Ikaro Daniel de Carvalho Barreto

THE INFLUENCE OF DAMS AND RESERVOIRS ON LONG-TERM CORRELATIONS AND COMPLEXITY OF SÃO FRANCISCO RIVER FLOW.

Recife

February, 07 2020

UNIVERSIDADE FEDERAL RURAL DE PERNAMBUCO

PRÓ-REITORIA DE PESQUISA E PÓS-GRADUAÇÃO

PROGRAMA DE PÓS-GRADUAÇÃO EM BIOMETRIA E ESTATÍSTICA APLICADA

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Thesis considered adequate to obtain the doctor's degree in Biometrics and Applied Statistics defended and approved unanimously on 02/07/2020 by the Examining Committee.

Concentration Field: Biometry and Applied Statistics

Supervisor: Prof. Ph.D. Tatijana Stosic
Co-supervisor: Prof. Ph.D. Vijay P. Singh

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Dedicated to my beloved son Pedro Miguel and
my grandfather José de Carvalho (in memoriam).

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"At that time Jesus said, "I praise you, Father, Lord of heaven and earth, because you have hidden these things from the wise and learned, and revealed them to little children".
Matthew 11:25. Holy Bible.

Abstract

We investigate the alterations in São Francisco River streamflow: long-term correlations, long-term cross-correlations, long-term direct effects and complexity considering the river damming process for hydroelectric generation and flow regulation. Long-term correlations were analyzed by magnitude/sign Detrended Fluctuations Analysis (DFA), cross-correlations by Detrended Cross Correlations Analysis (DCCA), direct effect by DFA-Based Linear Regression (DFA-LR) and complexity was analyzed by Sample Entropy, Multi-Scale Entropy method and Sliding Window technique. Daily streamflow series were collected from 3 stations in São Francisco River basin (São Francisco/MG, Juazeiro/BA, and Pão de Açúcar/AL) in different periods considering the construction of cascade dams (Sobradinho, Luiz Gonzaga, Apolônio Sales, and Xingó). The reservoir operation changed the streamflow dynamics in such a way that nonlinear properties indicated by correlations in magnitude series become stronger, and linear properties indicated by correlations in sign series that showed weak persistency at short scales and weak anti persistency at large scales also becomes stronger. The effects of flow regulation on cross-correlations and direct effects between streamflow series turns stronger at small scales and weaker at larger scales for which natural factors also could contribute. Finally, the reservoir operations changed the temporal variability of both original and deseasonalized streamflow series by decreasing the overall degree of regularity, as indicated by higher entropy values. The results of Multiscale entropy analysis showed decreased regularity for small time-scales and increased regularity for larger scales. All four methods: magnitude/sign DFA, long-term cross-correlations (DCCA), long-term direct effect (DFA-LR) and Multiscale entropy showed sensitive for the detection of hydrological alterations in Sao Francisco River basin caused by human activities, in particular dams and reservoirs construction.

Keywords:São Francisco River; Dams; Long-Term Correlations; Long-Term Cross-Correlations; Long-Term Direct Effect; Complexity.

Resumo

Investigamos as alterações na vazão do rio São Francisco: correlações de longo-alcance, correlações cruzadas de longo alcance, efeitos diretos de longo-alcance e complexidade considerando o processo de represamento do rio para a geração de energia hidrelétrica e a regulação da vazão. Correlações de longo-alcance foram analisadas usando os métodos Detrended Fluctuation Analysis (DFA) sobre séries de magnitude / sinal, correlações cruzadas por meio de Detrended Cross Correlation Analysis (DCCA), efeitos diretos de longo alcance por meio Regressão Linear baseada em DFA (DFA-RL) e a complexidade por meio dos métodos Sample Entropy, Multiscale Sample Entropy e a técnica de janelas móveis. Séries de vazões diárias foram coletadas em três estações da bacia do rio São Francisco (São Francisco/MG, Juazeiro/BA, e Pão de Açúcar/AL) em diferentes períodos considerando a construção de barragens (Sobradinho, Luiz Gonzaga, Apolônio Sales e Xingó). A operação do reservatório alterou a dinâmica da vazão de modo que propriedades não lineares indicadas por correlações em séries de magnitude se tornem mais fortes, e propriedades lineares indicadas por correlações em séries de sinais que mostraram persistência fraca em escalas curtas e fraca persistência em grandes escalas também se tornam mais fortes. Os efeitos da regulação de vazão nas correlações cruzadas e efeitos diretos entre as séries de vazões se tornaram mais fortes em pequenas escalas e mais fracas em escalas maiores para as quais fatores naturais também poderiam contribuir. Finalmente, a operação dos reservatórios alterou a variabilidade temporal das séries de vazões originais e dessazonalizadas, diminuindo o grau geral de regularidade, como indicado pelos valores mais altos de entropia. Os resultados da Multiscale Entropy mostraram regularidade diminuída para pequenas escalas de tempo e maior regularidade para escalas maiores. Todos os três métodos: sinal / magnitude DFA, correlações cruzadas de longo alcance (DCCA) efeitos diretos de longo alcance (DFA-LR) e Multiscale Entropy mostraram-se sensíveis para a detecção de alterações hidrológicas em bacia do rio São Francisco causadas pela atividade humana, em particular na construção de barragens e reservatórios.

Palavras-chave: Rio São Francisco; Barragens; Correlações de Longo Alcance; Correlações Cruzadas de Longo Alcance; Efeitos Diretos de Longo Alcance; Complexidade.

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1 Introduction

The sustainable use of water resources and their conservation is one of the biggest challenges of the 21st century (PFIRMAN, 2003). Rivers are the principal source of renewable water supply for humans and majority of freshwater ecosystems and they are influenced by various natural and anthropogenic factors, such as climate change (CHRISTENSEN et al., 2004), land-use changes (ZHANG; SCHILLING, 2006; MUMEKA, 1986), and management practices that increase human access to water (KUSTU; FAN; ROBOCK, 2010; MAGILLIGAN; NISLOW, 2005; DÖLL; FIEDLER; ZHANG, 2009).

Healthy, free-flowing rivers possess natural ability to absorb disturbances trough flow adjustments that buffer against impacts, but this ability is already severely limited in many world's river basins (POFF et al., 2007; PALMER et al., 2008). Analyzing underlying stochastic processes that govern this ability may improve our understanding of the relationships between alteration of natural flow and ecological responses, and thus enable the development of environmental flow standards that will be incorporated in water resources management practices in such a way to guarantee ecologically sustainable freshwater use (STOSIC et al., 2016c).

Dam construction and reservoir operation have major impacts on ecology and biological diversity of aquatic and riparian zone (POFF et al., 2007). Although full restoration of natural flow regime is possible only with complete dam removal, modification of dam operation can produce the flow that will resemble natural flow regime that is crucial for the preservation of the ecological integrity of river basins (RICHTER; THOMAS, 2007).

The planning of a successful dam reoperation project requires an interdisciplinary scientific approach that includes all aspects of the dam construction impact: hydrological, ecological, economic and social (WATTS et al., 2011). The first step in this direction is the assessment of dam-induced hydrological alteration, which requires a careful and extensive empirical analysis of streamflow data for the periods before and after dam construction (RICHTER; THOMAS, 2007; WATTS et al., 2011).

Traditionally hydrological alterations have been evaluated by classical statistical methods (ZHANG et al., 2014; MORÁN-TEJEDA et al., 2011; KROLL; CROTEAU; VOGEL, 2015), and methods that use the set of ecologically relevant hydrological indicators (RICHTER et al., 1996; GAO et al., 2009). These indicators were defined considering streamflow characteristics that are relevant for "river health": magnitude, frequency, duration, and period of occurrence and rate of change.

However, other streamflow characteristics that emerge because of the complexity of hydrological systems could also be relevant components of hydrological alterations. To study these properties various concepts and methods have been developed and applied in hydrological phenomena: chaos theory (PORPORATO; RIDOLFI, 1996; SIVAKUMAR, 2009), multifractal analysis (REGO; FROTA; GUSMÃO, 2013; KANTELHARDT et al., 2006), information measures (LI; ZHANG, 2008; SERINALDI; ZUNINO; ROSSO, 2014), and complex networks (FANG; SIVAKUMAR; WOLDEMESKEL, 2017; BRAGA et al., 2016).

These methods have been used to assess the degree of nonlinearity and the overall complexity of hydrological processes, and have been shown successfully in detecting hydrological alterations caused by natural and human factors (ZHOU; ZHANG; SINGH, 2014; ZHANG et al., 2012; STOSIC et al., 2016c).

The São Francisco river basin is the third largest basin in Brazil, after the Amazon River basin and Paraná River basin. It has approximately 638,466 km^2 of area (7.5% of the Brazilian national territory) covering the states of Bahia, Minas Gerais, Pernambuco, Alagoas, Sergipe, Goiás, and the Federal District, it is about the size of Finland and Philippines together (638,424 km^2) or France (640,679 km^2). From its headwaters in Serra da Canastra, Minas Gerais, it runs about 3200 km and reaches its mouth in the Atlantic Ocean in Piaçabuçu, Alagoas and Brejo Grande, Sergipe (ANA, 2018).

The São Francisco river basin has 503 municipalities and is divided into four physiographic regions: Upper, Middle, Sub-Middle and Lower São Francisco. The total population in São Francisco river basin is approximately 14.3 million inhabitants (about half located in the Upper São Francisco region) with a predominantly urban population, represented by 77% of the total population (ANA, 2018).

The vegetation cover within the basin is diverse: Atlantic Forest (headwaters), Cerrado (Upper and Middle São Francisco), Caatinga (Middle and Sub-Middle São Francisco), Atlantic Forest and native formations (mangrove and coastal vegetation) (Lower São Francisco). The climate is dry subhumid in the basin upper region, semiarid in the middle region, semiarid and arid in the sub-middle region, and subhumid in the Lower São Francisco region (ANA, 2018).

The average annual precipitation ranges from 1500 mm in the Upper São Francisco to 350 mm in the Sub-Middle São Francisco, where severe droughts occur frequently because of low rainfall and high evapotranspiration (BEZERRA et al., 2019). About 58% of the basin's territory is within the semi-arid region, mostly in the northeast part of

Brazil. Throughout the year the São Francisco River natural flow varies between 1,077 m^3/s and 5,290 m^3/s, the annual average being 2,846 m^3/s. Regarding uses, 77% of the total demand is used for irrigation, 11% for urban demand and 7% for industrial demand (ANA, 2018).

The major role of the São Francisco River is in generating electricity, with a potential installed in 2013 of 10,708 MW (12% of the country's total). Along the river, there are several large dams listed in the downstream order: Três Marias, Sobradinho, Luiz Gonzaga (Itaparica), Moxotó, Paulo Afonso I, II, III and IV, and Xingó, which were constructed between 1962 (Três Marias) and 1994 (Xingó) (ANA, 2018).

There are four reservoirs with large storage volume: Três Marias located in the Upper São Francisco, Sobradinho and Luiz Gonzaga located in the Sub-Middle São Francisco and Xingó, which is located in the Lower São Francisco. The largest hydroelectric plants are Xingó (3,162 MW), Paulo Afonso IV (2,462 MW), Luiz Gonzaga (1,479 MW) and Sobradinho (1,050 MW) (CHESF 2018). Fig. 1 shows the map of the São Francisco River basin with physiographic regions and location of dams and hydrological stations.

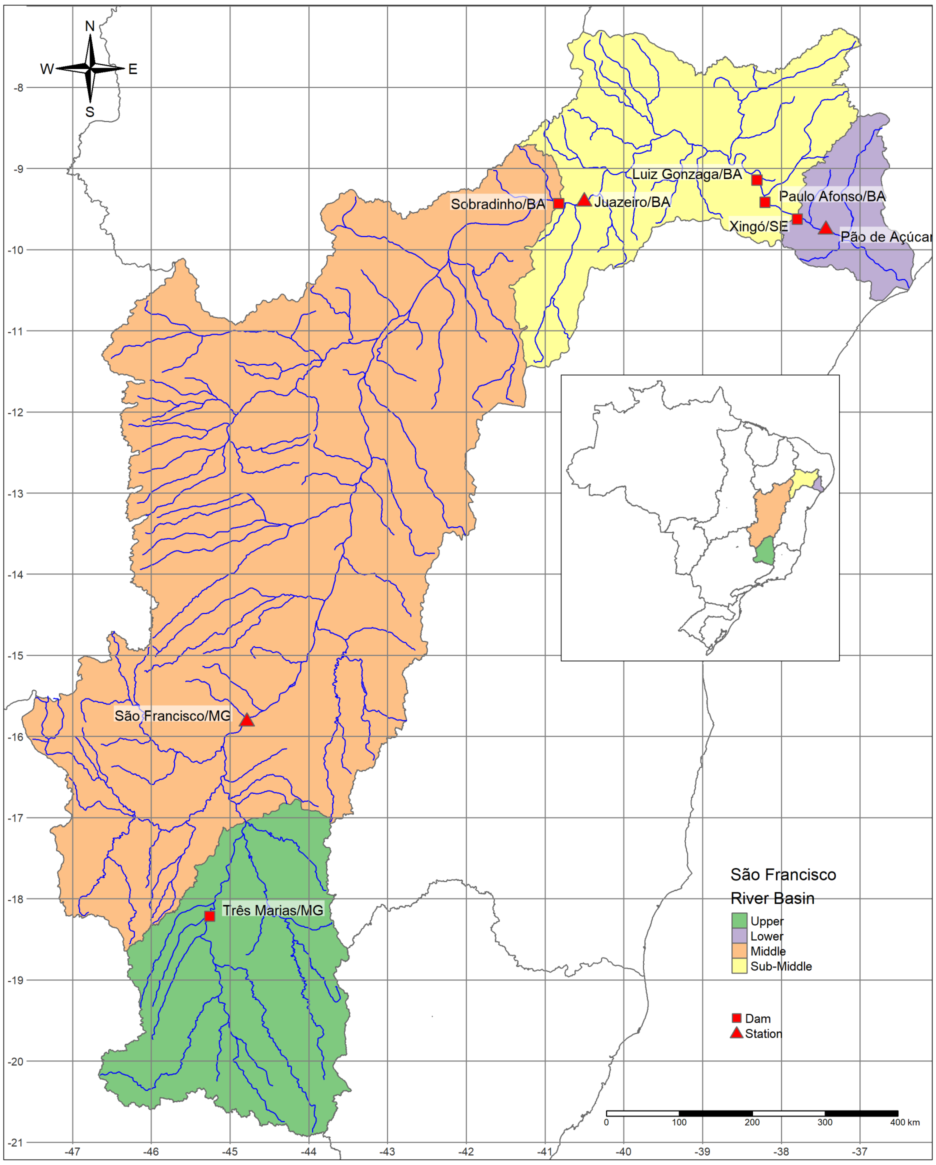


Figure 1 – Location of the São Francisco River basin, physiographic regions, dams, and hydrological stations.

Over the last decades, various studies have shown that hydrological systems display fluctuations that may be characterized by long-term power-law correlations (memory) which indicate fractal and multifractal nature of the underlying process dynamics (VOGEL; TSAI; LIMBRUNNER, 1998; SIVAKUMAR, 2000; KANTELHARDT et al., 2006). Long-term correlations of streamflow can be affected by both natural and anthropogenic factors, which are indicated by changes in scaling laws (ZHOU; ZHANG; SINGH, 2014; ARAÚJO et al., 2015).

The memory of temporal series is commonly evaluated by techniques such as Hurst exponent (HURST, 1951) and Detrended Fluctuation Analysis-DFA (PENG et al., 1994). However, (ASHKENAZY et al., 2001) showed that signals with identical long-term correlations could exhibit different temporal organization for the magnitude and sign series of signal increments.

They found that the magnitude (volatility) series relates to the nonlinear properties of the original time series, while the sign series relates to the linear properties. The existence of long-term correlations in magnitude series indicates multifractality of the underlying process (ASHKENAZY et al., 2001) and the decrease in DFA exponent indicates the loss of non-linearity and weakening of correlations (memory) (KALISKY; ASHKENAZY; HAVLIN, 2005).

Livina et al. (2003a) studied magnitudes of river flux increments and found that volatility series exhibits strong seasonal periodicity and strong power-law correlations for time scales less than one year, which can be reproduced by a simple nonlinear stochastic model (LIVINA et al., 2003b).

In this work, we evaluated the applicability of magnitude/sign DFA method to detect hydrological alterations caused by human activities, in this case, the Sobradinho dam construction, on the São Francisco River, Brazil. The dam is located in its Sub-Middle section, which since 1948 has been the preferential area for irrigation projects, inter-basin water transport and hydropower generation (IORIS, 2001; MANETA et al., 2009; ROMAN, 2017). We analyzed daily streamflow data recorded at Juazeiro/BA station (located downstream of Sobradinho dam), for the periods before and after dam construction.

Long-term cross-correlations are found in many phenomena as in physiology (HENNIG, 2014) engineering (ZEBENDE; FILHO, 2009), climatology (ANJOS et al., 2015) finances (PODOBNIK et al., 2009) and in human behavior (DELIGNIÈRES; MARMELAT, 2014). The most used method to analyze long-term cross-correlated temporal series is Detrended Cross-Correlation Analysis (DCCA) (PODOBNIK; STANLEY, 2008) that serves to quantify long-term cross-correlations, between nonstationary time series by evaluating scale dependence of covariance, while eliminating the trend.

Recently DFA-based Linear Regression (DFA-LR) (KRISTOUFEK, 2015a; SHEN, 2015) has been introduced and merges the ideas of simple (or multiple) linear regression creating the possibility of calculating the direct influence of an X-independent (or X-independents) time series has on Y-dependent time series. In order to analyze the Sobradinho dam construction impact on cross-correlations and scale-wise direct effect of San Francisco River flow, we applied DCCA/DFA-LR on streamflow records from stations Juazeiro/BA and Pão de Açúcar/AL for the periods before and after the construction of

Sobradinho dam and Xingó dam.

While fractal and multifractal analysis was extensively used to study streamflow fluctuations and showed themselves promising in detection of hydrological alterations caused by human activities (ARAÚJO et al., 2015; ZHOU; ZHANG; SINGH, 2014; TAN; GAN, 2017; JOVANOVIC et al., 2016; ZHANG et al., 2014; YE et al., 2018), information measures, such as entropies, have been less used for the analysis of hydrological phenomena, and their potential in the evaluation of hydrological alterations is still not clear (JOVANOVIC et al., 2017; STOSIC et al., 2016c; MIHAILOVIĆ et al., 2015; SERINALDI; ZUNINO; ROSSO, 2014).

The third part of this work is designed as a contribution in this direction. We used Sample Entropy (SampEn) and Multiscale entropy (MSE) method (RICHMAN; MOORMAN, 2000; COSTA; GOLDBERGER; PENG, 2002) to evaluate hydrological alterations caused by the dams and reservoirs construction on Sub-Middle and Low sections of São Francisco River. We analyzed long-term daily streamflow series recorded upstream (São Francisco station) and downstream (Juazeiro/BA and Pão de Açúcar/AL station) of dams and reservoirs. We also applied SampEn in sliding windows and analyzed the influence of dam construction on the temporal evolution of streamflow time series regularity.

This thesis is organized as follows. In Chapter 2 the results of magnitude/sign DFA analysis of streamflow records before and after the Sobradinho dam construction are presented and compared for the detection of changes in long-term correlations and in linear and nonlinear properties of streamflow fluctuations. In Chapter 3, we presented the results of DCCA and DFA-LR analysis in order to evaluate possible changes in long-term cross-correlations and long-term direct effects between streamflow fluctuations, caused by dams construction. In Chapter 4 the results of the application of SampEn and MSE on streamflow series recorded upstream and downstream of cascade dams for periods before and after dams construction are presented and compared to evaluate if there was a change in streamflow regularity after the dam constructions. The final considerations about the results of this work are presented in Chapter 5.

2 Long-term correlations in São Francisco River flow: the influence of Sobradinho dam

2.1 Introduction

The São Francisco River presents a strong alteration on its hydrological regime due to human activity such as the construction of several hydroelectric plants (PEREIRA et al., 2007; BARRETO et al., 2017), among which the Sobradinho plant has the largest reservoir and plays the greatest role in the downstream flow control. Sobradinho dam (coordinates: 09° 25' 54"S, 40° 49' 40"W; construction: 1973-1978) is located 742km from the mouth at the border between middle and lower portion of São Francisco river, in the Bahia state, about 40km upstream of cities Juazeiro (Bahia state) and Petrolina (Pernambuco state).

Its height is 41m and its length is 12.5km; the reservoir (considered one of the largest artificial lakes in the world) has 320km of extension, the surface area of 4214km^2 and storage capacity of $34.1 \cdot 10^6\text{m}^3$. It serves for electricity generation and represents a principal instrument of hydrological resource control in the region (CHESF, 2019).

The climate is semiarid, the average annual precipitation is 514 mm and the wet season is from April to July (SANTOS; POMPEU; KENJI, 2012). It is well known that streamflow fluctuations display long-term correlations that can be affected by human activity (ZHOU; ZHANG; SINGH, 2014; HIRPA; GEBREMICHAEL; OVER, 2010; ZHANG et al., 2012).

We apply the Detrended Fluctuation Analysis (PENG et al., 1994) to investigate the alterations in long-term correlations in São Francisco River streamflow fluctuations caused by the Sobradinho dam construction. We decompose the streamflow anomalies on magnitude and sign series (ASHKENAZY et al., 2001) and applied DFA on both of them, to quantify the changes in linear (indicated by correlations in sign series) and nonlinear (indicated by correlations in magnitude series) properties of streamflow fluctuations.

2.2 Data and methodology

2.2.1 Data

The data are daily streamflow series recorded in the São Francisco River basin, at the location near Juazeiro, about 40km downstream of the Sobradinho reservoir. The data are provided by the National Water Agency (Agência Nacional de Águas-ANA) (ANA, 2018) for station Juazeiro/BA, code 48020000, coordinates 09° 24' 23"S, 40° 30' 13"W and drainage area 516000km^2, for the period 1929 to 2009. This station was affected only by the Sobradinho dam, the reservoir of Três Marias, the largest reservoir upstream of Sobradinho is very distant (about 1087km) and the buffering effect mitigates any influence (ZHANG et al., 2012). Sobradinho dam was constructed between 1973 and 1979 being operational in the same year (Fig 1) (CHESF, 2019). We used R Core Team software an C language in all analysis.

2.2.2 Detrended Fluctuation Analysis (DFA)

Detrended Fluctuation Analysis (DFA) was introduced by Peng et al. (1994) as a modified root-mean-square analysis of a random walk and serves to detect long-term correlations in non-stationary time series (KANTELHARDT et al., 2001). The DFA method was successfully applied in physiology (GOLDBERGER et al., 2002; KIRCHNER et al., 2014), geophysics (ZHENG et al., 2012), ecology (STOSIC et al., 2016b), climatology (JIANG; ZHAO; WANG, 2016), and finance (LI et al., 2011).

The implementation of the DFA algorithm is described as follows (PENG et al., 1994):

First, the original temporal series $x(i), i = 1, ..., N$ is integrated to produce

$$X(k) = \sum_{i=1}^{k}[x(i) - \langle x \rangle], \_k = 1, \ldots, N \tag{2.1}$$

where $\langle x \rangle = \frac{1}{N}\sum_{i=1}^{N} x(i)$ is the average.

Next, the integrated series $X(k)$ is divided into $N_n = int\left(\frac{N}{n}\right)$ non-overlapping segments of length n and in each segment, $s = 1, ...N_n$ the local trend $X_{n,s}(k)$ is estimated as a linear or higher order polynomial least-square fit and subtracted from $X(k)$. The detrended variance is then calculated as

$$F^2(n) = \frac{1}{nN_n} \sum_{s=1}^{N_n} \sum_{k=(s-1)n+1}^{sn} [X(k) - X_{n,s}(k)]^2 \tag{2.2}$$

Repeating this calculation for different window sizes provides the relationship between the fluctuation function $F(n)$ and window size n. If long-term correlations are present in the original series, $F(n)$ increases with n according to a power law $F(n) \sim n^{\alpha}$.

The scaling exponent α is obtained as the slope of the linear regression of $\log F(n)$ versus $\log n$. For $0 < \alpha < 1$, DFA exponent is equal to Hurst exponent H and describes correlations in original series: the value $\alpha = 0.5$ indicates the absence of correlations (white noise), $\alpha > 0.5$ indicates persistent long-term correlations meaning that large (small) values are more likely to be followed by large (small) values, $\alpha < 0.5$ indicates anti-persistent long-term correlations, meaning that large values are more likely to be followed by small values and vice versa. The value $1 < \alpha < 2$ indicates fractional Brownian motion with increments described by Hurst exponent $\mathrm{H} = \alpha - 1$. The values $\alpha = 1$ and $\alpha = 1.5$ correspond to $\frac{1}{f}$ noise and a Brownian noise (integration of white noise) respectively (PENG et al., 1994; KANTELHARDT et al., 2001; LØVSLETTEN, 2017).

2.2.3 Results and Discussion

We analyze deseasonalized series (anomalies) of daily streamflow $x(t)$

$$X(t) = \frac{x(t) - \mu_t}{\sigma_t} \tag{2.3}$$

where μ_t is the mean daily streamflow calculated for each calendar date by averaging over all years in the record, and σ_t is the standard deviation of $x(t)$, also calculated for each calendar date (KANTELHARDT et al., 2006). We apply the DFA method on daily anomaly series and two subseries: magnitude of increments $(t) = |\Delta X(t)|$, where $\Delta X(t) = X(t) - X(t-1)$, and sign $S(t) = sign[\Delta X(t)]$ (ASHKENAZY et al., 2001).

These series are shown in Fig. 2 where we can see the change of streamflow dynamics after the construction of the Sobradinho reservoir: lower magnitude and less periodicity. This flow regime modification is associated with the reservoir operation (GURJÃO et al., 2012). Magnitude series shows different behavior: for the post-construction period, the magnitude of anomaly increments increases but similarly to original series exhibits less periodicity.

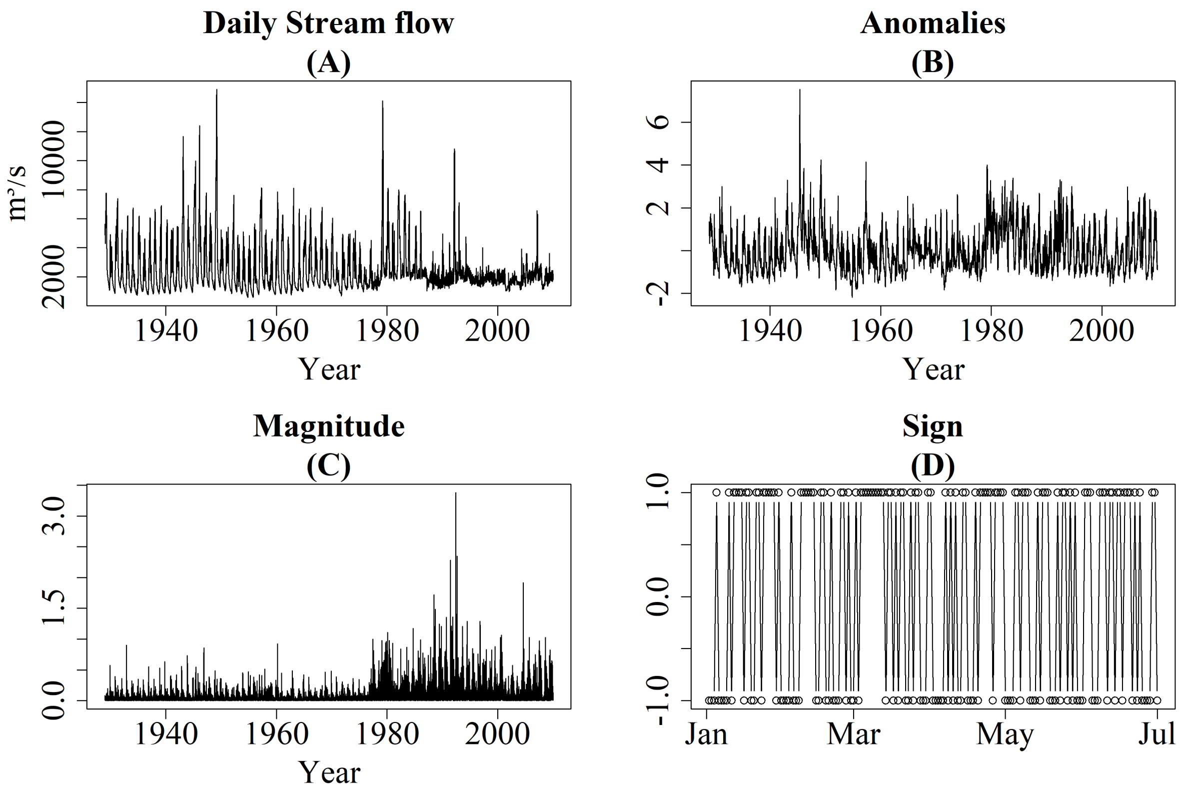


Figure 2 – Daily streamflow series (A), anomaly series (B), magnitude series (C) and sign series (D) for Juazeiro/BA hydrological station for the period 1929-2009.

We calculate DFA exponents for the entire series (1929-2009) and for pre-construction (1929-1972) and post-construction period (1980-2009) using a second order detrending polynomial. Fig. 3shoe the DFA graphs. In all cases, two scaling regimes can be observed: short-term memory regime for scales up to 1 year, and a long-term memory regime for scales greater than 1 year.

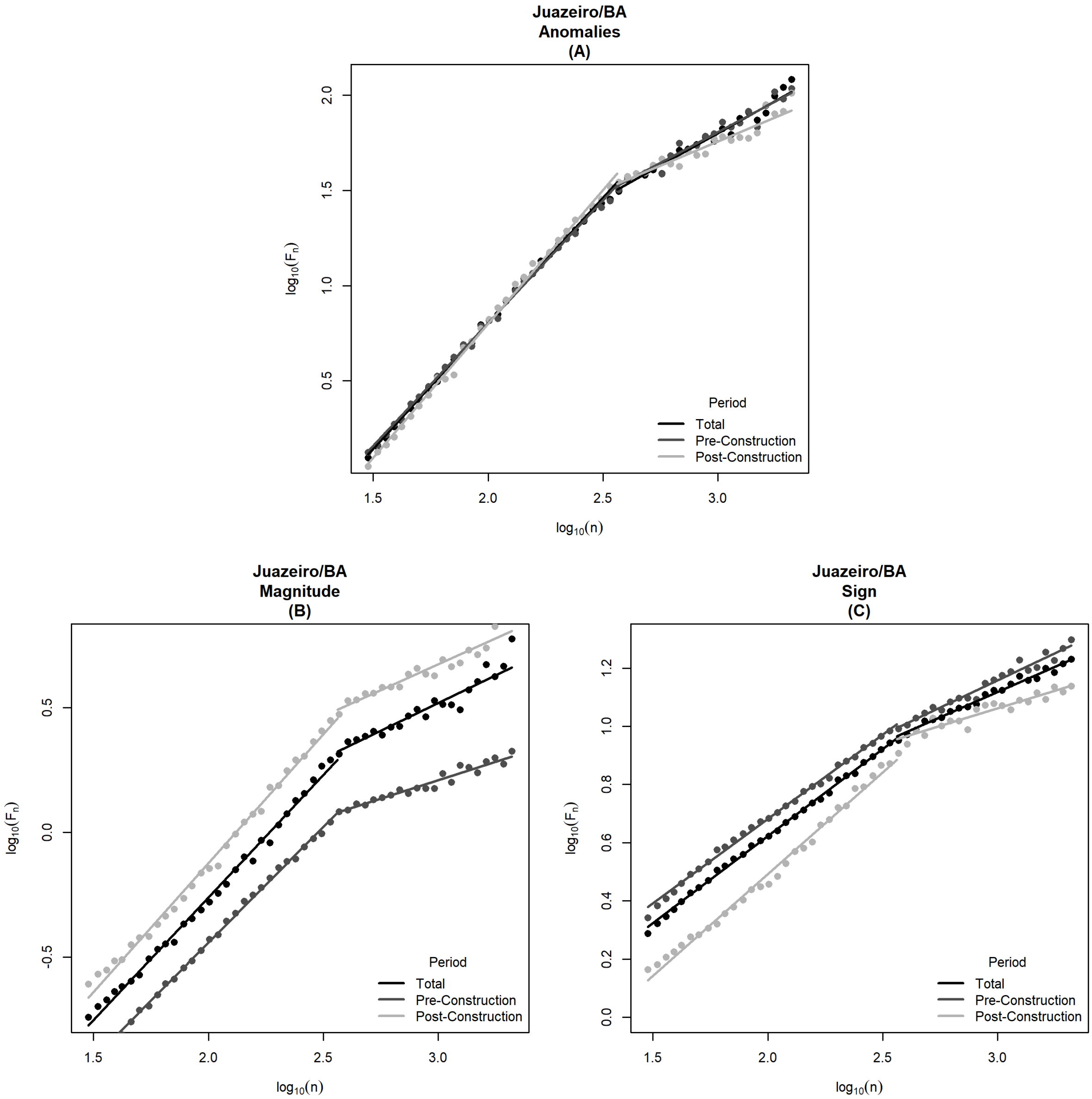


Figure 3 – DFA graphs for anomaly series (A), magnitude series (B) and sign series (C) for Juazeiro hydrological station.

Similar behavior was observed for karst springs (LABAT et al., 2011), and for the Yangtze River (ZHANG et al., 2012), and it can be contributed to synchronization between hydrological and solar cycle (LIVINA et al., 2003a; LABAT et al., 2004).

The values of DFA exponents (calculated as slopes of linear regressions from Fig.3 are presented in Table 1. For anomaly series, for all analyzed periods and for scales less than 1 year (short memory), the value of the DFA exponent is found to be between 1.0 and 1.5, indicating anti-persistent fractional Brownian motion ($H = \alpha - 1$): the small increments are more likely to be followed by large increments and vice versa.

Table 1 – DFA exponents for anomaly series, magnitude series, and sign series, for total (1929-2009), pre-construction (1020-1972) and post-construction (1980-2009) period for Juazeiro hydrological station.

	α_{DFA}	
	$n < 365$	$n > 365$
Anomalies		
1929-2009	1,316	0,803
1929-1972	1,275	0,757
1980-2009	1,410	0,750
Magnitude		
1929-2009	0,989	0,593
1929-1972	0,895	0,371
1980-2009	1,013	0,619
Sign		
1929-2009	0,602	0,353
1929-1972	0,586	0,381
1980-2009	0,692	0,259

The long memory (scales larger than 1 year) is characterized by persistence in anomaly series ($0.5 < \alpha < 1$). After the construction of the Sobradinho reservoir, the process for short memory regime shifts toward Brownian motion indicating that reservoir operation induces more randomness in streamflow increments. There is no difference in values of DFA exponents for scales larger than 1 year indicating that reservoir operation does not affect long memory of streamflow dynamics.

The behavior of the magnitude series reveals nonlinear properties of streamflow. For short scales, the values of DFA exponents are for all periods close to 1 indicating strong nonlinear properties of streamflow. After the reservoir construction, magnitude series exhibits the strongest persistence ($\alpha_{DFA} \approx 1$) indicating that the reservoir operation changes streamflow dynamics toward a more nonlinear regime. The persistence of magnitude series indicates that the original series has multifractal properties (there are clusters of high magnitude and clusters of low magnitude), which becomes stronger after the reservoir construction.

The river flow multifractality and its alteration due to human activities is found for rivers in different parts of the world and seems to be a good indicator of river health (ARAÚJO et al., 2015; ZHOU; ZHANG; SINGH, 2014). For large scales, nonlinear properties also become stronger (increase in DFA exponent) after the construction of the reservoir but non-linearity is weaker than for short scales. Linear properties of streamflow dynamics were also affected by reservoir operation.

For all periods sign series exhibits similar behavior: weak persistency at short scales (positive/negative increments are more likely to be followed by positive/negative increments) and weak anti persistency at long scales (positive increments are more likely to be followed by negative increments and vice versa). After the reservoir construction, the value of DFA exponent increases for short scales and decreases for long scales indicating that correlations (both persistent and anti-persistent) become stronger.

2.3 Conclusion

We investigated the changes in the memory properties of the São Francisco river streamflow caused by human activities, in particular, the Sobradinho reservoir operation. By applying Detrended Fluctuation Analysis (DFA) on magnitude and sign of streamflow anomaly increments, we analyzed nonlinear and linear properties of the underlying stochastic process for pre and post-construction periods.

We found that the reservoir operation induced changes in the streamflow temporal organization in such a way that after the reservoir construction nonlinear properties (indicated by the behavior of magnitude series) become stronger. Linear properties of streamflow dynamics were also affected by reservoir operation: weak persistency at short scales and weak anti persistency at long scales of increment sign series become stronger after the reservoir construction.

The long memory analysis of original anomaly series did not show sensitivity to reservoir operation, and in that case, magnitude/sign DFA could be used as an alternative method to quantify alterations in hydrological processes, caused by natural and anthropogenic factors.

3 Long-term cross-correlations and direct effects in São Francisco River flow: The influence of cascade dams

3.1 Introduction

Streamflow dynamics are strongly related to precipitation, forest cover, topography, geomorphology, climate (RICE; EMANUEL, 2017) and human activities such as cropland expansion agricultural irrigation, reservoirs and urbanization (LI et al., 2017).

Free-flow rivers present long-term correlations and the capacity to absorb disturbances through geological characteristics and flow adjustments (buffer effect) (CARLIER et al., 2018; STOSIC et al., 2016c) but human activity can affect these properties (ZHOU; ZHANG; SINGH, 2014; HIRPA; GEBREMICHAEL; OVER, 2010; ZHANG et al., 2012; POFF et al., 2007; PALMER et al., 2008).

Long-term correlations play a major role in the hydrologic process and development of hydrological models (DEY; MUJUMDAR, 2018). Several methods have been applied to analyze long-term correlations for hydrologic series such as Hurst exponent (JOVANOVIC et al., 2018), Detrended Fluctuation Analysis (SAWAF et al., 2017) and Multifractal Detrended Fluctuation Analysis (JOVANOVIC et al., 2016).

More recently, new methods were introduced attempting to understand long-term cross-correlations, intrinsic cross-correlations, multifractal cross-correlations and direct effect between simultaneous time series such as Detrended Cross-Correlation Analysis (DCCA) (PODOBNIK; STANLEY, 2008; ZEBENDE; SILVA; FILHO, 2013), Detrended Partial Cross-Correlation Analysis (DPCCA) (QIAN et al., 2015; YUAN et al., 2015) Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) (ZHOU et al., 2008) and DFA-based Linear-Regression (DFA-LR) (KRISTOUFEK, 2015a; SHEN, 2015).

Dams and reservoirs regulate the São Francisco River flow, minimizing downstream flood and drought risks, changing the hydrological regime in the process (MEDEIROS et al., 2018; MARTINS et al., 2011; BARRETO et al., 2017). Sobradinho is the largest reservoir in the São Francisco River basin and plays a major role in regulating the river flow (GURJÃO et al., 2012; CIRILO; MONTENEGRO; CAMPOS, 2017).

In this chapter, we investigate (by applying DCCA and DFA-LR methods) if São Francisco river streamflow series from different stations submitted to different conditions, such as multiple dams regulating flows, present the alterations in cross-correlations related to dam constructions and direct effect on streamflow scale-wise.

3.2 Data and methodology

3.2.1 Data

The streamflow data analyzed in this work were recorded in Juazeiro/BA and Pão de Açúcar/AL (Table 2). Juazeiro/BA station is located about 40km downstream of the Sobradinho dam and it is directly influenced by reservoir operation. Pão de Açúcar/AL station is located downstream of Xingó dam, Apolônio Sales dam and Luiz Gonzaga dam. The data were provided by the National Water Agency (ANA, 2018). We used R Core Team software and C language in all analysis.

Table 2 – Description of Fluviometric Stations

	Juazeiro/BA	Pão de Açúcar/AL
Station code	48020000	49370000
Latitude	-9.4064	-9.7514
Longitude	-40.5036	-37.4464
Altitude (m)	357.74	8.1
Drainage area (Km^2)	516000	615000
Data periode	1929-2009	1931-2007
Location in Basin	Sub-Middle	Low
Distance ($\approx$ _Km^2)		
Sobradinho dam	40	575
Luiz Gonzaga dam	Upstream	142
Apolônio Sales dam	Upstream	104
Xingó dam	Upstream	45

Fonte: ANA

3.2.2 Detrended Cross-Correlation Analysis (DCCA)

Detrended Cross-Correlation Analysis (DCCA) was first presented by Podobnik and Stanley (PODOBNIK; STANLEY, 2008), designed to analyze power-law cross-correlations between two simultaneously recorded non-stationary time series as a generalization of the DFA method. It has been used in the analysis of physiological signals (HENNIG, 2014; CHEN et al., 2018; YU et al., 2018), meteorological series (ANJOS et al., 2015; ZHANG; NI; NI, 2015; SHEN; LI; SI, 2015) and financial data (PODOBNIK et al., 2009; LIMA et al., 2018; FERREIRA; DIONÍSIO; ZEBENDE, 2016; HUSSAIN et al., 2017). The DCCA algorithm proceeds as follows (PODOBNIK; STANLEY, 2008):

Two simultaneously recorded time series $x(i)$ and $y(i), i = 1, ..., N$ are integrated to produce $X(k) = \sum_{i=1}^{k} x(i)$ and $Y(k) = \sum_{i=1}^{k} y(i)$, where k is an integer between 1 and N.

Next, the integrated series is divided into $N_n = \text{int}\frac{N}{n}$ non-overlapping windows of equal length n and detrended by subtracting the local trends $X_{n,s}(k)$ and $Y_{n,s}(k)$ (ordinates of the straight line or polynomials) from the data in each window $s = 1, ..., N_n$. The detrended covariance is calculated as

$$F^2_{DCCA}(n) = \frac{1}{nN_n} \sum_{s=1}^{N_n} \sum_{k=(s-1)n+1}^{sn} [X(k) - X_{n,s}(k)][Y(k) - Y_{n,s}(k)] \tag{3.1}$$

Repeating this calculation for all window sizes provides the relationship between $F_{DCCA}(n)$ and the window size n. If the original series are power-law cross-correlated, then $F_{DCCA}(n) \approx n^{\lambda}$ and the scaling exponent λ is determined from the linear regression of $\log[F_{DCCA}(n)]$ versus $\log(n)$.

The interpretation of λ is similar to DFA exponent α (PENG et al., 1994). Long-term cross-correlations between two series imply each series has a long memory from previous values, as well as a long memory from previous values of the other series. In case only one series is analyzed, DCCA and DFA methods are equivalent (PODOBNIK; STANLEY, 2008).

3.2.3 DCCA cross-correlation coefficient

Zebende (2011) used DFA and DCCA methods to define the cross-correlation coefficient (limited by -1 and 1 for perfect negative and perfect positive cross-correlation respectively)

$$\rho_{DCCA}(n) = \frac{F^2_{DCCA}(n)}{F_{DFA_1}(n) F_{DFA_2}(n)} \tag{3.2}$$

where $F^2_{DCCA}(n)$ is the detrended covariance between two series, F_{DFA_1} and F_{DFA_2} are fluctuation functions of individual series. If the two series are not cross-correlated $\rho_{DCCA}(n)$ oscillates about zero, for anti-cross-correlated series $\rho_{DCCA}(n)$ is negative, for positively cross-correlated series $\rho_{DCCA}(n)$ is positive and $\rho_{DCCA}(n) \approx n^{\omega}$, such that $\omega = 2\lambda - \alpha_1 - \alpha_2$ (ZEBENDE; SILVA; FILHO, 2013). DCCA cross-correlation coefficient was used in the analysis of enviromental series (VASSOLER; ZEBENDE, 2012; DEY; MUJUMDAR, 2018) financial data (KRISTOUFEK, 2015b; ZHAO et al., 2018) and human behavior records (FILHO; SILVA; ZEBENDE, 2014).

3.2.4 DFA-based Linear-Regression (DFA-LR)

Kristoufek (2015a) introduced a method, which merges the ideas of simple linear regression, DFA, and DCCA creating a new framework, which he called DFA-based linear regression (DFA-LR) creating the possibility of calculating the direct influence of an X-independent time series on Y-dependent time series. However, Shen (2015) extended Kristoufek's ideas to a multiple linear regression allowing the X-independent time series to be a X-independent multiple time series, naming the method as DFA-based Multiple-Linear-Regression (DFA-MLR).

This new methodology has been applied in stock market (KRISTOUFEK, 2015a; CAO; HE; XU, 2016; ZHOU; CHEN, 2016; PEREIRA et al., 2007; KRISTOUFEK; FERREIRA, 2018; KRISTOUFEK, 2016; KRISTOUFEK, 2018; TILFANI; FERREIRA; BOUKFAOUI, 2019; TILFANI; FERREIRA; BOUKFAOUI, 2020), health sciences (LIKENS et al., 2019), and environment sciences (SHEN, 2015; SHEN; LI; SI, 2015; WANG; WANG; CHEN, 2018).

Assuming we are studying the relationship between two time series, we consider a linear model of the form $Y = \beta_0 + \beta_1 X + u$, where Y and X a time series, u is an error term and $\beta's$ are parameters representing the linear relation between X and Y. Using ordinary least squares, $\beta's$ can be easily estimated by $\dfrac{\mathrm{Cov}(Y,X)}{\mathrm{Var}(X)}$ where $\mathrm{Cov}(Y,X)$ is the covariance of X and Y and $\mathrm{Var}(X)$ is the variance of X. So, extending this estimator to a DFA-based framework, Kristoufek (2015a) proposed:

$$\beta^{DFA}(n) = \frac{F^2_{XY}(n)}{F^2_X(n)} \tag{3.3}$$

where $\beta^{DFA}(n)$ is the estimated linear regression parameter between variables X and Y, $F^2_{XY}(n)$ is the detrended covariance function between X and Y time series obtained from DCCA analysis and $F^2_X(s)$ is detrended variance function from X time series. Scale-specific residuals can be obtained by $\hat{u}_t(n) = y_t - x_t\hat{\beta}^{DFA}(n) - \overline{y_t - x_t\hat{\beta}^{DFA}(n)}$ whit zero mean value. These are further plugged into DFA procedure so that the fluctuation $F^2_u(n)$ can be used to estimate the variance of $\beta^{DFA}(n)$ by $\mathrm{Var}(\hat{\beta}^{DFA}(n)) = \dfrac{1}{T-2}\dfrac{F^2_u(n)}{F^2_x(n)}$. Kristoufek (2015a) also proposed a coefficient of determination R^2 which can be calculated by $R^{2DFA}(n) = 1 - \dfrac{F^2_u(n)}{F^2_Y(n)}$.

Ferreira and Kristoufek (2017) proposed as standard error to $\beta^{DFA}(n)$ the equation $SE(\beta^{DFA}(n)) = \frac{1}{\lfloor T/n \rfloor}\frac{F_u(n)}{F_x(n)}$, which could allow us the calculation of confidence intervals and T tests. However, as long as no study has been made about asymptotic distribution of $\hat{\beta}^{DFA}(n)$ Kristoufek and Ferreira (2018) proposed another statistical test and confidence intervals based on surrogate residuals which was used by Tilfani, Ferreira and Boukfaoui (2020). Shen (2015) proposed the use of Podobnik et al. (2011) statistical tests for power law cross-correlated process, which consists on shuffling the dependent time series and construct posteriori distributions and stablishing critical values for $\hat{\beta}^{DFA}(n)$ in each scale to achieve inferences on $\hat{\beta}^{DFA}(n)$, which was used by Cao, He and Xu (2016) and (WANG; WANG; CHEN, 2018).

Likens et al (2019) showed that DFA-LR parameter estimates are generally unbiased, but sensible to small samples (T $<$ 512) and choice of detrending polynomial degree under existence of trends of any degree or type can increase standard error. They suggests the use of some method of surrogation to generate confidence intervals or Monte-Carlo simulation. DMLR can be very useful in contexts of noisy, autocorrelated, and nonstationary data.

Shen (2015) arguments the superiority of the method on non-gaussian data above classical least squares methods because if error terms are normally distributed both methods are able to estimate the effects correctly. However, if error term are power law distributed classical least squares fails in estimate the effects correctly once normal distribution is a special case of power law distribution. Wang, Wang and Chen (2018) founded DFA-LR are unbiased under different levels of long-range dependence and found similar distributional results as (SHEN, 2015).

3.3 Results and Discussion

We used in analysis original and deseasonalized series (anomalies) of daily streamflow $x(t)$:

$$X(t) = \frac{x(t) - \mu_t}{\sigma_t} \tag{3.4}$$

where μ_t is the mean daily streamflow calculated for each calendar date by averaging over all years in the record, and σ_t is the standard deviation of $x(t)$, also calculated for each calendar date (KANTELHARDT et al., 2006). Fig. 4 (a) and (b) shows the lower magnitude and less periodicity on streamflow dynamics after the Sobradinho reservoir construction. This flow regime change is related to the reservoir operation and although downstream flood risks were minimized it affects negatively downstream riparian communities, fishing, navigation and agriculture (MARTINS et al., 2011). Fig 4 (c) and (d) show streamflow anomalies from the two stations where we can observe fewer spikes after the 90s'.

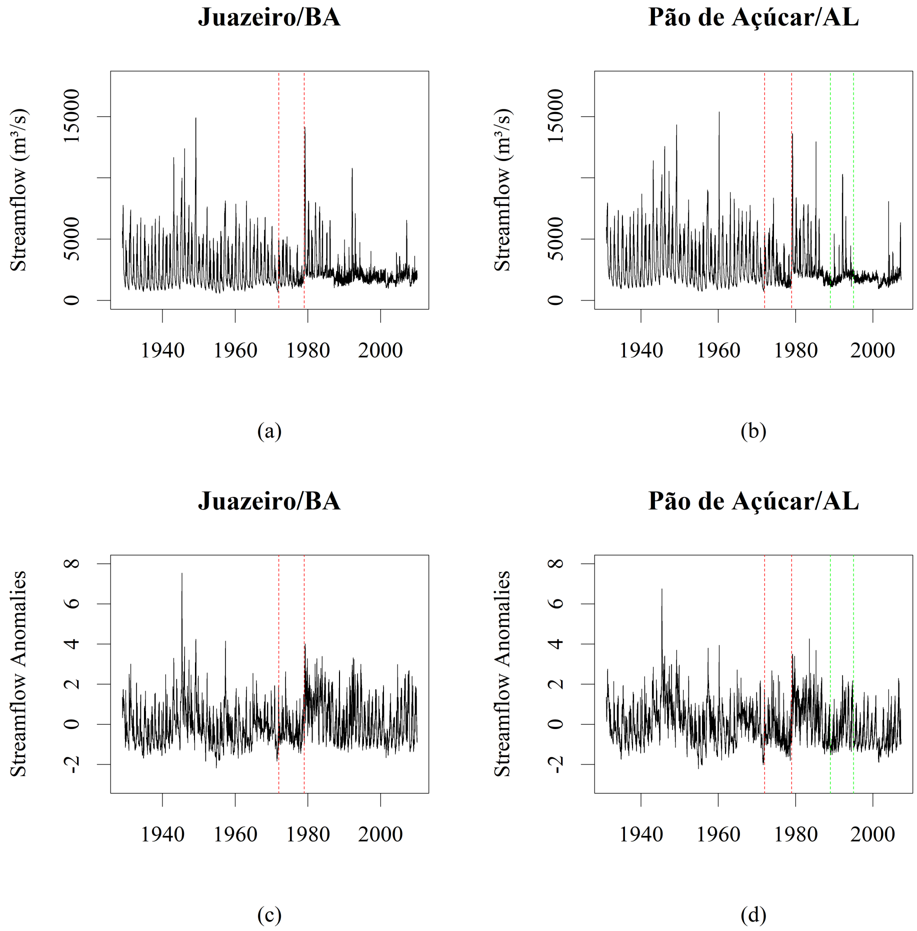


Figure 4 – Original and anomaly (deseasonalized) streamflow time series. The vertical lines indicate the beginning of construction and the beginning of the operation of the Sobradinho dam (red) and Xingó dam (green).

We divided streamflow series into 3 different periods: March 1966 to May 1973 (before Sobradinho dam construction), December 1979 to February 1987 (after the construction of Sobradinho dam and before the construction of Xingó dam) and January 1995 to March 2002 (after the construction of Xingó dam) and calculated $\rho_{DCCA}(n)$ cross-correlation coefficients for streamflow series from Juazeiro/BA and Pão de Açúcar/AL stations.

Fig. 5 (a) and (b) depicts $\rho_{DCCA}(n)$ cross-correlation coefficient as a function of scale n of original and anomalies series. In Fig. 5 blue line represents the cross-correlations of the first period between two stations and has a logistic function form. The cross-correlations start at near 0,32 in original series and 0,22 in anomalies and ends near 0,99 and 0,97, respectively in higher scales.

Green line represents the cross-correlations of the second period between two stations and has a logistic function form too. The cross-correlations start at near 0 and ends near 0,98 in original series and 0,96 in anomalies for higher scales. Red line represents the cross-correlations of the third period between two stations and has a different form of the other two starting at 0,39, decreasing until 0,16 and increasing until the end at 0,89 in original series and starting at 0,36, decreasing until 0,28 and increasing until the end at 0,95.

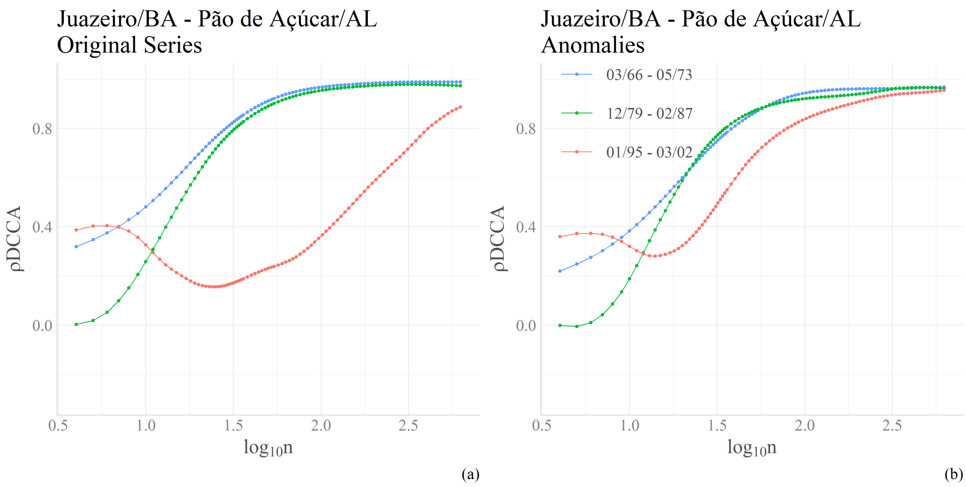


Figure 5 – $\rho DCCA$ results from Juazeiro/BA and Pão de Açúcar/AL stations original streamflow and anomaly time series.

Correlations are high in the first and second period in higher scales but are not in the third period. Correlations are low in the second period in small scales and relatively higher in first and third period against the second one. Sobradinho and Xingó operation affected cross-correlations between stations only in small scales as first and second period only differs in it.

Xingó and Sobradinho operation affected cross-correlations in larger scales decreasing them. However, it's important to note the differences in higher scales are stronger in original series where seasonal component are present. Once we removed the seasonality influence, cross-correlations were greater in higher scales. We believe seasonality are affected by Sobradinho and Xingó operation.

We conducted a DFA-LR analysis investigating what is the direct effect of Sobradinho dam represented by Juazeiro/BA streamflow series in Pão de Açúcar/AL streamflow series that is affected by Xingó dam too as an asymmetric measure of multiscale relationship between two time series preserving original metric scale (LIKENS et al., 2019).

We adopted a detrending order of 1 because higher order makes standard errors higher. Critical regions were constructed with the procedure proposed by Podobnik et al. (2011).

Fig. 6 (a) and (b) depicts $\hat{\beta}^{DFA}(n)$ and the critical region as a function of scale n and fig. 6 (c) and (d) depict $R^2(n)$ of original series and anomaly series. We observe the non-significant effect of Juazeiro/BA in Pão de Açúcar/AL stations in small scales ($n < 10$) in the second period for original series and anomalies. Juazeiro/BA presents positive effects on Pão de Açúcar/AL in first and third period for small effects. Juazeiro/BA effects on Pão de Açúcar/AL increases as a scale-function for first and second period more rapidly than third period in original series. However, this result are not confirmed in anomalies.

It's not know exactly what is the extension of seasonality effects on DMLR estimates, but we observe that when seasonality are removed some known differences disappear. Likens et al. (2019) argue against the hypothesis that asymptotic behavior are related to seasonality. It is in agreement with our results because $\hat{\beta}^{DFA}(n)$ for anomalies has no seasonal component and has an asymptotic behavior, so asymptotic long-range effects are not exclusively related to seasonality.

$R^2(n)$ results (Fig. 6 (c) and (d)) indicates influence as an increasing logistic function for first and second period in original series and for all periods in anomalies. Only third period of original series showed different structure as a decreasing function in small scales and increasing function in higher scales. The influence of Juazeiro/BA on Pão de Açúcar/AL has decreased in higher scales with Sobradinho and Xingó operation in a stronger way with original series and weaker way with anomalies.

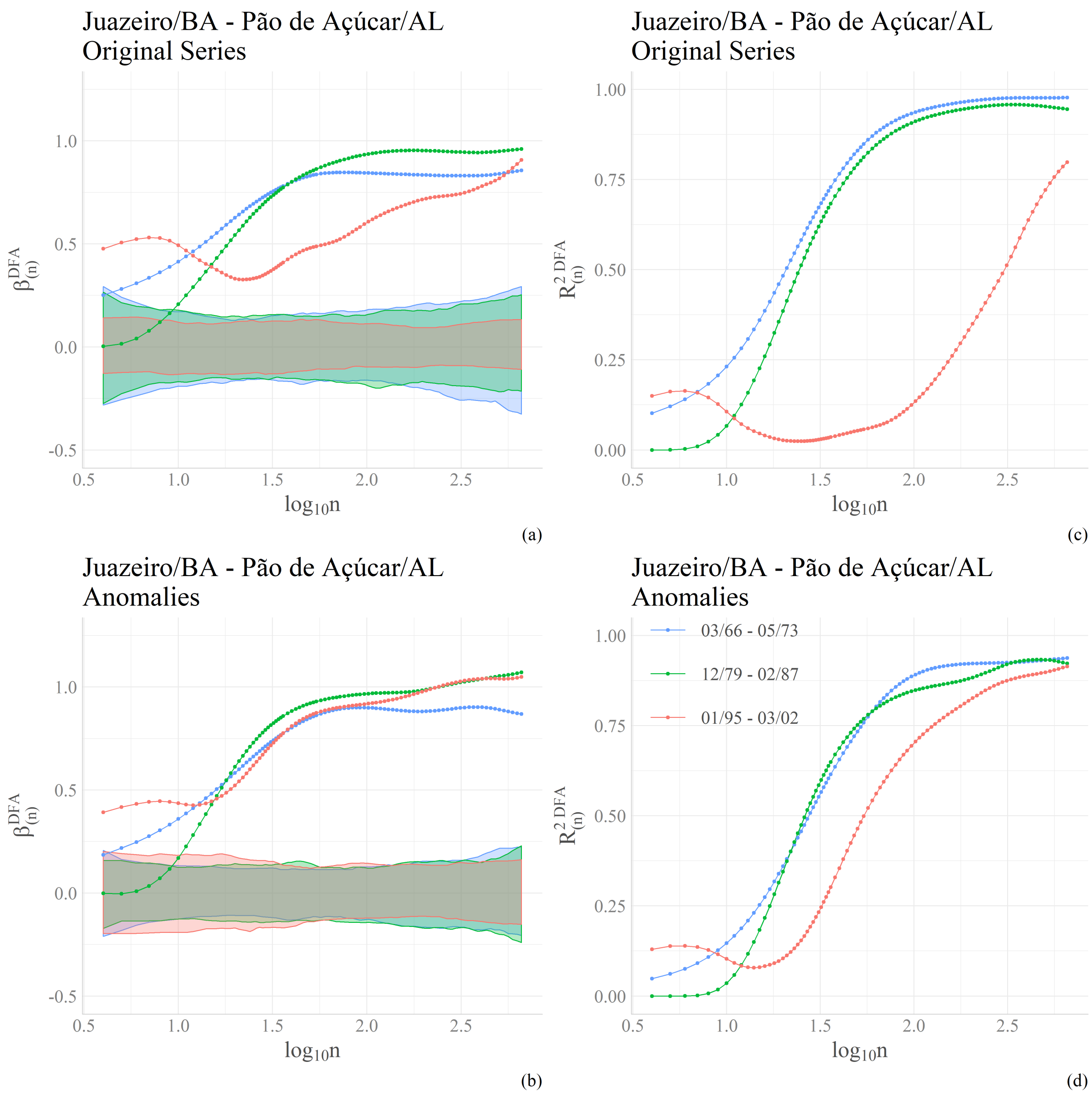


Figure 6 – DFA-LR results from Juazeiro/BA and Pão de Açúcar/AL stations original streamflow and anomaly time series.

3.4 Conclusion

We investigated how the construction of cascade dams and reservoirs affected the daily streamflow cross-correlation and direct effect between stations of Juazeiro/BA and Pão de Açúcar/AL by using Detrended Cross-Correlation Analysis (DCCA) and DFA-based Linear-Regression (DFA-LR).

For DCCA in the analysis of original series Sobradinho and Xingó increased cross-correlations in small scales and decreased cross-correlations in higher scales strongly related to seasonality. Anomalies revealed similar but weaker results, pointing in the hypothesis of Sobradinho and Xingó weakened common seasonality between stations' streamflow series.

For DFA-LR, Juazeiro/BA decreased the direct effect on Pão de Açúcar/AL in the period after dam constructions for original series for higher scales but not in anomalies. In small scales the direct effect are stronger after dam constructions as consequence of dam operation.

We could infer that dam operation affects cross-correlations at higher scales weakening them and small scales increasing them creating human induced streamflow not preserving natural seasonality.

4 Complexity analyses of São Francisco River streamflow: the influence of dams and reservoirs

4.1 Introduction

The complexity of streamflow fluctuations have been studied using methods originated in information science (LI; ZHANG, 2008; SERINALDI; ZUNINO; ROSSO, 2014), but its potential in detecting hydrological alterations was less explored (JOVANOVIC et al., 2017; STOSIC et al., 2016c) with the use of Permutation Entropy Complexity Plane.

We applied Sample Entropy (SampEn) and Multiscale entropy (MSE) method (RICHMAN; MOORMAN, 2000; COSTA; GOLDBERGER; PENG, 2002) on daily streamflow series recorded upstream and downstream of dams and reservoirs on Sub-Middle and Low sections of São Francisco River which is highly affected by diverse water use practices (MANETA et al., 2009; ROMAN, 2017).

By analyzing streamflow fluctuations for periods before and after dam construction, we evaluate the potential of these methods to detect hydrological alterations caused by human activities. We also applied SampEn in sliding windows and analyzed the influence of dam construction on the temporal evolution of the regularity of streamflow time series.

4.2 Data and methodology

4.2.1 Data

The data used in this work are daily streamflow series recorded in three gauge stations: Juazeiro/BA, Pão de Açúcar/AL, and São Francisco/MG. Juazeiro/BA station is located about 40 km downstream of the Sobradinho dam and it is influenced by reservoir operation.

Pão de Açúcar/AL station is located about 45km downstream of Xingó dam which is the most downstream and the last constructed of the cascade dams, while São Francisco/MG station can serve as a control, being located upstream of all dams except Três Marias which is very distant (about 350km) and can be considered without influence because of the buffering effect (ZHANG et al., 2012).

The data were provided by the National Water Agency (Agência Nacional de Águas – ANA). Table 3 presents Information about stations and data records (ANA, 2018).

Table 3 – Description of Fluviometric Stations

	São Francisco/MG	Juazeiro/BA	Pão de Açúcar/AL
Station code	44200000	48020000	49370000
Latitude	-15.9494	-9.4064	-9.7514
Longitude	-44.8678	-40.5036	-37.4464
Altitude (m)	448.00	357.74	8.10
Drainage area (Km^2)	1840000	516000	615000
Data periode	1934-2015	1929-2009	1931-2007
Location in Basin	Midle	Sub-Middle	Low

We analyzed both original and deseasonalized (anomalies) series. The streamflow anomalies were calculated by $z_{i,k} = \frac{x_{i,k} - \mu_i}{\sigma_i}$ where μ_i and σ_i are mean and standard deviation calculated for each calendar day i over the years k (e.g. $k = 1934, \ldots, 2015$ for São Francisco/MG station). Fig. 7 presents the original daily streamflow series and the daily anomaly series. We used R Core Team software and C language in all analysis.

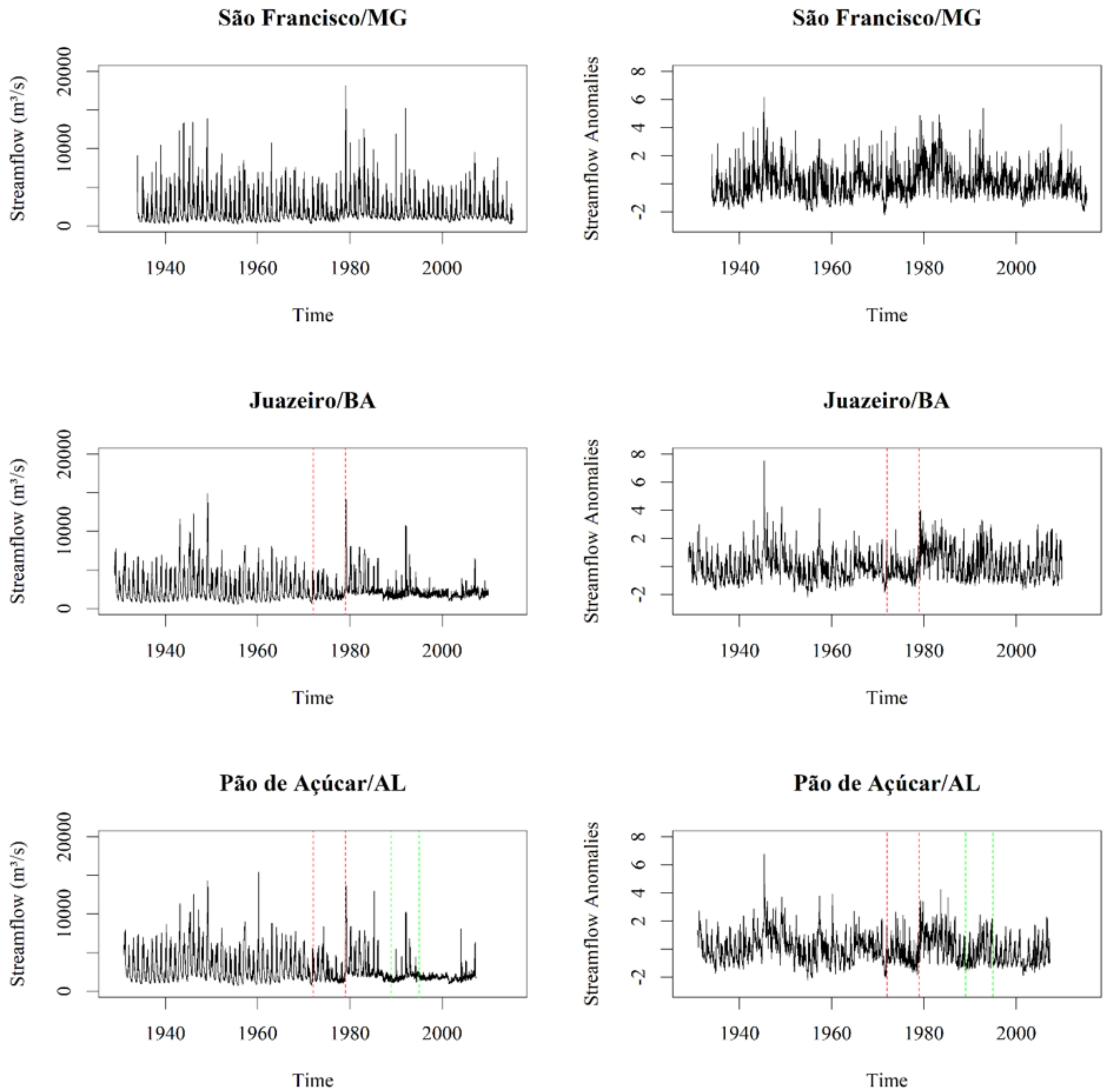


Figure 7 – Original and anomaly (deseasonalized) streamflow time series. The vertical lines indicate the beginning of construction and the beginning of the Sobradinho dam (red) and Xingó dam (green) operation.

4.2.2 Sample Entropy

Sample entropy (SampEn) was introduced by Richman and Moorman (2000), as a modification of the approximate entropy method (PINCUS, 1991). It measures the rate of generation of new information by examining a time series for similar epochs: more frequent and more similar epochs (more regularity in the time series) lead to lower values of Sample Entropy. SampEn (m,r,N) is defined as the negative natural logarithm of the conditional probability that two sequences of length N, similar on the scale of m points at tolerance level r, remain similar on the scale of $m+1$ points at the same tolerance level, where self-matches are not included in calculating the probability.

Sample entropy algorithm proceeds as follows (RICHMAN; MOORMAN, 2000):

i. For a time series of length N, $u(j), j = 1, ..., N$, one first forms of $N-m+1$ vectors $x_m(i), i = 1, ..., N-m+1$ where $x_m(i) = \{u(i+k) : k = 0, ..., m-1\}$ is the vector of length m starting at the position $i = 1, ...N-m+1$.

ii The distance between vectors $x_m(i)$ and $x_m(j)$ is defined as the maximum difference of their corresponding scalar components:

$$d[x_m(i), x_m(j)] = \max\{|u(i+k) - u(j+k)| : k = 0, ..., m-1\} \tag{4.1}$$

iii. Next one counts the number B_i of vectors $x_m(j)$ such that $d[x_m(i), x_m(j)] \leq r$, where r is the tolerance level of accepting matches, $j = 1, ...N-m$ and $j \neq i$ to exclude self-matches (tolerance level $r : r \equiv r\sigma$, σ - standard deviation of $u(i), i = 1, ..., N$).

iv. One then defines

$$B_i^m(r) = \frac{B_i}{N-m-1} \text{ and } B^m(r) = \frac{\sum_{i=1}^{N-m} B_i^m(r)}{N-m} \tag{4.2}$$

where $B^m(r)$ is the probability that two vectors will match for m points.

v. Steps i-iv are repeated for vectors of length $m+1$ to find

$$A_i^m(r) = \frac{A_i}{N-m-1} \text{ and } A^m(r) = \frac{\sum_{i=1}^{N-m} A_i^m(r)}{N-m} \tag{4.3}$$

where, A_i is the number of vectors $x_{m+1}(j)$ which are within r of $x_{m+1}(i)$, again excluding self-matches. $A^m(r)$ is the probability that two vectors will match for $m+1$ points.

vi. Sample entropy (SampEn) is finally defined as

$$S_E(m, r) = \lim_{N \to \infty} \left[-ln \frac{A^m(r)}{B^m(r)} \right] \tag{4.4}$$

which is estimated by the statistics

$$S_E(m, r) = -ln \frac{A^m(r)}{B^m(r)} \tag{4.5}$$

Sample entropy method has been used in analyzing physiological processes (LAKE et al., 2002; WENG et al., 2017), geophysical signals (BALASIS et al., 2009), climatic data (SHUANGCHENG et al., 2006), hydrological processes (CHOU, 2014; MIHAILOVIĆ et al., 2014; MIHAILOVIĆ et al., 2015) and engineering problems (WIDODO et al., 2011; ZHAO; YANG, 2012).

4.2.3 Time-dependent SampEn

Since entropy describes the average uncertainty of a sequence, it is not always useful for analyzing nonstationary data (DARBELLAY; WUERTZ, 2000). Time-dependent entropy measures have been introduced using the sliding window technique to yield a temporal evolution of entropy (STOSIC et al., 2016a; BEZERIANOS; TONG; THAKOR, 2003).

In hydrology, time-dependent entropy was applied to analyze trends in the complexity of streamflow (CHOU, 2014), and to detect hydrological alterations caused by dam construction (STOSIC et al., 2016c). For a time series $x_1, ..., x_N$ the sliding window is defined as $X_t = x_t, x_{t+1}, \ldots, x_{t+w-1}$ where $w \leq N$ is the window size and $t = 1, 2, ..., N-w$ is the position.

The values of the time series in each window X_t are used to calculate the sample entropy SampEn (m, r, w) at a given time t. The time-dependent entropy method corresponds to the quantification of irregularity in the series as a function of time.

4.2.4 Multiscale Sample Entropy (MSE)

Multiscale sample entropy was introduced by Costa, Goldberger and Peng (2002), as a generalization of the sample entropy method (RICHMAN; MOORMAN, 2000). Entropy-based measures, such as Shannon entropy (SHANNON, 1948), Kolmogorov entropy (GRASSBERGER; PROCACCIA, 1983), Approximate entropy (PINCUS, 1991) and its extension Sample entropy (RICHMAN; MOORMAN, 2000), grow monotonically with the degree of randomness and fail to quantify complexity as a “meaningful structural richness,” which exhibits higher regularity than a random process.

Both completely random (white noise) and completely regular (e.g. periodic) signals should exhibit less complexity than a structurally “complex” process (e.g. $\frac{1}{f}$ noise) (COSTA; GOLDBERGER; PENG, 2002). Multiscale entropy takes into account multiple time scales by calculating sample entropy for consecutive coarse-grained time series $x^{\tau}(j) = 1, ..., \frac{N}{\tau}$ determined by the scale factor $\tau : x^{\tau}(j) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x(i)$ where $x^{\tau}(i) = 1, ..., N$ is original time series.

By plotting MSE versus scale factor τ, we can analyze the structural complexity of different components of underlying stochastic processes, which can serve to discriminate time series generated either by different systems or by the same system under different conditions (COSTA; GOLDBERGER; PENG, 2002).

It was shown by Costa, Goldberger and Peng (2002) that uncorrelated random signals have, for larger scales, lower MSE values than correlated noise, making MSE more appropriate for quantifying complexity in short and noisy time series than traditional entropy methods that evaluate pattern repetition on a single temporal scale.

The MSE method was used in analyzing physiological signals (COSTA et al., 2003; LIU; GAO, 2017), financial time series (XIA et al., 2014), earthquake sequences (GUZMAN-VARGAS; RAMÍREZ-ROJAS; ANGULO-BROWN, 2008), and hydrological processes (LI; ZHANG, 2008; ZHANG et al., 2012; CHOU, 2012).

4.3 Results and Discussion

Table 4 presents the values of SampEn for daily streamflow series (original data) and daily anomalies for all stations and periods before and after the construction of reservoirs for embedding dimension $m = 2$ and tolerance ratio $r = 0.2$ standard deviations.

It is seen from Table 4 that SampEn values for original series are lower than anomalies, which confirms that the original series is more regular due to seasonality. For both original series and anomalies, during the natural regime before 1972, the values of SampEn are lower for Juazeiro/BA and Pão de Açúcar/AL station than for São Francisco/MG station, indicating that streamflow randomness decreases with drainage area.

Table 4 – Sample Entropy values for original and deseasonalized (anomalies) streamflow series

Station (time period)	Sample Entropy (Original data)	Sample Entropy (Anomalies)
São Francisco/MG (1934-1972)	0.096	0.311
São Francisco/MG (1980-2015)	0.083	0.344
Juazeiro/BA (1929-1972)	0.072	0.187
Juazeiro/BA (1980-2009)	0.190	0.345
Pão de Açúcar/AL (1931-1972)	0.093	0.227
Pão de Açúcar/AL (1980-1993)	0.208	0.452
Pão de Açúcar/AL (1994-2007)	0.134	0.263

After the Sobradinho dam construction in 1979, the randomness of streamflow at downstream stations Juazeiro/BA and Pão de Açúcar/AL increases as indicated by higher entropy values. After the construction of Xingó dam in 1994 (last of a series of dam cascades downstream of Sobradinho), the randomness of streamflow at Pão de Açúcar/AL station decreases (lower entropy value) but is still higher than during the natural regime.

Zhou et al. (2012) studied the effect of water reservoirs on streamflow in the East River (China) basin and also observed the decreases of randomness with drainage area during the natural regime and the increase of randomness after the construction of reservoirs. Tongal, Demirel e Moradkhani (2017) used Sample Entropy to investigate the impact of dam construction on streamflow dynamics in the South Fork of the Flathead River, Montana, USA, and also found that the entropies of the post-dam period were higher than those of the pre-dam period.

In order to analyze the temporal evolution of the degree of regularity of streamflow, we calculated SampEn in sliding windows of 10 years and shifting the window for 1 day. The time-dependent SampEn graph for all stations is shown in Fig. 8 where the effect of the Sobradinho reservoir construction can be observed: the entropy of streamflow at downstream stations Juazeiro/BA and Pão de Açúcar/AL increases while the entropy of streamflow at São Francisco/MG station stays unchanged (Fig 8(a)).

The decrease in entropy of Juazeiro/BA and Pão de Açúcar/AL streamflow in the 1990s could be related to the construction of Luiz Gonzaga reservoir (1988) for which regularized discharge was adopted to be in synchronization with Sobradinho reservoir (at 2,060m^3/s) (ANA, 2018). The anomaly series shows higher entropy values (lower degree of regularity) with a clear effect of drainage area: lower SampEn values for Juazeiro/BA and Pão de Açúcar/AL station (Fig.8(b)).

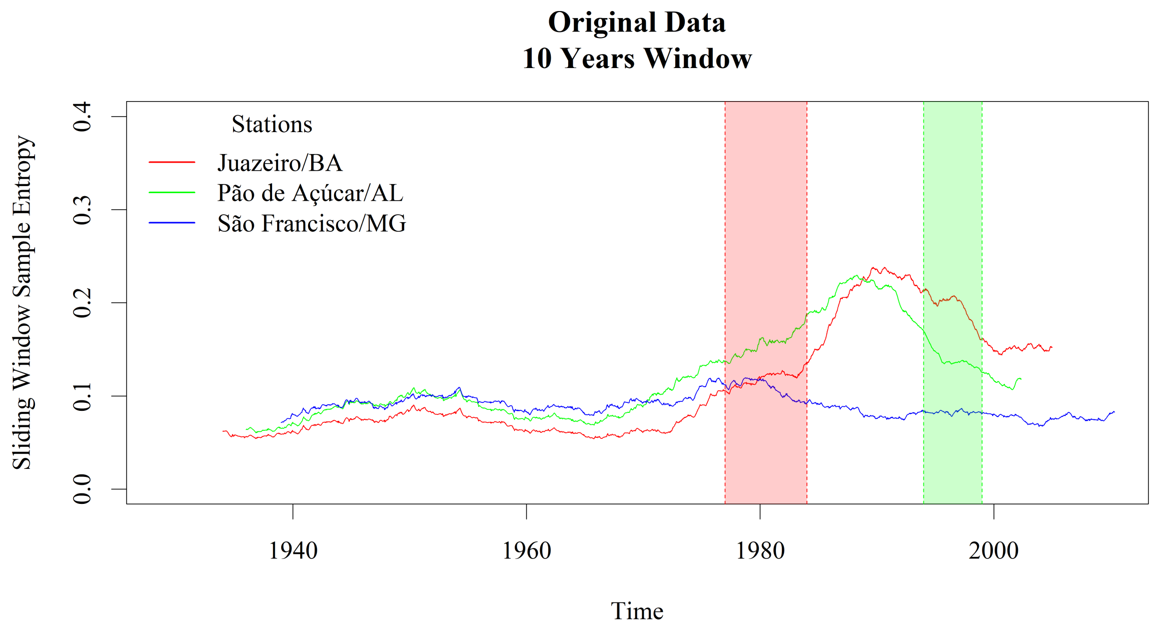
After the Sobradinho dam construction (1979), the entropy values for these stations became higher than for São Francisco/MG station and lower again after the construction of Luiz Gonzaga dam (1988) indicating that synchronized flow regularization of two reservoirs induces fluctuations in streamflow anomalies that are similar to those during the natural regime.

After all cascade dams construction (1994) entropy values for Juazeiro/BA and Pão de Açúcar/AL stations became very similar, indicating that reservoir operations induce a downstream streamflow regime characterized by a similar degree of regularity, which is not affected by drainage area.

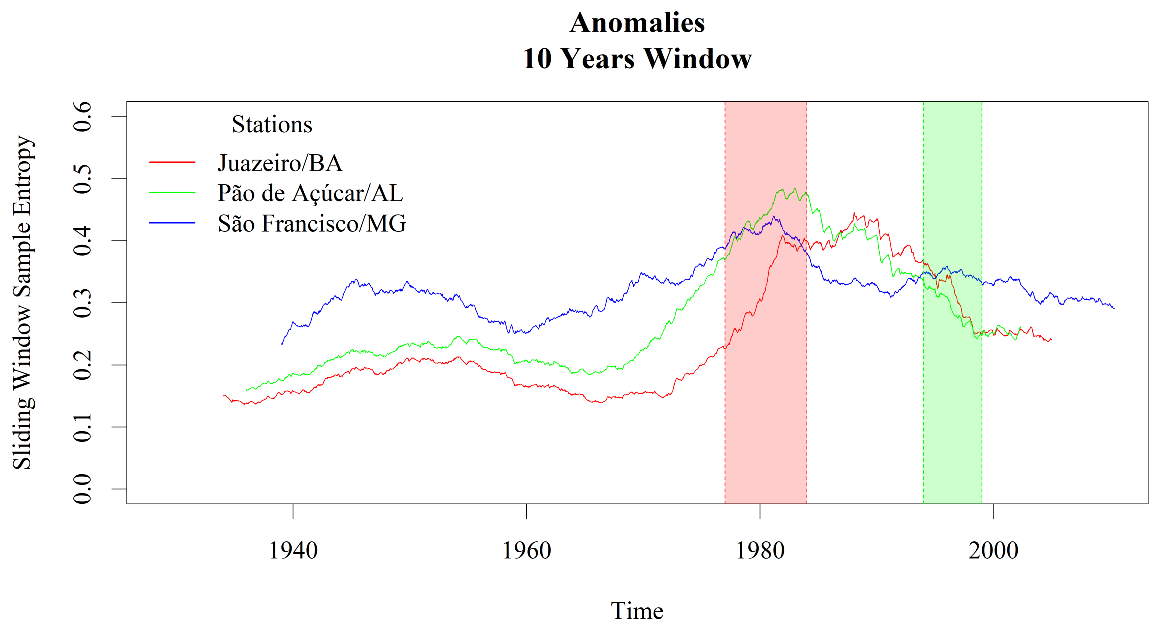
In MSE analysis, streamflow records for all stations and periods before and after the construction of dams were analyzed by calculating SampEn for coarse-grained time series with a scale factor up to 30 days and plotted as a function of scale. The plots of sample entropy over multiple scale factors are shown in Figs. 9, 10 and 11, for gauge stations Juazeiro/BA, Pão de Açúcar/AL, and São Francisco/MG, respectively.

It is seen from Fig. 10(a) and 11(a) that hydrological alterations induced by reservoir operations results in decreased regularity of streamflow for small time scales (higher entropy values), while for larger scales streamflow is more regular (lower entropy values), the effect been more pronounced for Pão de Açúcar/AL station for the period after the construction of the last, Xingó dam (Fig. 11(a)) than for Juazeiro/BA station (Fig. 10(a)).

For control station São Francisco/AL (Fig. 9(a)), the entropy values remain similar over the whole period, although entropy is slightly lower for the period after the construction of Sobradinho dam, which can be attributed to natural factors as dam is located about 350km downstream and doesn't have an influence on the streamflow at this location.



(a)



(b)

Figure 8 – Sliding window Sample Entropy for original data (a) and anomalies (b). The window size is 10 years; the windows are presented with their midpoint. The vertical lines indicate the beginning of the Sobradinho dam (red area) and Xingó dam (green area) construction.

As seen from Figs. 9(b), 10(b), and 11(b), for all stations anomalies series, show similar behavior: after the construction of reservoirs the entropy for small scales shows higher values (less regularity in anomaly series) than for pre-construction period, and then for larger scales, the entropy values become lower (more regular anomaly series) than before the construction of reservoirs, again this effect being more pronounced for Pão de Açúcar station after the construction of Xingó dam (Fig. 11(b)).

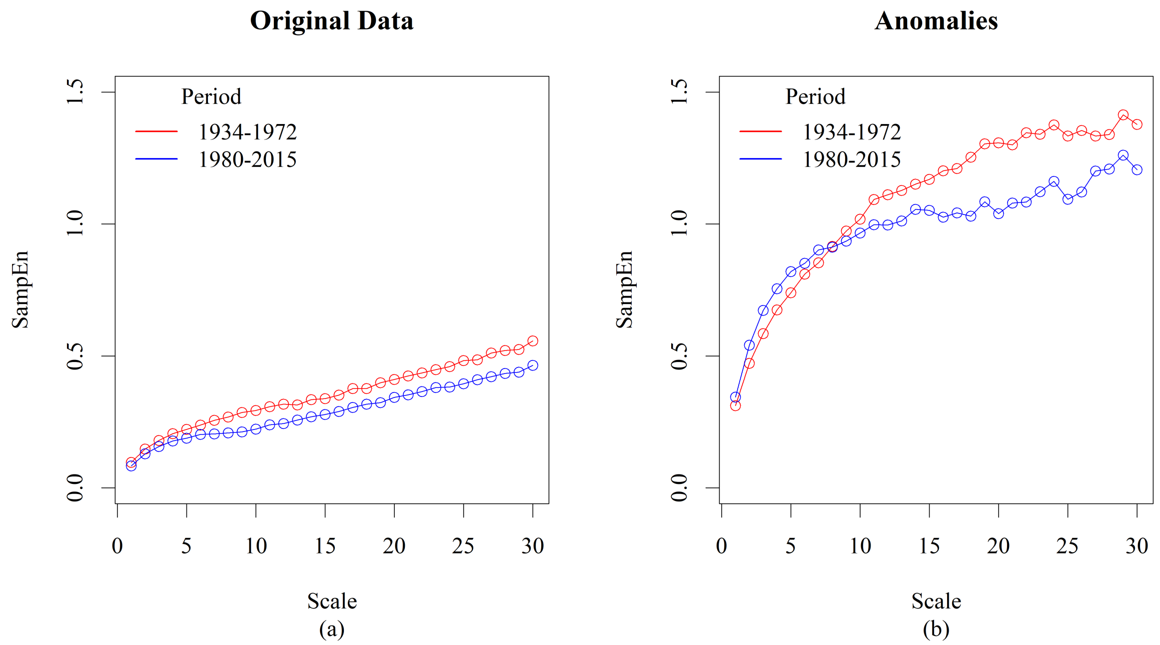


Figure 9 – MSE for São Francisco/MG station for original data (a) and anomalies (b).

In both time-dependent SampEn and MSE analyses, the streamflow recorded at São Francisco/MG station (which is located upstream of dams and reservoirs) did not show the change in entropy values due to reservoir operation. However, anomalies series showed a similar (although somewhat less pronounced) behavior as that of downstream stations, which indicates that some natural factors could have co-induced such a shift toward lower regularity of streamflow regime.

Stosic et al. (2016a) analyzed São Francisco/MG streamflow series recorded in Juazeiro/BA station using permutation entropy-complexity method and found that the change in the time variation of entropy and complexity towards higher randomness (indicated by higher entropy values), after the Sobradinho dam construction, could have been co-induced by reservoir operation and ENSO phenomenon, as indicated by the comparison of time variation of long-term trends of complexity and entropy anomaly series with the long-term trend of Multivariate ENSO Index (MEI).

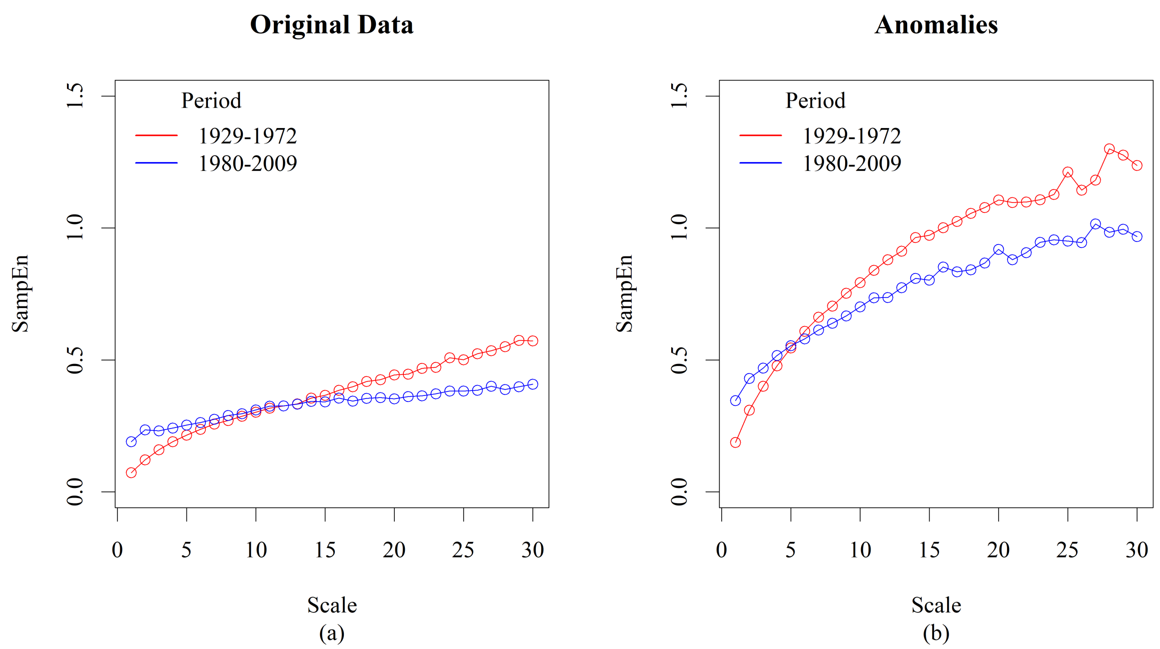


Figure 10 – MSE for Juazeiro/BA station for original data (a) and anomalies (b).

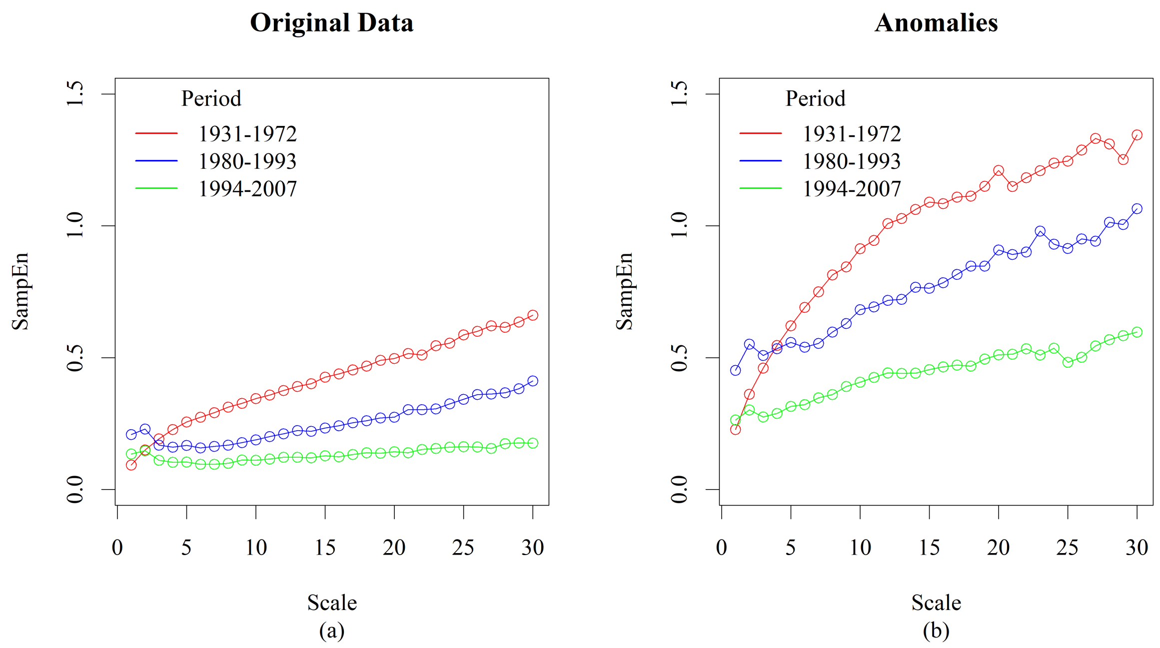


Figure 11 – MSE for Pão de Açúcar/AL station for original data (a) and anomalies (b).

4.4 Conclusion

We investigated how the construction of cascade dams and reservoirs affected the daily streamflow of São Francisco River, Brazil, by using Sample Entropy (SampEn) and Multiscale Entropy (MSE) methods.

We found that the reservoir operations changed the temporal variability of both original and deseasonalized streamflow series by decreasing the degree of regularity, as indicated by Slinding Window Technique (SWT) because of higher entropy values. The effect is more pronounced for the Pão de Açúcar/AL station, which is located downstream of all cascade dams.

The results from MSE analysis indicate that for both the original and deseasonalized streamflow series after the construction of dams, decreased regularity (higher entropy) for small time scales and increased regularity (lower entropy) for larger scales. The effect is also more pronounced for the Pão de Açúcar/AL station, which is located, downstream of all cascade dams.

The change of entropy and complexity towards higher randomness and lower complexity after the Sobradinho dam construction could have induced by both reservoir operations and the ENSO phenomenon.

5 General Conclusions

The São Francisco River basin, as a non-free-flowing river with several impoundment and diversion dams, presents profound alterations in many river related issues such as ecology, geology, hydrologic cycle, fishing, navigation and human activity.

This thesis investigates the alterations in São Francisco River streamflow by analyzing the long-term correlations, long-term cross-correlations and complexity, considering the river damming process for hydroelectric generation and river flow regulation.

The reservoir operation induced changes in the streamflow in such way that after the reservoir construction nonlinear properties of streamflow dynamics become stronger and linear properties that showed weak persistency at short scales and weak anti persistency at long scales become stronger.

The effects of river regulation are detected by alterations in long-term cross-correlations between streamflow fluctuations downstream of dams and reservoirs: i) cross-correlations and direct effects at higher scales become weaker after the construction of cascade dams. ii) cross-correlations and direct effect at small scales become stronger after the construction of cascade dams. We found that the reservoir operations changed the temporal variability of both original and deseasonalized streamflow series by decreasing the degree of regularity, as indicated by higher entropy values. Considering different temporal scales, streamflow regularity decreased for short-scales and increased for larger scales.

All applied methods: sign/magnitude DFA, long-term cross-correlations (DCCA), scale-wise direct effect (DFA-LR), Sliding Window method and Multiscale Sample Entropy showed sensitive in detection of hydrological alterations caused by human activities in particular dams and reservoirs construction.

This thesis shades new light on the use of fractal methods and information theory in the hydrological alteration issue and gives opportunities to new policies in water management based on conservation of previous streamflow dynamics. Future work could include the multifractal analysis of intrinsic cross-correlations (Multifractal DPCCA), Detrended Multiple Cross Correlation Coefficient (DMC^2), and other methods from information theory.

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