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Trends in Hydrological Series: Methods and Application

D.H.M. Detzel & M.R.M. Mine
Federal University of Paraná, Curitiba, Brazil

ABSTRACT: Climate change and anthropic activities in river basins have been pointed as inductors of nonstationarities in hydrological time series. To better understand these issues, researchers have used diverse methods mainly based in hypothesis testing and frequency domain analysis. This paper presents a brief review of linear regression analysis, Student's t, Mann-Whitney's U, Spearman's rho, Mann-Kendall hypothesis testing and continuous wavelet transform, some of the most widely applied methods for trend assessment in hydrology. All techniques are also applied in Iguaçu River basin, southern Brazil, showing that conclusions based on isolated results may be misleading. The paper ends with comments about multiple scale stochastic process approach, which considers hydrological time series fluctuations as its expected behavior.

Keywords: Trend, Hydrological time series, Hypothesis testing, Wavelet analysis, Stochastic modelling

1 INTRODUCTION

In time series analysis, one can define statistical stationarity as an equilibrium state in which the process statistical properties are independent of time. Therefore, if the properties of a times series $z_{i+\tau}$ are the same as z_i, for any time steps $\tau \in T$ and $i = 1, \dots, n$, it is statistical stationary. However, natural phenomena rarely meet this condition, being highly affected by seasonality and other important mechanisms. Thus, modelling such series requires mathematical nuances to overcome nonstationarity.

Concerning hydrological time series, initial studies aiming to analyze statistical stationarity date back to the early 1970s, motivated by linear stochastic models (e.g. ARIMA models, see Box et al., 2008) increasing applications. Over the years, authors focused in analyzing how nonstationarity manifests in hydrological series. Of these, the majority considers the presence of linear trends in records as possible indicators of changes in the hydrological regime.

Two causes are often pointed as disturbances inductors in hydrological series (Clarke, 2007; Milly et al., 2008): (i) anthropogenic activities in watersheds and (ii) climate change. In the first cause, modifications in watersheds land use mainly caused by agricultural fields and urbanization are highlighted. The second aspect is related to greenhouse gases emission, possibly reflecting in a gradual increase of global atmospheric temperatures.

Emphasizing the growing number of studies in the area and the fertile discussions originated by its results, this paper aims to develop a critical analysis of the most common methods for detecting trends in hydrological series. A thorough literature review allowed identifying hypothesis testing as most used technique for this purpose. Frequency domain analyses are also employed, either in series decomposition or spectral properties evaluation. Among the methods researched, six are discussed: (i) linear regression with significance test over the adjusted slope, (ii) Student's t test, (iii) Mann-Whitney U test, (iv) Spearman's rho test, (v) Mann-Kendall test and (vi) wavelet transform.

To illustrate the discussed techniques, a case study applied to Iguaçu River basin in southern Brazil is presented. All six aforementioned methods were submitted to mean, maximum and minimum annual streamflow series and to total annual precipitated amounts of Porto Amazonas gauging station, in Paraná state. To complement the paper, comments about multiple scale stochastic process are made. In this approach, hydrological time series fluctuations are treated as an expected behavior.

2 TREND ASSESSMENT IN HYDROLOGICAL SERIES

2.1 *Hypothesis testing*

The existing hypothesis tests can be grouped in two categories: parametric and nonparametric. In the first category, one assumes that data probability distribution is known. On the other hand, nonparametric tests are formulated in such way that data probability distribution is not relevant (Wilks, 2006, p. 131). Evidently, in dealing with hydrological variables this information is unknown and approximations are needed. Thus, researchers choose nonparametric tests even knowing that they are less powerful than the parametric ones (Chebana et al., 2013).

An important assumption in hypothesis testing is that the null hypothesis should be enunciated prior to series examination, so the researcher is not influenced by time series behavior (von Storch and Navarra, 1999, p. 13; Koutsoyiannis, 2006). Moreover, sample elements must be mutually independent, which does not occur in most hydrological time series, mainly streamflow data. In general, autocorrelation may lead to long periods of values above or below the series mean (aka Joseph Effect, see Mandelbrot and Wallis, 1968), causing false trend detections (Fleming and Weber, 2012). If the persistence in a time series can be represented by a markovian model, autocorrelation effect can be removed using effective sample size estimation (Wilks, 2006, p. 144) or by means of pre-whitening (von Storch and Navarra, 1999, p. 13). However, when persistence structure is more complex, Monte Carlo simulations are recommended.

As said in the introduction, linear trends are frequently pointed as evidences for nonstationary behavior in hydrological series. Therefore, the most direct way to evaluate them is to fit an ordinary least-square linear regression (OLS) and test if the adjusted slope is statistically significant using the parametric t statistic (Sharma et al., 2000). This method was also used in Rhine River (Pinter et al., 2006) and in 78 other German rivers (Bormann et al., 2011) with positive trends detected. In Sweden, Lindström and Bergström (2004) applied OLS analysis in centenary streamflow series, but significant trends were detected only when the main samples were reduced into minor length subsamples.

Another approach consists in dividing the time series in two subsamples using, for example, rescaled adjusted partial sums method (RAPS, see Alexandre et al., 2010), followed by Student's t (Wilks, 2006, p. 140) or Mann-Whitney's U (Wilks, 2006, p. 157) tests application. Being a well-known statistical inferences, Student's t is a parametric test that requires normally distributed data and examines the equality of subsamples means. It has been widely used in Brazil (Müller et al., 1998; Batista et al., 2009; Detzel et al., 2011; Fill, 2011) to investigate whether land use changes after the 1970s affected streamflow regimes. It was also used in northeast China with five- and ten-years length moving windows to find jumps in precipitation series (Liang et al., 2011). On the other hand, U-statistic (also known by Wilcoxon rank-sum test) is a nonparametric inference assuming that two subsamples were drawn from the same population. Cluis and Laberge (2001) applied U-statistic in Asia, detecting negative trends in southern region rivers. Also using this test, Thomas (2007) studied the interactions between atmospheric variables and Colorado River streamflow in a climatic variability context. Xu et al. (2003), in turn, examined Japanese annual precipitation series with U-statistic.

In analyzing monotonic trends rather than jumps in time series, Spearman's rho (S) and Mann-Kendall (MK) tests are the most commonly used inferences. Both are nonparametric ranked-based tests and have very similar power in detecting a trend (Yue et al., 2002), even though only MK has been recommended by the World Meteorological Organization (Liang et al., 2011) for this task. Villarini et al. (2011) applied S and MK in maximum streamflow series for 196 North American gauges, finding few significant trends. Fleming and Weber (2012) used S test in annual inflows for Canadian reservoirs, detecting positive trends in winter season. Gautam et al. (2010) also used S test in Nepal, confirming positive trends in streamflow and precipitation regimes. In turn, MK was recently used in China (Wang et al., 2008), British Columbia (Cunderlik and Burn, 2004), Italy and Switzerland (Kottegoda et al., 2011), Australia (Li et al., 2012) and United States (Rougé et al., 2013). MK can also be carried out sequentially to determine the beginning of the trend (if any), as shown in Liang et al. (2011). In this variant, a sample $(z_1, z_2, \dots, z_n)$ is divided into $n-1$ subsamples, formed by (z_1, z_2), (z_1, z_2, z_3) and so on. MK statistic is then calculated for all subsamples, resulting in a MK_i (say MK1) vector $(i = 1,2, \dots, n-1)$. The same procedure is repeated with the inverted series, resulting in a second MK_i (say MK2) vector. Plotting both vectors, one should be able to detect the trend starting point if the intersection of MK1 and MK2 curves is statistically significant.

2.2 *Frequency domain analyses*

Although less common than hypothesis tests, these analyses are interesting as elements are represented by its contribution in time series as a whole. In particular, spectral density function plots (Fourier transform of the autocorrelation function) allow identifying trends promptly just by the presence of high densities near the null frequency (Andreo et al., 2006).

However, Fourier transform analyses have an intrinsic statistical equilibrium assumption and may not be suitable for nonstationary series. One alternative is to use windowed Fourier transform, nonetheless besides the subjective window length definition, it has limited application in finding multiple frequency signals with a fixed window length (Weng and Lau, 1994). Thus, the solution lies on wavelet transform, which consists in dilate and translate a wave function (denominated mother-wavelet) through the time series (Torrence and Compo, 1998). Among the existing mother-wavelets, Morlet (Pasquini and Depetris, 2007), Haar (Saco and Kumar, 2000) and Paul (Rossi et al., 2009) are the most frequently adopted for hydrological time series.

Continuous wavelet transform (CWT) is often used in analyzing periodicities and trends, mainly because its graphical interpretation. For example, Pasquini and Depetris (2007) and Rossi et al. (2009) explain trends in series with changes in signal intensity over time, easily seen in a CWT scalogram. Nevertheless, discrete wavelet transform (DWT) is also employed for decompose and analyze time series in particular frequency bands. Partal and Kuçuk (2006) used DWT to decompose Turkish precipitation series in five modals, coupling each one with MK test for trend detection. As results, the authors were able to identify the 16 years modal as responsible for the observed trend.

3 CASE STUDY

3.1 *Study area*

To illustrate the discussed techniques, this paper presents a case study in Iguaçu River basin. Iguaçu River is an important Paraná River tributary which, together with Paraguay and Uruguay Rivers, forms the La Plata River basin. In Brazilian territories, Iguaçu River basin covers almost 70,800 km² surface area and, particularly in Paraná State, it occupies 57,400 km² (28% of the State area). In its upper part, large urban areas are located, including State capital Curitiba, and from middle to lower parts agriculture and livestock activities are predominant. The basin has approximately 4.5 million inhabitants.

According to Köppen-Geider climate classification (Peel et al., 2007), almost the entirely basin is in Cfa type and a minor portion in its upper region is in Cfb type. The unique relation of geographic location, relief and air masses provides a rather regular precipitation (only rainfall) distribution over the year, with averages varying from 1,250 mm to 2,000 mm. Temperature distribution, though, has defined seasonality, being January the warmest month (~25ºC) and July the coolest (~11ºC). In addition, El Niño phenomenon has direct reflexes in the region, causing temperature and precipitation volumes elevations.

Another important feature is the hydropower generation provided by seven large plants installed in Iguaçu River basin, summing nearly 7 GW of capacity (8.5% of Brazilian power generation). In hydrological terms, these plants are important because alter the rivers regimes. Therefore, Porto Amazonas (PA) gauging station (25º32'S – 49º53'W) was chosen, avoiding influences by any dam. It operates 780 m above sea level and drains a 3,662 km² area. Annual streamflow (Q) and total annual precipitation (P) descriptive statistics are provided in Table 1. PA time series were collected from Brazilian National Water Agency, all consisted and containing no missing values. Figure 1 displays the overall location of the Iguaçu River basin, as well as its important features.

Table 1. Porto Amazonas annual streamflow (Q) and total annual precipitation (P) descriptive statistics

Type	Record	Mean (m³/s and mm)	Standard Deviation (m³/s and mm)	Lag 1 auto-correlation
Min. Q	1936-2005	33.2	13.5	0.29
Mean Q	1936-2005	67.9	25.4	0.26
Max. Q	1936-2005	129.6	50.6	0.22
Total P	1941-2012	1,634.8	352.2	0.22

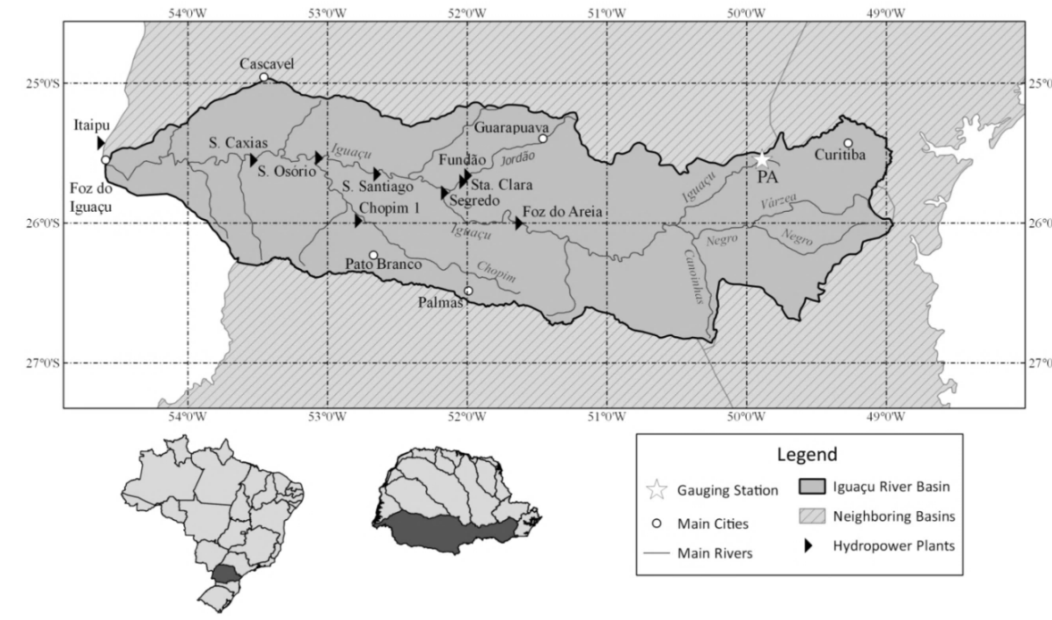

Figure 1. Iguaçu River basin and gauging station location

3.1 *Methods assumptions*

All five hypothesis tests and wavelet analysis were applied to the series depicted in Table 1. Subsample division for t and U tests was made in two ways: (i) central, resulting two equally sized samples and (ii) reserving the last 30 years and testing against the remainder of the series. Hypothesis (ii), also considered in OLS analysis, was elaborated to evaluate the possible land use changes effects on streamflow, as suggest some local studies (Tucci, 2002; Batista et al., 2009). Moreover, it is assumed that this window length is enough to represent climatic fluctuations (Koutsoyiannis, 2006). For the parametric tests, log transform was applied to make the data approximately normal distributed. MK test, specifically, was applied both in its traditional form as in its sequential format, where MK1 and MK2 curves were obtained for forward and backward computations, respectively. In all tests, pre-whitening was applied to remove autocorrelation influence; as shown in the last column of Table 1, first order persistence is low, but not negligible.

Lastly, wavelet analysis was elaborated through CWT, using Paul as mother-wavelet, which has good temporal resolution in comparison to other functions (Rossi et al., 2009). For the streamflow series, it was used a wavenumber of 4, while for the precipitation series this parameter was set as 10. Scalograms were obtained using the wavelet software kindly supplied by C. Torrence and G. Compo (Torrence and Compo, 1998), available at http://paos.colorado.edu/research/wavelets/.

3.2 *Results*

Table 2 exhibits the p-values obtained for the hypothesis tests. Specifically for OLS, subsamples 1 and 2 are the ones resulting from division (ii), as explained in last section.

Table 2. P-values for the hypothesis tests. In all cases, values below 0.050 indicate null hypothesis (no trend) rejection, at a 5% significance level

	OLS			t | U		S | MK
	Full Sample	Subsample 1	Subsample 2	Division (i)	Division (ii)	Full Sample
Min. Q	0.029	0.954	0.043	0.597 | 0.946	0.483 | 0.814	0.088 | 0.081
Mean Q	0.001	0.191	0.103	0.374 | 0.179	0.136 | 0.094	0.012 | 0.012
Max. Q	0.001	0.069	0.130	0.018 | 0.013	0.004 | 0.006	0.011 | 0.010
Total P	0.009	0.107	0.988	0.286 | 0.231	0.021 | 0.025	0.017 | 0.017

Adopting the standard 5% significance level, a trend was detected by all full sample based tests (OLS, S and MK), except for Min. Q, in which S and MK failed to reject the null hypothesis. However, considering subsamples distinction for OLS one can note substantially different results, since only Min. Q, subsample 2, had a trend identified. For t and U statistics null hypothesis rejections occurred for Max. Q (both sample divisions) and Total P, division (ii).

Figure 2 shows results for the OLS fits and the sequential MK test. In the first case, trends accused by the p-values in Table 2 can be visually confirmed. For all three streamflow series, subsample 2 fits also revealed increasing trends, but statistically significant only for Min. Q. In this series it may be somewhat confusing how slopes for the full sample are milder, yet statistically significant in comparison with slopes for subsample 2. However, it should be remembered that the adjusted angular coefficient significance depends on sample size, mean and standard deviation. Therefore, visual trends do not necessarily correspond to statistical significance, even for rather steep slopes.

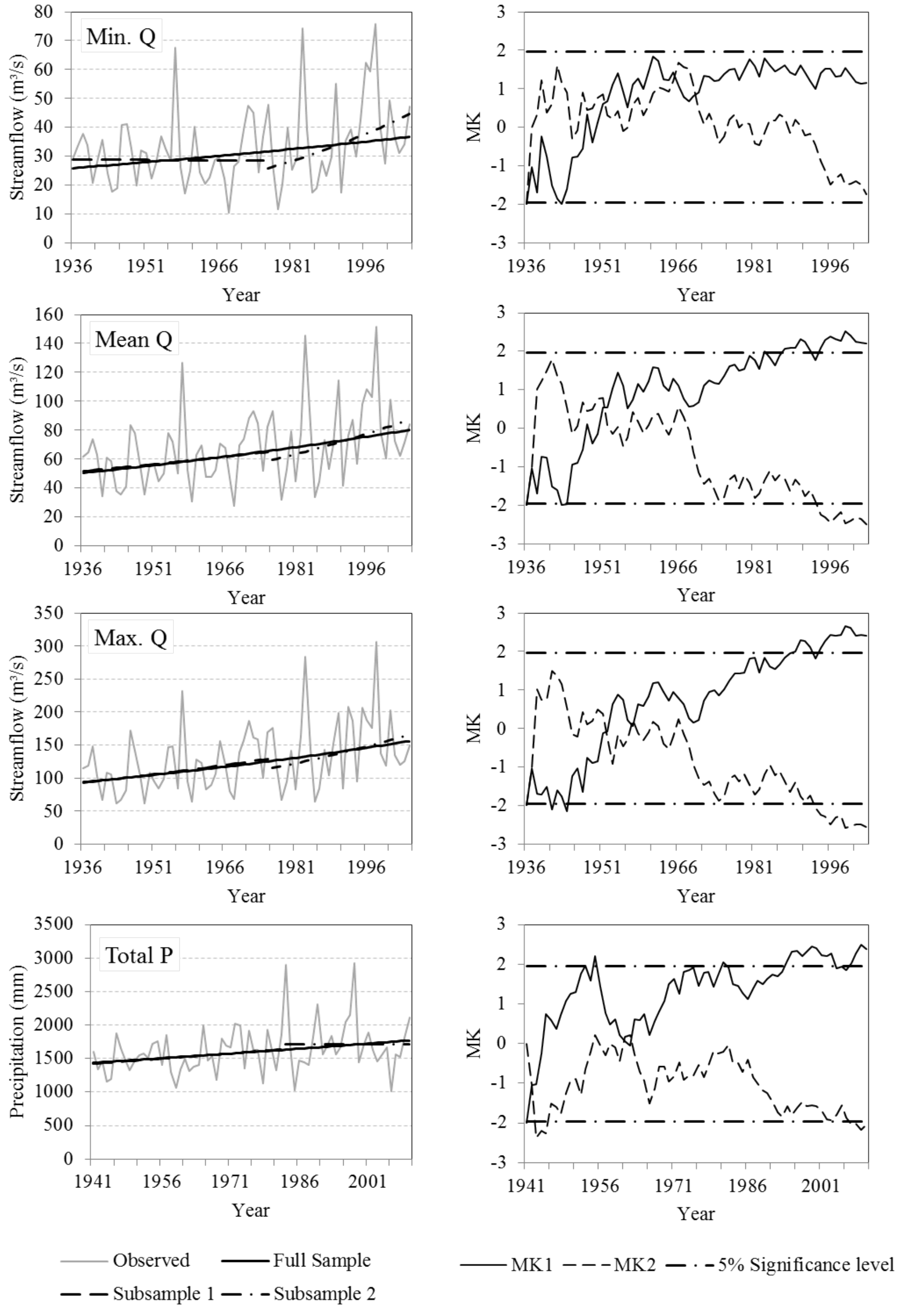

Figure 2. Results for OLS fits (left) and sequential MK test (right). Series are identified on the upper-left corner of OLS fits

Sequential MK provided some interesting insights for the analysis. Regarding streamflow series, positive trends begun in early 1950s as indicated by the signal of MK1 statistic. Nevertheless, the trend starting point was not statistically significant in any of these series, for MK1 and MK2 intersections occurred within the significance level limits. In Mean Q and Max. Q, positive trends become significant in 1987 and 1989, respectively; for Min. Q trend is not significant, agreeing with traditional MK results showed in Table 2. Total P results showed slightly different behavior, as MK1 surpass the (upper) significance level once in 1955, followed by a decreasing period until 1962. After that, positive trend continues until the end of the series, becoming significant 1994 onwards. As in streamflow series, the trend starting point could not be established for Total P series.

Completing the case study, Figure 3 displays the scalograms for CWT analyses. For all series, predominant signals were located in 8-band period, expressing more intensively every 10 years, approximately. An expansion for 16-band period is observed from 1970s decade. Statistically significant peak signals occurred in 1983 for all cases and in 1998 for Min. Q. Moreover, grayscale distribution changes over the years with a gradual migration from darker to lighter shades, indicating an increase in signal power.

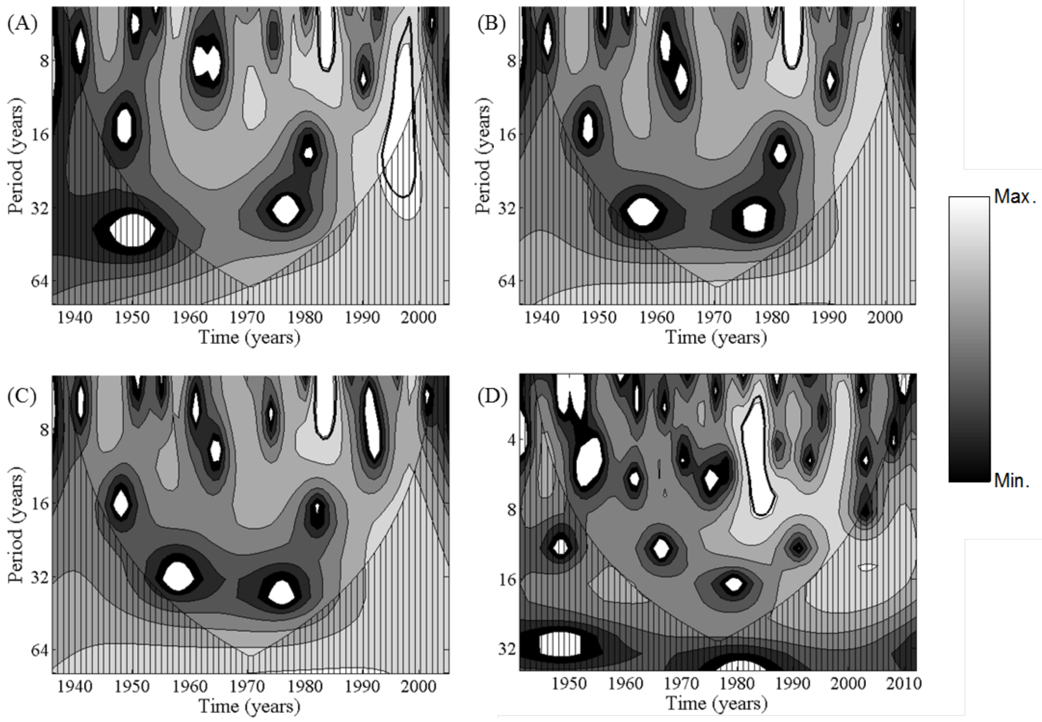

Figure 3. CWT analyses for (A) Min. Q; (B) Mean Q.; (C) Max. Q; (D) Total P. Thicker lines define 5% statistical significance and hatched areas delimit the cone of influence, where edge effects becomes important.

4 DISCUSSION

Focusing on the streamflow series, results indicated an overall positive trend with exceptions for Min Q in S and MK tests. Interestingly enough, this specific series was the only with a significant trend in past 30 years, as shown by OLS analysis, subsample 2. Sequential MK and CWT graphical analyses corroborated these results. Furthermore, a step change can be pointed between 1970s and 1980s for Max Q series, based on t and U tests results.

Given the above, one may conclude that these findings are, indeed, a consequence of basin land use change in last 30 years. Tucci (2002, p. 87) explains that in late 1970s Paraná State had native forest areas replaced by soy, corn and wheat cultures, which might have increased the overland flow. Besides, a soil conservation process was initiated at the same time, contributing with higher infiltration capacity and, therefore, increasing minimum streamflow. In addition, urbanization in the PA gauging station surrounding region could explain variations in mean and maximum streamflows.

However, results for the precipitation series proved to be quite similar to the ones obtained for the streamflow series, raising questions about the true influence of land use change. Through the graphical analysis it is possible to identify two extreme events occurred in 1983 and 1998, with clear consequence on all streamflow series. In fact, these years were marked with very intense El Niño manifestation, mainly 1983 which is considered the most violent El Niño event of the last century in Brazil (Mendonça and Danni-Oliveira, 2007, p. 192). Alone, these two years may be responsible for elevating streamflow series mean level, causing the positive trends detected by hypothesis testing. To further complicate these analyses, there is a peak streamflow event in 1957 that has no direct link with precipitation series or land use changes whatsoever. This event occurs in all three streamflow series and it is comparable in magnitude with 1983 and 1998 events, but has no straight forward explanation.

Regarding the methods used, a distinction between full sample and subsample based tests is clear and reflects the purpose of each technique. It is important to emphasize sample selection relevance, which can be crucial for hypothesis testing verdicts. The presented OLS analysis is a good example of how results depend on this matter, corroborating discussions in previous studies, as in Lindström and Bergström

(2004). Moreover, the tests underlying assumptions are equally (or more) relevant for the analyses. In modeling terms, these questions are critical and are left for hydrologists' subjectivity.

Recently, fluctuations observed in hydrological time series have gained an alternative interpretation. Koutsoyiannis (2006, 2013) criticizes the lack of physical sounding in considering a (deterministic) linear trend as representative of such variabilities. Instead, it is proposed that fluctuations are natural phenomena expected behavior, due to multiple time scale climatic oscillations. Among all analyses presented in the present paper, CWT spectrograms (Figure 3) can be pointed as evidence of these multiple time scale fluctuations.

In Koutsoyiannis (2006, 2013) point of view, it is correct to adjust mathematical models to receive hydrological series as observed, dispensing trend detection/correction exercise. Traditional stochastic processes theory is expanded to multiple scale stochastic processes, being able to handle the natural phenomena fluctuations. In this approach, "trends" are no longer treated as a deterministic component, but rather another stochastic element to be modelled. As result, low frequency events (as Joseph Effect) or extreme hydrologic episodes (as El Niño manifestations) are better represented.

5 CONCLUSIONS

Nonstationarity issue on hydrological time series has long moved from modelling requirements to become a specific research topic. Climate change and anthropic activities in river basins suggest consequences in precipitation and streamflow regimes, although these disturbances have not been completely understood yet. Therefore, many distinct methods have been proposed to study nonstationarity manifestation in the hydrological series. This paper presented a brief literature review based on parametric and nonparametric hypothesis testing, along with wavelet analysis, some of the most applied techniques in this topic.

The case study shown in this paper to illustrate such methods was clear enough to expose the inherent subjectivity contained in each one. Thus, it is highly recommended that any conclusion drawn from these analyses should be presented together with its underlying assumptions. In modelling terms, this question is critical and may bias the results, especially considering the uncertainty about future hydrological series behavior. Due to natural phenomena complexity mechanisms, the true influence of a changing environment in hydrological regimes proves to be a prolific research topic.

NOTATION

OLS	ordinary least-square linear regression
t	Student's t test
U	Mann-Whitney's U test
S	Spearman's rho test
MK	Mann Kendall test
CWT	Continuous wavelet transform
PA	Porto Amazonas gauging stations
Q	streamflow series
P	precipitation series

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