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# The River Po: Time trend coefficients under a long memory specification

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**Abstract:** This paper focuses on the analysis of the heights relative to the average of the water level at different stations of the River Po, in Italy, testing if there are linear trends in its behaviour. The most interesting result obtained in the work is that under the assumption of I(0) behaviour for the error term, several time trends are found to be statistically significant. However, allowing the order of integration to be unknown and estimated from the data, the series display long memory patterns, and most of the time trend coefficients become now insignificantly different from zero.

**Key words:** River Po; time trends; long memory; fractional integration.

## 1. INTRODUCTION

This paper deals with the analysis of the water level in the River Po by looking at eight different locations and testing if there are significant trends in its behaviour across time. For this purpose we use linear regression models where first the errors are assumed to be well behaved, in the sense that it is supposed that they are integrated of order 0 (also named short memory). Then, the possibility of long memory errors is also taken into account, and we will observe then that the estimated values of the time trend coefficients are radically different.

Long memory is a property of the data that has been observed in many time series in different contexts, including hydrology. In fact, Hurst (1951) was the first that heuristically proved the presence of long memory in the series of annual minima of the Nile River. This property (long memory) is so called because the observations display a large degree of association even being distant in time. Following this pioneering work, many studies have proved the existence of long memory in hydrological data (e.g., Hipel and McLeod, 1994; Montanari et al., 1996; Pelletier and Turcotte, 1997; Montanari and Rosso, 1997; Corduas and Piccolo, 2006; Mudelsee, 2007; Koutsoyiannis and Montanari, 2007; Gil-Alana, 2009; Iliopoulou et al., 2018; Habid, 2020; Li et al., 2021). A proper description of the long memory property and its applications in hydrology is described in the methodological section.

The water level of the River Po has been examined in many scientific works. Many authors have investigated the Po River from a hydrological viewpoint, including among others Marchi (1994), Visentini (1953), Piccoli (1976) and Zanchettini et al. (2008), while others have focussed more on a time series viewpoint, examining the property of long range dependence or long memory in the data. Examples on this account are the papers by Cohn and Lins (2005), Mudelsee (2007), Koutsoyiannis (2003, 2010) and Montanari (2012). Marchi (1994) investigated hydraulical aspects of the River Po flood occurred in 1951, and the same flood was earlier studied by Visentini (1953), while Montanari (2012) examined changing patterns in the river discharge; Piccoli (196) studied the River Po floods during the time period 1900 - 1970, and Zanchettini et al. (2008) extended the analysis to 300 years of data. In a more recent study, Manzo et al. (2018) perform spatio-temporal analysis of river plume dispersion for the identification of zones sensitive to water discharge, proving geostatistical patterns of turbidity linked to meteo-marine forcing. They implement the analysis in the Po River prodelta for the time period 2013-2016. Other recent papers involving River Po data are Ninfo et al. (2018) and Formetta et al. (2022).

The objectives of this article are twofold. First, we want to investigate if long memory is present in the river Po data, and based on this hypothesis, we examine the presence of linear time trends. The rest of this paper is structured as follows: Section 2 briefly describes the methodology used. Section 3 presents the dataset examined. Section 4 is devoted to the empirical results, while section 5 contains some concluding comments.

## 2. METHODOLOGY AND A SHORT LITERATURE REVIEW

Hurst (1951, 1957) was the first in using the concept of long memory in a hydrological context. He examined records on the level of the River Nile, noticing that the series exhibited a persistent trend-cyclical pattern over a certain period, but when the same data were observed for a longer period, this persistent behaviour tended to disappear.

In a more rigorous way, we say that a (covariance) stationary process $\{x_t, t = 0, \pm 1, \ldots\}$ displays the property of long memory (sometimes called long range dependence or strong dependence) if the infinite sum of the autocovariances, denoted by $\gamma_u = Cov(x_t, x_{t+u})$, is infinite, i.e.,

$$\lim_{T \to \infty} \sum_{j=-T}^{T} \left| \gamma_u \right| = \infty. \tag{1}$$

Alternatively, and using the frequency domain, if we define the spectral density function, $f(\lambda)$ as the Fourier transform of the autocovariances, we say that $x_t$ is long memory if that function is unbounded at some frequency $\lambda$ in the interval $[0, \pi]$, e.g., as the frequency approaches zero, i.e.,

$$f(\lambda) \to \infty, \qquad as \;\; \lambda \to 0^+, \tag{2}$$

(see McLeod and Hipel, 1978). Though there exist many models satisfying the above two properties, (for instance, the Fractional Gaussian noise model proposed in Mandelbrot and Wallis, 1969), in practice, one model, very commonly used in time series, is the one based on the concept of fractional integration.

We say that $x_t$ is fractionally integrated, or integrated of order d, and denoted as I(d) if it admits the following representation,

$$(1 - L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{3}$$

with $x_t = 0$ for $t \leq 0$, and $d > 0$, where L is the lag -operator ($Lx_t = x_{t-1}$) and $u_t$ is I(0) or short memory, defined as a covariance stationary process where the infinite sum of the autocovariances is finite or, alternatively in the frequency domain, as a process with a spectral density function that is positive and finite at all frequencies. Note that by using a Binomial expansion on the polynomial in L in the left hand side of (1), $x_t$ can be expressed in terms of all its past history, adopting the form of an infinite AR process,

$$x_t = d\, x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \frac{d(d-1)(d-2)}{6} x_{t-3} - \ldots. + u_t,$$

and thus, the fractionally integrated parameter d can be taken as a measure of the degree of persistence of the data, since the higher the value of d is, the higher the association between observations is, even if they are far apart in time. Long memory is satisfied as long as d is positive. The specification described in (3) is very general and allows us to consider a wide range of alternatives, including

i. short memory processes, if $d = 0$,
ii. long memory covariance stationary processes, if $0 < d < 0.5$,
iii. nonstationary though mean reverting processes ($0.5 \leq d < 1$),
iv. unit roots ($d = 1$), and

v. explosive processes ($d \geq 1$).

Thus, long memory holds if $d > 0$; stationary remains valid for $d < 0.5$, and shocks will revert to their original trends (i.e., showing a transitory effect) if $d < 1$, while≥d1 indicates lack of reversion and permanency of shocks.

Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981) were the first to propose these types of models, and they have been widely used since then in the modelization of time series in many disciplines including climatology (Bloomfield, 1992; Koscielny-Bunde et al., 1998; Percival et al., 2001; Monetti et al., 2003; Gil-Alana, 2005, 2012, 2017; Ludescher et al., 2016; etc.), economics (Sowell, 1992, Crato and Rothman, 1994; Gil-Alana and Robinson, 1997); finance (Baillie et al., 2007; Abbritti et al., 2016), internet traffic time series data (Karagiannis et al., 2004), energy (Elder and Serletis, 2008; Gil-Alana and Gupta, 2014) and of course also in hydrology. Within this latter area of research, we could mention the papers by Montanari et al. (1997), Rao and Bhattacharya (1999), Corduas and Piccolo (2006), Mudelsee (2007), Szolgayova et al (2014), Maftei et al. (2016), etc. Montanari et al. (1997) applied several models based on fractional integration in the analysis of monthly and daily inflows of Lake Maggiore, Italy. Rao and Bhattacharya (1999) examined monthly and annual data, including average monthly streamflow, maximum monthly streamflow, average monthly temperature and monthly precipitation, at various stations in the mid-western United States. They found no evidence of long memory with the monthly data and inconclusive results with the annual ones. Corduas and Piccolo (2006) used a fractional ARIMA (ARFIMA) model that incorporates both long memory and short memory components in the analysis of hydrological data. Mudelsee (2007) examined 28 long time series from six European, American and African rivers, finding evidence of long memory in all them, and being explained in terms of spatial aggregation of the data. Maftei et al. (2016) found evidence of long range dependence and trends in the Taita River discharges. Other authors such as Montanari et al. 2000; Ooms and Franses, 2001; Lohre and Sibbertsen, 2001; Wang et al., 2002, though focusing also on the long memory property, also investigated the issue of seasonality on the data.

## 3. DATA

We use data of water level time series variations around average height at the River Po, Italy, collected at eight specific locations (Table 1) and obtained from Schwatke et al. (2015) from the Database for Hydrological Time Series of Inland Waters (DAHIT, https://dahiti.dgfi.tum.de /en/virtual_stations). The database is maintained by the Deutsches Geodätisches Forschungsinstitut, at the Technische Universität München, and contains data from different stations all over the world. For Italy, there are 40 virtual stations and the eight series for the River Po are: 1076 (11.36 °E, 44.98 °N); 1130 (10.65 °E, 44.95 °N); 1137 (11.23 °E, 45.05 °N); 4416 (12.08 °E, 44.97 °N); 10350 (11.57 °E, 44.92 °N); 10361 (10.99 °E, 45.06 °N); 10368 (10.48 °E, 44.94 °N) and 10369 (11.91 °E, 44.98 °N). The starting and ending dates along with other features of the data are reported in Table 1 and the time series plots are displayed in Figure 1.

*Table 1. Description of the water level time series*

| Number | Longitude | Latitude | Starting date | Ending date | No. of observations |
|---|---|---|---|---|---|
| 1076 | 11.3560 | 44.9847 | 09-07-2002 | 31-08-2010 | 77 |
| 1130 | 10.6542 | 44.9542 | 28-07-2002 | 19-09-2010 | 75 |
| 1137 | 11.2347 | 45.0456 | 15-05-2002 | 20-10-2010 | 82 |
| 4416 | 12.0826 | 44.9747 | 20-06-2002 | 15-05-2016 | 106 |
| 10350 | 11.5650 | 44.9190 | 25-07-2008 | 25-04-2019 | 290 |
| 10361 | 10.9886 | 45.0634 | 26-07-2008 | 27-04-2019 | 394 |
| 10368 | 10.4633 | 44.9373 | 12-08-2002 | 01-06-2016 | 112 |
| 10369 | 11.9145 | 44.9751 | 05-07-2002 | 29-05-2016 | 109 |

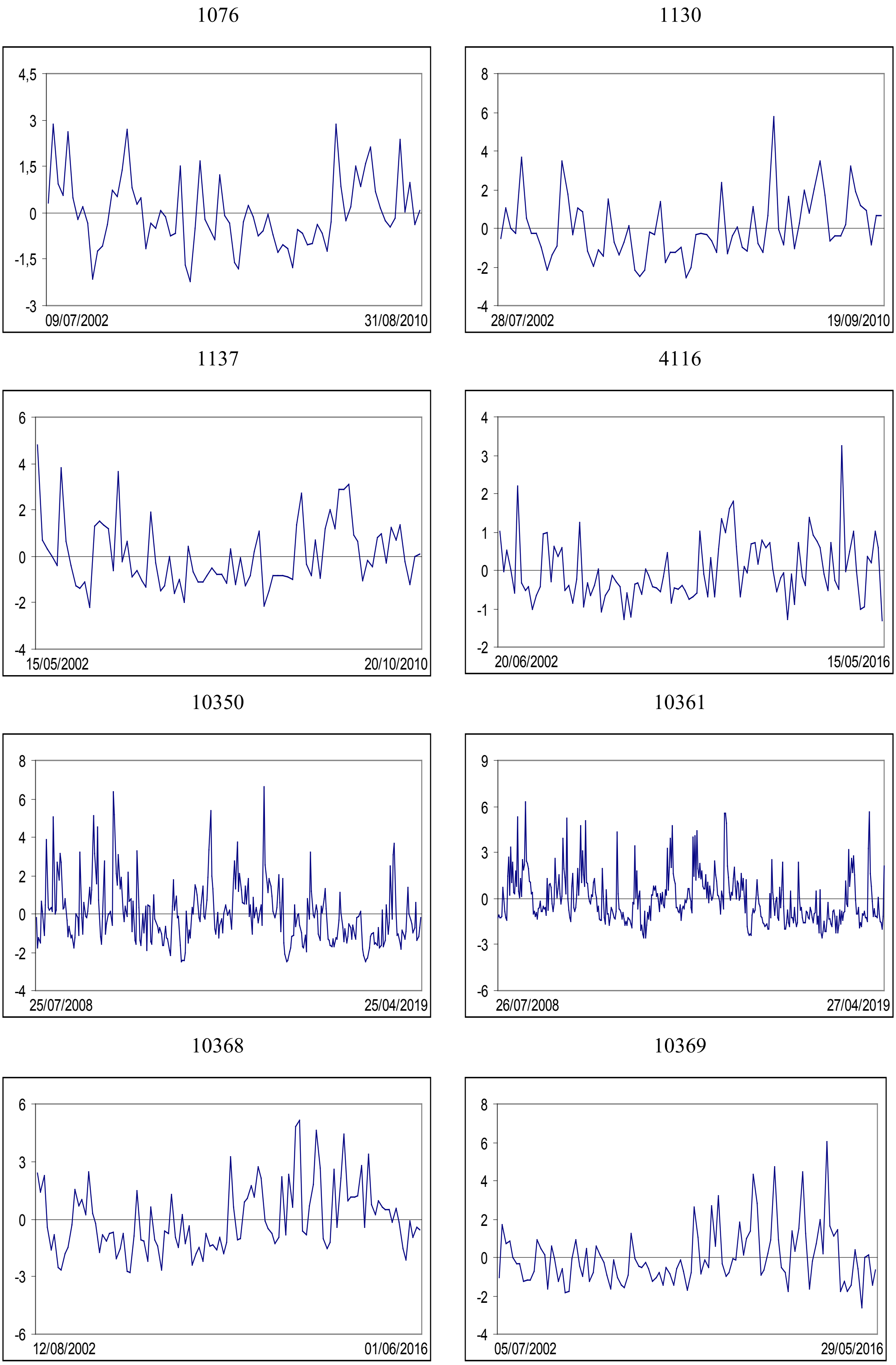


*Figure 1. Water level time series plots*

## 4. EMPIRICAL RESULTS

Since we are interested in estimating linear trends, the first model we consider is the following:

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad t = 1, 2, \ldots, \tag{4}$$

where $y_t$ indicates the time series we observe, in our case, the water level variations around the average height for each of the specific locations examined; $\beta_0$ and $\beta_1$ are unknown parameters to be estimated from the data and correspond respectively to an intercept and a linear time trend, and $x_t$ is the error term that it is initially supposed to be I(0), i.e., short memory. Since we are specifically interested in estimating $\beta_1$, we test then the null hypothesis,

$$H_o = \beta_1 = 0, \tag{5}$$

in equation (4) against the alternative: $\beta_1 \neq 0$. Here, we suppose that $x_t$ is a white noise process, and the estimated coefficients for each of the specific locations are displayed in Table 2. We also tried with weak autocorrelation in $x_t$, and the results were very similar to those based on white noise errors. If $x_t$ is an AR(1) process, we use the Prais-Winsten (1954) transformation, obtaining a t-statistic, which converges in distribution to a N(0,1) random variable.

*Table 2. Estimates of $\beta_0$ and $\beta_1$ in the model: $y_t = \beta_0 + \beta_1 t + x_t$*

| Series number | Intercept, $\beta_0$ (t-value) | Time trend, $\beta_1$ (t-value) |
|---|---|---|
| 1076 | 0.0420 (0.16) | -0.0010 (-0.18) |
| 1130 | *-0.6170 (-1.72)* | *0.0162 (1.98)* |
| 1137 | -0.0452 (-0.14) | 0.0027 (0.41) |
| 4416 | *-0.2251 (-1.68)* | *0.0042 (1.70)* |
| 10350 | *0.6922 (3.84)* | *-0.0047 (-4.42)* |
| 10361 | *0.6621 (4.18)* | *-0.0033 (-4.83)* |
| 10368 | *-0.8444 (-2.69)* | *0.0149 (3.10)* |
| 10369 | *-0.5381 (-1.93)* | *0.0097 (2.22)* |

*In italics, significant coefficients at the 5% level.*

We observe that for six out of the eight locations, the time trend coefficient becomes statistically significantly different from zero. It is positive in the cases of 1130, 4416, 10368 and 10369, and negative for 10350 and 10361. In the cases of 1076 and 1137, the $\beta_1$-coefficient is found to be insignificant. However, these coefficients have been obtained under the strong assumption that the error term displays short memory behaviour, i.e., it is assumed to be I(0), which is a strong assumption which might not be satisfied in the context of hydrological data. Thus, in what follows, we estimate $\beta_0$ and $\beta_1$ along with the order of integration of the error term, i.e., d, by means of using a model that combines equations (3) and (4), i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{6}$$

where $u_t$ is now the process to be I(0).

Table 3 displays the estimated coefficients under the assumption that the I(0) term is uncorrelated (white noise), while in Table 4 we impose autocorrelated disturbances by means of using a non-parametric approach proposed by Bloomfield (1973). This model of Bloomfield (1973) is not explicitly defined but is described only in terms of its spectral density function, which is given by:

$$f(\lambda) = \frac{\sigma^2}{2\pi} \exp\left( 2 \sum_{r=1}^{m} \tau_r \cos(\lambda r) \right), \tag{7}$$

where $\sigma^2$ is the variance of $u_t$ and $m$ refers to the last of the Fourier frequencies which is associated with the short-run dynamic components. He showed that the above expression approximates very well the spectrum of highly parameterized ARMA processes and thus can be used as an approximation for I(0) autocorrelated processes. The estimation is carried out in both cases by means of the Whittle function in the frequency domain (see, e.g., Dahlhaus, 1989) throughout a procedure developed in Robinson (1994), and in which functional form can be found in any of its numerous applications in several fields (see, e.g., Gil-Alana and Robinson, 1997).

Starting with the results based on white noise errors (Table 3) the first thing we observe is that the I(0) hypothesis is rejected in all cases, since the estimates of d are significantly positive in all locations. The values range between 0.15 (4416) and 0.43 (10361), and surprisingly, none of the time trend coefficients are found to be statistically significant.

*Table 3. Estimates of d, $\beta_0$ and $\beta_1$ in the model: $y_t = \beta_0 + \beta_1 t + x_t$, $(1-L)^d x_t = u_t$ and white noise $u_t$.*

| Series number | d (95% interval) | Intercept, $\beta_0$ (t-value) | Time trend, $\beta_1$ (t-value) |
|---|---|---|---|
| 1076 | 0.35 (0.20, 0.57) | 0.3998 (0.67) | -0.0050 (-0.38) |
| 1130 | 0.19 (0.05, 0.41) | -0.4576 (-0.77) | 0.0139 (1.07) |
| 1137 | 0.29 (0.14, 0.55) | 0.6511 (0.99) | -0.0075 (-0.56) |
| 4416 | 0.15 (0.04, 0.32) | -0.1350 (-0.56) | 0.0028 (0.76) |
| 10350 | 0.39 (0.30, 0.50) | 0.2767 (0.40) | -0.0030 (-0.72) |
| 10361 | 0.43 (0.36, 0.51) | 0.0092 (0.01) | -0.0012 (-0.35) |
| 10368 | 0.35 (0.20, 0.55) | -0.0075 (-0.01) | 0.0034 (0.27) |
| 10369 | 0.25 (0.10, 0.45) | -0.3469 (-0.60) | 0.0059 (0.67) |

*Table 4. Estimates of d, $\beta_0$ and $\beta_1$ in the model: $y_t = \beta_0 + \beta_1 t + x_t$, $(1-L)^d x_t = u_t$ and autocorrelated $u_t$.*

| Series number | d (95% interval) | Intercept, $\beta_0$ (t-value) | Time trend, $\beta_1$ (t-value) |
|---|---|---|---|
| 1076 | 0.11 (-0.10, 0.43) | 0.1151 (0.35) | -0.0019 (-0.27) |
| 1130 | 0.01 (-0.18, 0.25) | *-0.6170 (-1.76)* | *0.0162 (2.02)* |
| 1137 | 0.24 (0.02, 0.81) | 0.4626 (0.79) | -0.0049 (-0.42) |
| 4416 | 0.16 (-0.07, 0.58) | -0.1269 (-0.51) | 0.0027 (0.71) |
| 10350 | 0.28 (0.12, 0.48) | 0.4745 (0.99) | -0.0038 (-1.37) |
| 10361 | 0.45 (0.29, 0.65) | -0.0598 (-0.07) | -0.0010 (-0.27) |
| 10368 | 0.15 (-0.09, 0.53) | -0.6037 (-1.30) | 0.0111 (1.62) |
| 10369 | -0.02 (-0.27, 0.28) | *-0.5516 (-2.20)* | *0.0100 (2.53)* |

*In italics, significant coefficients at the 5% level.*

If we allow for autocorrelated errors throughout the model of Bloomfield (1973) (Table 4), we notice that for five locations the I(0) hypothesis cannot be rejected, though the estimates of d are relative far from zero in some cases. This is due to the wide confidence bands in some cases as a consequence of the small sample sizes. However, the time trend coefficients remain once more insignificantly different from zero in the majority of the cases. In fact, there are only two locations where the time trend is significantly positive (1130 and 10369) which are precisely the two locations with the estimates of d around 0 (0.01 and -0.02). For the rest of the cases, the values of d range between 0.11 (1130) and 0.45 (10361) and the time trends are insignificant in all cases.

## 5. CONCLUSIONS

We have examined in this article eight stations at the River Po, Italy in order to determine the existence of time trends and potential long memory features. A natural conclusion derived from this paper is that it is very important to determine the nature of the error term in the analysis of hydrological data because otherwise we may draw invalid conclusions about the properties of the data. Thus, for example, if we impose a priori that the errors are well behaved in the sense that they are I(0) or short memory, and we estimate the (linear) time trend coefficients, our results based on the water level at the River Po indicate that the time trends are statistically significant. However, if we remove this assumption and allow the error term to be I(d) where d is a potentially fractional value, jointly estimated with the other parameters in the model, we find evidence in favour of long memory patterns (i.e., d > 0), and the significance of the time trend coefficients disappear in the majority of the cases. This evidence of long memory is consistent with many other previous works based on water flows since the seminal papers by Hurst (1951, 1956) and is a feature that should be taken into account when modelling this type of data. Further work should also analyse the potential presence of structural breaks in the data, since this is an issue that is very much related with the long memory characteristic observed in the data.

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