847, 1.006)	0.410 (0.311, 0.534)	0.411 (0.311, 0.534)
(c) Kenya			
KISUMU	0.857 (0.792, 0.923)	0.389 (0.295, 0.512)	0.391 (0.294, 0.516)
MOMBASA	0.992 (0.906, 1.095)	0.555 (0.431, 0.707)	0.555 (0.432, 0.705)
NAIROBI	0.877 (0.807, 0.966)	0.409 (0.307, 0.541)	0.408 (0.302, 0.542)

In bold: the significant estimates according to the deterministic terms. In parenthesis: the 95% confidence bands of the estimates of d .

TABLE 3: Estimated coefficients on the selected model.

	d (95% band)	Intercept coefficients	Seasonal AR coefficients
(a) South Africa			
DURBAN	0.244 (0.162, 0.346)	21.212 (49.797)	0.925
PRETORIA	0.225 (0.142, 0.327)	18.833 (32.497)	0.913
CAPE TOWN	0.151 (0.077, 0.242)	16.828 (52.471)	0.940
(b) Côte d'Ivoire			
BONDOUKOU	0.318 (0.241, 0.417)	26.387 (70.713)	0.825
GAGNOA	0.295 (0.216, 0.407)	26.162 (114.91)	0.686
ABIDJAN	0.410 (0.311, 0.534)	26.731 (70.713)	0.673
(c) Kenya			
KISUMU	0.389 (0.295, 0.512)	23.327 (71.079)	0.465
MOMBASA	0.555 (0.431, 0.707)	26.687 (35.602)	0.826
NAIROBI	0.409 (0.307, 0.541)	19.211 (42.905)	0.754

TABLE 4: Estimates of d in the deseasonalized monthly data using a long memory model with white noise disturbances.

	No regressors	An intercept	A linear time trend
(a) South Africa			
DURBAN	0.251 (0.201, 0.316)	0.251 (0.202, 0.317)	0.244 (0.198, 0.303)
PRETORIA	0.274 (0.215, 0.347)	0.274 (0.216, 0.349)	0.278 (0.218, 0.356)
CAPE TOWN	0.185 (0.137, 0.244)	0.185 (0.137, 0.244)	0.184 (0.136, 0.244)
(b) Côte d'Ivoire			
BONDOUKOU	0.311 (0.263, 0.365)	0.309 (0.261, 0.367)	0.297 (0.244, 0.355)
GAGNOA	0.367 (0.303, 0.441)	0.370 (0.307, 0.455)	0.359 (0.282, 0.444)
ABIDJAN	0.330 (0.270, 0.404)	0.330 (0.270, 0.404)	0.330 (0.270, 0.404)
(c) Kenya			
KISUMU	0.357 (0.296, 0.435)	0.360 (0.298, 0.434)	0.358 (0.291, 0.443)
MOMBASA	1.117 (0.949, 1.291)	1.116 (0.948, 1.290)	1.116 (0.948, 1.290)
NAIROBI	0.448 (0.353, 0.567)	0.452 (0.365, 0.576)	0.441 (0.336, 0.563)

In bold: the significant estimates according to the deterministic terms. In parenthesis: the 95% confidence bands of the estimates of d .

Figure 2 displays the deseasonalized monthly series. Apparently the seasonal component has been now removed, and some outliers can be observed in some of the series (removing these outliers did not alter the main results reported in the paper).

Table 4 displays the estimates of d in (3) for the deseasonalized data under the assumption of white noise errors, while Table 5 imposes an AR(1) structure for the $I(0)$ error term u_t . Starting with the results with uncorrelated errors (in Table 4) the first thing we observe here is that no deterministic terms

FIGURE 2: Seasonal anomaly series.

are required in any of the series and the estimated values of d are now constrained between 0.185 (Cape Town) and 1.117 (Mombasa). However, for the more realistic case of autocorrelated errors (in Table 5) the time trend is found statistically significant in the three Kenyan series, implying a positive trend in the three cases (performing LR tests in order to decide between the white noise and the AR(1) specifications, the latter was found to be more appropriate in all cases.). We observe here that the estimated values of d are 0.217, 0.352, and -0.019 , respectively, for Kisumu, Mombasa, and Nairobi, and d is found to be positive and statistically

significant in the first two cases, while the $I(0)$ null cannot be rejected for the case of Nairobi. Examining now the time trend coefficients we see that the highest value corresponds to Nairobi (0.00198) followed by Mombasa (0.00165) and Kisumu (0.00077). According to these results, temperatures have increased approximately by $0.02376^{\circ}\text{C}/\text{year}$ in Nairobi, $0.0198^{\circ}\text{C}/\text{year}$ in Mombasa, and $0.00924^{\circ}\text{C}/\text{year}$ in Kisumu, representing significant increase in the three cases (one reviewer found a significant trend for the data in Pretoria when using data starting in 1950 after removing the seasonal cycle. Note, however, that our data starts in 1973. We have

TABLE 5: Estimates of d in the deseasonalized monthly data using a long memory model with AR(1) disturbances.

	No regressors	An intercept	A linear time trend
(a) South Africa			
DURBAN	0.252 (0.175, 0.351)	0.252 (0.175, 0.352)	0.237 (0.156, 0.343)
PRETORIA	0.195 (0.095, 0.319)	0.196 (0.095, 0.324)	0.201 (0.097, 0.347)
CAPE TOWN	0.208 (0.136, 0.299)	0.208 (0.136, 0.299)	0.207 (0.134, 0.299)
(b) Côte d'Ivoire			
BONDOUKOU	0.383 (0.301, 0.486)	0.377 (0.295, 0.474)	0.361 (0.266, 0.473)
GAGNOA	0.254 (0.173, 0.356)	0.255 (0.174, 0.365)	0.181 (0.0612, 0.333)
ABIDJAN	0.259 (0.171, 0.370)	0.259 (0.171, 0.370)	0.259 (0.171, 0.370)
(c) Kenya			
KISUMU	0.263 (0.143, 0.414)	0.268 (0.142, 0.436)	0.217 (0.011, 0.447)
MOMBASA	0.356 (0.298, 0.423)	0.356 (0.298, 0.423)	0.352 (0.292, 0.421)
NAIROBI	0.144 (0.084, 0.220)	0.145 (0.081, 0.221)	-0.019 (-0.107, 0.086)
	Intercept	Time trend	Seasonal AR
KISUMU	-0.12903 (-1.949)	0.00077 (1.932)	0.184
MOMBASA	-0.26021 (-1.915)	0.00165 (1.955)	0.623
NAIROBI	-0.46857 (-9.171)	0.00198 (10.468)	0.530

In bold: the significant estimates according to the deterministic terms. In parenthesis: the 95% confidence bands of the estimates of d .

preferred to keep this dataset in order to be homogeneous across the series in the three countries).

5. Concluding Comments

In this paper we have examined the monthly averaged temperatures in various locations in South Africa, Côte d'Ivoire, and Kenya in order to determine if the temperatures have increased in these places during the last 30 years. For this purpose we have used various techniques based on the concept of fractional integration. Our results first indicate that fractional integration seems to be a plausible approach when modelling these series since the orders of integration are constrained between 0 and 1 in all cases. More interestingly, the time trend coefficients are found to be statistically significant only in the three Kenyan series, suggesting that climate change is not affecting so strongly the other two countries. Further research is required to corroborate these results. It would have been interesting to analyse the evolution of maximum and minimum temperatures; however, this was not possible due to lack of data availability. In future work we are planning to extend these results and present spatial distributions of the results obtained.

Appendix

A. Description of the Dataset

A.1. South Africa

A.1.1. Climate of Durban Louis Botha

Data reported by the weather station: 685880 (FADN)
Latitude: -29.96 | Longitude: 30.95 | Altitude: 14

A.1.2. Climate of Pretoria

Data reported by the weather station: 682620 (FAPR)
Latitude: -25.73 | Longitude: 28.18 | Altitude: 1330

A.1.3. Climate of Cape Town D. F. Malan

Data reported by the weather station: 688160 (FACT)
Latitude: -33.96 | Longitude: 18.6 | Altitude: 4

A.2. Côte d'Ivoire

A.2.1. Climate of Bondoukou

Data reported by the weather station: 655450 (DIBU)
Latitude: 8.05 | Longitude: -2.78 | Altitude: 369

A.2.2. Climate of Gagnoa

Data reported by the weather station: 655570 (DIGA)
Latitude: 6.13 | Longitude: -5.95 | Altitude: 205

A.2.3. Climate of Abidjan

Data reported by the weather station: 655780 (DIAP)
Latitude: 5.25 | Longitude: -3.93 | Altitude: 7

A.3. Kenya

A.3.1. Climate of Kisumu

Data reported by the weather station: 637080 (HKKI)
Latitude: -0.1 | Longitude: 34.75 | Altitude: 1157

A.3.2. Climate of Mombasa

Data reported by the weather station: 638200 (HKMO)

Latitude: -4.03 | Longitude: 39.61 | Altitude: 57

A.3.3. Climate of Nairobi Jomo Kenyatta from 1957 to 2013

Data reported by the weather station: 637400 (HKNA)

Latitude: -1.31 | Longitude: 36.91 | Altitude: 1624

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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