Chaos arising from the hydrological behaviour of a floodplain river during the last century

Federico Giri[1] and Melina Devercelli[1]

[1]Instituto Nacional de Limnologia

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Abstract

The hydrological regime is the main factor governing the functioning of floodplain rivers. An understanding of its dynamic leads to a better idea of the system behaviour for which proper methods must be used. We analysed the daily water level of the Paraná River during the last century at three-gauge stations using linear and non-linear tools to characterise the hydrological dynamic and to analyse to what extent chaotic behaviour prevails. The three water level time series were characterised as non-linear and non-stationary by power spectrum, autocorrelation function, and surrogate test analyses. A strange attractor was developed when the phase space was reconstructed, having a low dimensional chaos, supported by the correlation dimension, the positive maximum Lyapunov exponents, and the recurrence quantification analysis. In line with this, the system resulted unpredictable with a threshold by sample entropy, and with an intermediate hydrological complexity, while Hurst exponent characterised the system as persistent and with sensitive dependence on initial conditions. In a general overview, all the evidence obtained indicated that the Paraná River behaviour is at the edge of chaos. A latitudinal gradient of decreasing chaoticity was observed as the floodplain extent increases, whereas complexity was highest at the intermediate river station due to the inflow of tributaries with different hydrology. This paper attempts to offer some additional insights into the understanding of hydrological behaviour of floodplain rivers and proper methods to catch their complexity.

INTRODUCTION

Floodplain rivers are among the most complex freshwater systems (Thorp, Thoms, & Delong, 2006; Amoros & Bornette, 2002). They configure a network of environments integrated by hydrological fluctuations in a unique system, where the main channel and multiple floodplain water bodies interact by lateral exchanges of water (Bayley, 1995). Hydrological regime is considered the factor that governs system functioning and maintains its ecological integrity (Power, 1995; Ward & Stanford, 1995; Bellmore, Baxter, Martens, & Connolly, 2013). It connects biogeochemical processes (Tabacchi et al., 1998; Fisher, Heffernan, Sponseller & Welter, 2007; Hamilton, 2010), modules the fate and storage of organic matter (Casco, Galassi, Mari, Poi, & Neiff, 2016; Mayora, Scarabotti, Schneider, Alvarenga, & Marchese, 2020), and enables the high biodiversity that these systems sustain with organism cycles coupled to a large extent to water level fluctuations (Neiff, 1990; Ward, Tockner, & Schiemer, 1999; Thomaz et al., 2007). Hence, understanding the hydrological dynamic is an important feature to partially elucidate river functioning and biological communities' assembly.

The hydrological dynamic is the result of a wide set of factors that act at different spatial and temporal scales. In the spatial scale, landscape and geomorphic elements model and are modelled by water (Schum & Licht, 1965). Temporarily, long-term climate variability such as the Atlantic Multidecadal Oscillation, and other of shorter-term like the North Atlantic Oscillation, the Pacific Decadal Oscillation, and El Niño-Southern Oscillation are forces that have shaped rivers hydrology during the last century (Probst & Tardy, 1989; Puckridge, Sheldon, Walker & Boulton, 1998; Millimam, Farnsworth, Jones, Xu, & Smith, 2008; Antico, Schlotthauer, & Torres, 2014; Robledo, Vera, & Olga, 2016). More frequent forces acting on river flow are seasonal dynamics, headwater and local rainfalls, water runoff from floodplains (Tavares Lima, Rosa, Ramos,

& de Moraes Novo, 2003), sediments transport (Sivakumar et al., 2007), and also anthropogenic modifications such as dam regulation, infrastructure works, or flow bypass (Poff et al., 1997; Pinter, 2005; Opperman et al., 2009; Jardim et al., 2020).

Linear and non-linear models are alternative approximations to capture the variability that results from the multiplicity of factors involved in hydrological behaviour (Sivakumar, 2016). Recently it was stated that from the outcome of non-linear river dynamic, chaos is much more widespread than expected (Sivakumar, 2000, 2005; Sivakumar & Jayawardena, 2002; Khokhlov, Glushkov, Loboda, Serbov, & Zhurbenko, 2008; Ghorbani, Khatibi, Sivakumar, & Cobb, 2010; Ghorbani, Asadi, Makarynskyy, Makarynska, & Yaseen, 2017; Khatibi et al., 2012; Sivakumar & Singh, 2012; Tongal & Berndtsson, 2014). In general terms, chaotic deterministic systems are mainly characterised by high sensitivity to initial conditions (Wilks, 1991), instability, non-linearity, and fractal symmetry, among others. They are systems in constant change with patterns that are never repeated in the same way but within certain limits (attractor) and periodicity (Rosenstein, Collins, & De Luca, 1993; Lewin, 1999). In the realm of chaotic systems, they differ from random systems because they are susceptible to modelling and predictable in the short term as they arise from deterministic systems, but unpredictable in the long term due to the sensitivity to the conditions under which the pattern was formed (Kantz & Schriber, 2004). By contrast, random systems are irreproducible, not able to be modelled, and unpredictable. Stationarity or non-stationarity is another key property that describes the presence of regularities or irregularities in river dynamics, identifying the presence of rare events in the series under study (Kantz & Schreiber, op cit.). Exploring the mentioned general properties of systems behaviour, among others, should give us a better idea of their functioning.

The Paraná River is the second largest in South America and fifth in the world. The main channel transports most of the water flow while the amount stored at the adjacent floodplain depends on the slope and spatial extent of the different river stretches. The hydrograph is characteristically variable with permanent fluctuations that lead to floods and droughts of different magnitude and duration (Neiff, Mendiondo, & Depetris, 1990; Depetris, 2007). This fluvial dynamic together with the consequent spatiotemporal heterogeneity, make the river a hotspot of biodiversity (Agostinho, Gomes, Veríssimo, & Okada, 2004). It is emplaced in an area of social and economic importance, it provides water and energy to the region through hydroelectric power, and it is used as a natural waterway. Therefore, the river constitutes a hotspot of ecosystem services (Viglizzo & Frank, 2006), and the hydrological behaviour has become an issue of concern in theoretical and practical terms.

Several studies were focused in analysing the hydroclimatic variability and water discharge trends of the Paraná River (e.g., García & Vargas, 1998; Dettinger & Diaz, 2000; Labat, Ronchail & Guyot, 2005; Pasquini & Depetris, 2007; Dai, Qian, Trenberth, & Milliman, 2009; Antico et al., 2014; Antico, Aguiar, & Amsler, 2018; Puig, Olguín Salinas, & Borús, 2016). Linkages were found between river flow and sea surface temperatures (Mechoso & Pérez Iribarren, 1992; Robertson & Mechoso, 1998; Camilloni & Barros, 2003) with changes in land cover (Barros, Clarke, & Dias, 2006; Lee et al., 2018). Precipitation regimes were related with inter-annual and interdecadal hydrological variability and with ENSO phenomenon (Aceituno, 1988; Ropelewski & Halpert, 1987, 1989; Kiladis & Diaz, 1989; Barros, Doyle, & Camilioni, 2008; Berri, Ghietto, & García, 2002; Boulanger et al., 2005; Robledo, Vera, & Penalba, 2020).

As regards the developed models, some of them analysed the long-term non-linear trend (Genta, Pérez-Iribarren, & Mechoso, 1998; Robertson & Mechoso, 1998), many were prompted to analyse flooding events or to solve flood related problems (Neiff et al., 2000; Depetris, 2007; Antico et al., 2014), and recently the effect of dam-regulation was explored (Zanon, 2021). Nevertheless, according to our knowledge, the hydrology of the Paraná River was not studied under models that consider chaotic behaviour. We hypothesised that the Paraná fluvial system presents a chaotic dynamic due to the multiplicity of factors acting at different spatial and temporal scales on the hydrological regime. This would evidence a non-linear system at the edge of chaos (*sensu* Kauffman, 1993). In this frame, the aim of our work was to analyse the hydrological behaviour of the Paraná River during the last century and to elucidate to what extent chaotic dynamics prevails. Daily variation of water level over 111 years was analysed for this purpose at three different river stretches. We selected water level to evaluate system behaviour since it is a variable sensitive to system changes and it directly reflects the hydrological connectivity. We additionally analysed water discharge that is also a variable closely related to hydrological behaviour but the uncertainties inherent to its calculation process could be amplified in time series analyses introducing noise in the models (Khatibi et al., 2011).

We performed different linear and non-linear techniques. They include power spectrum, autocorrelation function, surrogate test, mutual information function, and false nearest neighbour algorithm for exploring the time series data and searching for the parameters. Then we used correlation dimension, sample entropy, maximal Lyapunov exponent, and Hurst exponent for identifying system dynamics. With the employment of this set of techniques, we look for a consensus of results rather than focusing on one method.

MATERIAL AND METHODS

The studied river and data

The Paraná River flows latitudinally from North to South along 3800 km, draining an area of 2.6 x 10^6 km^2(Fig. 1). The upper stretch of the river flows through an area of steep terrain that extends from the headwaters at the confluence of the Grande and Paranaíba rivers up to the confluence with the Paraguay River (Tossini, 1959). About 130 reservoir dams are in operation at this stretch modulating its discharge and sediment transport (Forget et al., 2009). Downriver, it begins the middle stretch where the river reduces its general slope and receives throughout the Paraguay River a high amount of sediments coming from the Andean tributaries. A lateral floodplain of about 13 to 40 km wide is developed characterised by multiple lotic and lentic water bodies. The lower stretch splits the mainstem in two arms that at the end becomes a delta (Pasquini & Depetris, 2007).

The studied time series were based on daily observations of water levels (HL) at three selected gauging stations located along the Paraná River main channel. Itatí station is located in the upper stretch (27º 15' 58.50"S - 58º 14' 39.50"W), whereas Corrientes Station (27º 27' 35"S - 58º 49' 60"W), and Túnel Subfluvial Station (Túnel, 31º 43' 11.50"S - 60º 31' 3.10"W) are located in the middle stretch of the river. The analyses were also performed on a frequency of 7 and 15 days, as well as considering water discharge variables in order to evaluate, with different parameters and evidence, the results reached with daily water level time series. The study covered a 111-year period from 1910 to 2015 for Itatí, from 1904 to 1990 for Corrientes, and from 1904 to 2015 for Túnel stations. The three time series data set were obtained from the integrated data base of COHIFE (Consejo Hídrico Federal, Secretaría de Infraestructura y Política Hídrica de la Nación Argentina,*http://bdhi.hidricosargentina.gob.ar/*).

Data analysis

As a first step, we performed linear (power spectrum and autocorrelation function) and non-linear analyses (surrogate test) to evaluate the dynamic of the three hydrological time series using the package '*nonlinearTseries* ', version 0.2.11 (García & Sawitzki, 2021) under the software environment R (R Core Team 2021) as well as the other analyses carried out in this work. The power spectrum and autocorrelation function were used as a measure of the stationarity of the time series. A time series is stationary if it is free of trend or seasonality, implying that the statistical parameters of the data remain constant through time not depending on which part of the time series we are considering. If such parameters do not remain constant through time, then the time series is non-stationary (Sivakumar, 2016).

The power spectrum (PS) allows to study the oscillations of the time series by the decomposition of variance as a function of frequency. As a requirement, the data set should cover a stretch of time much longer than the longest time scale, relevant for the evolution of the system (Sivakumar, 2016). The PS shows the contribution of possible periods, indicating the frequencies at which the variations are strong and weak. As a result, the time series is considered non-stationary if there is much power in the low frequencies (Kantz & Schreiber, 2004). The PS was graphically performed using the R package *'psd'* , version 0.2.1.0 (Barbour, Kennel & Parker, 2020).

Autocorrelation function (ACF) measures the internal correlation within a time series. It was performed to determine the degree of dependence present in the values. Stationary series have a constant value of ACF over time whereas decaying values are indicative of non-stationary series.

The surrogate data testing was performed to contrast the null hypothesis that data come from a linear stochastic process. The method generates a surrogate data set which is consistent with the null hypothesis, and finally computes a discriminating statistic for the original and for each of the surrogate data sets. If the value computed for the original data is significantly different from the ensemble of values computed for the surrogate data, then the null hypothesis is rejected, and non-linearity is assumed (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992).

After that, we searched for the parameters to evaluate the dynamic of the time series with methods appropriate for non-linear and large data sets. The delay time (time lag, τ) was calculated using the average mutual information function (AMI). This function estimates a suitable time lag at which the time series has to be plotted against itself (Frazer & Swinney, 1986). We used the *first.e.decay*method that selects the τ values where the AMI function decays to 1/e of its value at lag zero (García & Sawitzki, 2021).

False nearest neighbour method (FNN) was applied as a technique to estimate the minimal embedding dimension m (Ghorbani et al., 2010). The method assumes that two points are neighbours if they remain close when dimension increases. Hence, it examines the number of neighbours in increasing embedding dimension until it finds a dimension where the effect of false neighbours is trivial. An appropriate embedding dimension is determined by checking how the neighbours change as a function of dimension (Krakovská, Mezeiová, & Budáčová, 2015).

Noise reduction was performed to decompose each value of the time series into two components: the one that contains the signal, and the other that contains the random fluctuation. We evaluate the noise of the data series at different radii and, finally, we select the most representative series with reduced noise at each sample site (Kantz & Schreiber, 2004).

The nature of a dynamical system can be modelled by a phase space diagram (Ghorbani et al., 2017). We reconstructed the phase space of each one of the three-time series using the Takens' theorem to obtain the geometric structure of the multidimensional dynamic or attractor. This method constructs two fictitious observables from the original time series by displacing time intervals. The attractor was built in three dimensions using the embedding dimension m and the delay timeτ parameters (Takens, 1981), and it was implemented using the package *'plot3D'* , version 1.3 (Soetaert, 2021).

With the three noise-free time series, we evaluated and identified the degree of chaos present in the water level dynamic of the Paraná River. For this purpose, we computed the correlation dimension, sample entropy, maximal Lyapunov exponent, and Hurst exponent.

The correlation dimension (D^2) is a non-linear measure of an attractor dimension that indicates the correlation between pairs lying in the phase space (Khatibi et al., 2012). This D^2 method involves the reconstruction of phase space at different embedding dimensions (Grassberger & Procaccia, 1983a; Kantz & Scheriber, 1997). Chaotic deterministic and random processes are differentiated by D^2 because, in the former, it varies linearly with an increasing m and saturates after a certain value, whereas the latter varies linearly without reaching a saturation value. In this analysis, we also consider the Zounemat-Kermani (2016) criterion (inspired in Casdagli (1992)) which characterises the system as low-dimensional (D^2 [?] 3.0) to high dimensional ($D^2 > 3$) chaoticity.

The sample entropy (hq) or Kolgomorov-Sinai entropy was assessed as a measure of the unpredictability of the time series using the D^2 sum (Grassberger & Procaccia, 1983b). This method measures the rate of information produced by the system. The entropy value $K = 0$ is indicative of periodic or quasi-periodic time series (completely predictable); K = [?] for white noise (unpredictable by definition); and $0 < K <$ [?] for chaotic deterministic system (unpredictable with a threshold) (Kantz & Schreiber, 2004).

The recurrence quantification analysis ($M_{i,j(r)}$) was performed to quantify the number and duration of the recurrences in the phase space and to graphically identify with the recurrence plot if the dynamic of the system behaviour is periodic, random, or chaotic. A recurrence is the trajectory return to a neighbourhood of a region that was visited before in the phase space. For this, the computation of the recurrence matrix was required (Garcia et al., 2017).

The recurrence plot is graphically defined on the trajectory of the underlying system phase space which is used to extract qualitative characteristics of a dynamical system (Eckmann, Kamporst & Ruelle, 1987). It represents the distance correlations of a time series in a two-dimensional graph. The recurrence plots were constructed for each time series using the embedding dimension and the delay time values already detailed above, and were implemented with the '*tseriesChaos* ' package, version 0.1-13.1 (Di Narzo, 2013). They were performed as an array of a matrix (Ni x Nj), where$N$ is the number of states of the systems (i , $j = 1, \ldots, N$). Similar states (minor transition or lower distance) were indicated by a cero in the matrix, whereas different states (major transition or higher distance) were indicated with a one (Marwan, Romano, Thiel, & Kurths, 2007). According to which patterns are presented in the recurrence plot, it is possible to identify: I) homogeneous recurrence plots (uniformly distributed noise) that are typical of stationary random time series; II) diagonal oriented, periodic or quasi-periodic recurrent structures of recurrence plots that are typical of periodic or quasi-periodic systems (super-positioned harmonic oscillations); III) drift structures (logistic map corrupted with a linearly increasing term) that are proper of slowly varying parameters like non-stationary systems; and IV) disrupted recurrence plots with white areas of bands characteristic of systems with abrupt changes in the dynamics (Brownian motion) (Marwan et al., 2007).

The maximal Lyapunov exponent (λ) was performed as a measure of the strength of chaos. It quantifies the exponential rate by which two typical nearby trajectories diverge in time (Kantz & Schreiber, 2004). Also, Lyapunov exponent is a measure of the sensitivity of a dynamical system to initial conditions, also a characteristic of chaotic systems (Taylor, 2010). A system with at least one positive Lyapunov exponent is defined to be chaotic. The attractor presents trajectories that diverge, on average, at an exponential rate characterised by the largest Lyapunov exponent (Rosenstein et al., 1993). We computed the λ for 15 different embedding dimensions to evaluate its invariance and non-dependence (García et al., 2017).

Finally, Hurst exponent (H) which measures the intensity of long-range dependence in a time series (Hurst, 1951), was performed using the modification proposed by Weron (2002). The parameter H indicates the persistence of the system showing to which extent it is resistant to changes in the face of external stimuli. Persistence ($0.5 < \mathrm{H} < 1$) means that the series has a clear tendency and that it is retained for a long period of time, hence, the response is not a consequence of an instantaneous stimulus but rather it depends on its prior history. Anti-persistence ($0 < \mathrm{H} < 0.5$) is the tendency to return constantly to the point of origin (Gavilan-Moreno, 2010) and hence, the instantaneous stimulus is important. Persistence and anti-persistence are characteristics of a chaotic and random dynamical system, respectively. H is also related with the autocorrelation and the fractal dimension of the time series (Eke et al., 2000). In this study, H was evaluated at different window's length$d$ (from 50 to 10000) that slid through the data series using the corrected empirical H, and finally, a $d = 60$ was selected. The package '*pracma* ', version 2.2.9 was used to implement H analysis (Borchers, 2019).

The equations used for sample entropy, recurrence quantification analysis, maximum Lyapunov exponent, and Hurst exponent are indicated in Supplementary Methods S1.

RESULTS

The Paraná River exhibited a fluctuating hydrological regime at the three-gauge stations (Fig. 1), with periods of high and low waters that alternated with peaks of extreme values of water level that represent extraordinary floods and drought (Fig. 2a). The mean water level was about 3.3 m at Corrientes and Itatí stations, and it slightly decreased down river at Túnel Station (Table 1).

The power spectrum presented high energy at low frequencies (much power), and then it was asymptotic at higher frequencies (Fig. 2b), indicating non-stationary time series. Few peaks were observed in the signal. The shape of the curves and the spectrum shown in the graphs were indicative of non-linearity. Similarly, the autocorrelation function accounted for a slow autocorrelation decay in the three-time series and, hence, they were considered non-stationary (Fig. 2c).

Surrogate data analyses revealed that the original data sets were significantly larger than surrogate data. We rejected the null hypothesis that data come from linear stochastic processes, and non-linearity was assumed for the time series of the three hydrological gauge stations (Fig. S1).

According to those results, the parameter reconstructions of the time series were adequately performed using methods for non-linear systems. The determination of the delay time for the phase space reconstruction by means of the average mutual information (AMI) function was calculated at a lag of 300 days. The first local minimum values for the AMI function were 6, 8, and 12 days for Itatí, Corrientes, and Túnel gauge stations, respectively (Fig. S2). An embedding dimension m of 10 was sufficient to explain the dynamic of the daily water level data for Itatí Station, whereas a value of 8 was adequate for Corrientes, and 5 for Túnel Station (Fig. S3).

The noise in the time series was found to be almost imperceptible in the three data sets by observing the attractor shapes at different radii. Hence, we performed the denoise of the time series with a radius of 1. The subsequent analyses to identify possible chaotic dynamics were run with the denoised time series.

A clear attractor in a well-defined region emerged from the phase space reconstruction of the three-time series. We inferred, according to the shape of the attractor, that the system is low dimensional chaos (Fig. 3). Comparing the three-time series, the orbits of the attractor were more similar in both northern stations than in the southern station.

The correlation dimension (D^2) values suggested a chaotic deterministic behaviour of the water level time series at the three river stations. The values of D^2 in the graphs stabilised after m reached a certain value which is indicative of the existence of chaos in the time series (Fig. 4). D^2values varied among 2.4 and 3.3 (Table 2). Thus, according to the D^2 values, the hydrological regime of the Paraná River was characterised as having different dimensional chaoticity. If we analyse in detail the behaviour at each river gauge station, we observe a latitudinal gradient from low to high dimensional chaoticity of daily water level time series.

The sample entropy revealed that the water level at the three river stations had positive values (Table 2) providing evidence about the unpredictability with a threshold of the system. Túnel Station presented the lowest K value, being highest at Corrientes, and intermediate at Itatí Station (Table 2).

The recurrence quantification analysis showed that the Túnel time series has a recurrence value (REC = 0.128828) higher than that of Corrientes (REC = 0.05294243) and Itatí (REC = 0.04802505) time series. Regarding the percentage of recurrence points that form diagonal lines (DET), the three-time series had high DET values (Túnel = 0.995422, Corrientes = 0.9861203, Itatí = 0.983693). The maximum length of the longest diagonal line (MDL), excluding the main diagonal (Túnel = 28.05198; Corrientes = 15.30455; Itatí = 15.53112), and the average diagonal lines (ADL: Túnel = 28.04659; Corrientes = 15.29503; Itatí = 15.52243) revealed similar pattern than the observed in the REC values at the three river stations (Fig. 5, Table S1).

Comparing and interpreting the recurrence plots of the three-time series, we observed that they present similar patterns (Fig. 5) corresponding to a superposition of patterns II (periodic or quasi-periodic) and III (non-stationary systems). The examination of these plots revealed the existence of short line segments parallel to the diagonal of the recurrence plots, which are related to the inverse of the largest positive Lyapunov exponent. We again found a latitudinal pattern indicating that the northern station presented a major transition in the process (Itatí Station, more different states) than the southern station (Túnel Station, more similar states), whereas the middle station (Corrientes) presented an intermediate transition pattern. In random time series, these short line segments would not be observed.

The maximal Lyapunov exponent presented positive values ($\lambda > 0.03$) for the three-time series (Table 2). This means an exponential divergence of nearby trajectories that is interpreted as low-dimensional chaos. Itatí Station data set presented the highest λ-value, whereas Corrientes intermediate value, and Túnel the lowest value (Table 2).

According to the Hurst exponent, the time series revealed a persistent behaviour (H > 0.5), indicating that the system has a trend according to their state (Table 2). The river stations presented a latitudinal pattern where H increased downriver.

Discussion

According to our hypothesis, the hydrological fluctuations of the Paraná floodplain River present behaviour at the edge of chaos. In a general overview of our study, all the evidence obtained indicates a low to high dimensional chaos. The analyses were performed on daily water level variations recorded during the last century at three different river stations. We additionally evaluate the river behaviour in other coarser time frequencies (7 and 15 days) and on water discharge data (Table S2, S3), arriving to similar results. These findings reinforce the idea that the Paraná River has a chaotic dynamic, independently of the temporal interval (1, 7 or 15 days) and variable (water level or water discharge) used.

Considering the general chaotic dynamic observed in the hydrological regime of the Paraná, we found similar behaviour in other floodplain rivers such as the Mississippi and Chao Phraya (Sivakumar et al., 2007), and in rivers with different morphological characteristics (Porporato & Ridolfi, 1997; Ghorbani et al., 2010; Khatibi et al., 2012; Kedra, 2014; Albostan & Onoz, 2015; Adenan, Hamid, Mohamed, & Noorani, 2017; Salter, Voller, & Paola, 2020). Also, the analyses of the channel pathway of floodplain rivers exhibited chaotic behaviour (Zibret & Verbovsek, 2008).

The time series used in our study were large enough and with low or negligible noise, emphasising the robustness of our data set and overcoming the problems of short and noisy series in which estimators could have erratic fluctuations into signalling chaos (Theiler *et al.,* 1992). The noise reduction over the time series did not evidence differences with the original data, confirming that the time series were not characterised by high noise. Then, noise reduction enabled us to preserve non-linear interactions, as an important way of maintaining the deterministic nature of the hydrological variability in the context of chaos theory (Porporato & Rodolfi, 1997).

The preliminary analyses, power spectrum (PS), autocorrelation function (ACF), and surrogate test, performed to evaluate the nature of the Paraná system dynamic revealed that the water level time series at the three stretches correspond to non-linear and non-stationary processes. The PS presented the information in the frequency domain while the ACF in the time domain. Although Sivakumar (2000) and Kantz & Schreiber (2004) affirm that signal and noise are readily distinguished in the PS, we agree in that both analyses are not appropriate enough to distinguish between random and chaos and should be used as a first evaluation of the characterisation of the time series. Since the ACF only measures the linear dependency between the variables, it is not necessarily suitable for non-linear systems that can better catch the realm of hydrological complexity (Abarbanel, Brown, Sidorowich, & Tsimring, 1993; Frazer & Swinney, 1986). In this regard, the surrogate test provides a strict statistical approach (Theiler et al., 1992; Schreiber, 1999; Luo, Nakamura, & Small, 2005) to definitely reject the hypothesis of linearity of the hydrological processes. Nevertheless, linear tools in combination with non-linear methods are still useful in the overall scheme of systems evaluation to provide evidence about seasonal and annual cycles, long-term persistence, and scale invariance (Sivakumar et al., 2007).

The slow decay of the ACF also shows that the future values of the time series heavily depend on past values, and the mean will change over time, indicating the non-stationary nature of the time series. The properties of the dynamic found at Paraná River give evidence to move forward from the traditional stationary and lineal approaches used in hydrology as other authors already did (e.g., Sivakumar, 2016; Poff, Tharme, & Arthington, 2017), settling the possibility to apply a different universe of analyses to properly understand the nature of the system.

Assessing the occurrence of non-stationary patterns allows a meaningful understanding of the hydrological regime in the frame of changes in the Paraná basin such as meteorological extremes (Xavier et al., 2020) and land uses (Lee et al., 2018). It is also an opportunity to evolve in recognizing the non-stationarity of many ecological systems (Poff et al., 2017) from which the water regime is the driving factor (Thomaz et al., 2007; Webb, Stewardson, & Koster, 2010; Arthington, Naiman, Mcclain, & Nilsson, 2010; Devercelli, Scarabotti, Mayora, Schneider, & Giri, 2016).

In this perspective, the phase space reconstruction and correlation dimension are more adequate analyses for system identification than the commonly used linear tools. The phase space reconstruction reveals that the Paraná River is characterised by a strange attractor having a low dimensional chaos. In a chaotic system, orbits of an attractor are non-periodic, then points anywhere in space are never visited more than once, and there are regions that are never visited. Those sets of points are fractal in their nature and have a non-integer dimension (Taylor, 2010). The fractal structure of the times series studied were also evidenced by the results obtained in the analyses of correlation dimension, Lyapunov exponent, sample entropy, and Hurst exponent, and contributes to gain insight into chaotic dynamics (Serquina, Lai, & Chen, 2008).

The strange attractor in which the Paraná system evolves resembles that of other large rivers (Sivakumar, Jayawardena, & Li, 2007). Investigations of various hydrological time series also suggest that strange attractors are far more prevalent in fluvial systems when compared to point attractor and limit cycle (Ghorbani et al., 2010; Khatibi et al., 2012; Sivakumar, 2016). We observe in the space-time movement of the attractor at the three river stations a spatially coherent distribution, where the hydrological regime presents periods of high and low waters with extraordinary periods of both floods and droughts.

The orbits of the strange attractor have a limited predictability of the system, which is defined by global and local Lyapunov exponents (Khokhlov et al., 2008). The maximum Lyapunov exponent of the Paraná time series appears indicating that the trajectories of the attractor diverge in a dissipative way with values that confirm the behaviour in the edge of chaos of the hydrological processes as was observed in previous results. In line with this, the positive value of sample entropy showed that the system is unpredictable with a threshold. As a measure of complexity (Belot & Earman, 1997), sample entropy also denotes an intermediate hydrological complexity which is another element for understanding the chaotic dynamic of the Paraná River hydrology. Considering the Hurst exponent, it allows characterizing our system as persistent having a long-term memory. This implies that the present state of the system will impact its future state (Peters, 1994). That is, if the water level begins to increase, it tends to continue increasing for an indeterminate period (*a priori*) and then, suddenly the tendency can change. After that, the water level began to decrease, acquiring a new tendency. As in other rivers, the long-term persistence behaviour supported by an estimated Hurst exponent provides insight for hydrology understanding, as well as for linking hydrology with the transport of sediments and flow management (Maftei, Barbulescu, & Carsteanu, 2016; Adarsh et al., 2020). Hurst values also evidenced that the system is chaotic since they showed sensitive dependence on initial conditions.

A guiding principle of the study of the hydrological behaviour of rivers is that it constitutes the 'master factor' that regulates many others (Power, 1995). In floodplain systems such as the Paraná River, the ecological functioning, biodiversity patterns, and cycles of biological communities mainly depend on the hydrological regime (Junk, Bayley, & Sparks, 1989; Neiff, 1990; Bunn & Arthington, 2002; Thomaz et al., 2007). Investigating the complexity of the hydrological processes is fundamental for a proper planning and managing of rivers (Ma et al., 2020) and to understand the underlying processes of diversity assembly (Devercelli et al., 2016). Medvinsky et al. (2001) pointed out the importance of chaotic regimes in the organization of aquatic ecosystems, and it is well known the higher potential of adaptation to changes of chaotic systems in comparison with others that have a stable equilibrium point (Hastings, Hom, Ellner, Turchin & Godfray, 1993; Huisman & Weissing, 1999; Benincà et al., 2008).

As regards the longitudinal dimension of the Paraná River, a spatial difference was found in the characterization of the hydrological behaviour as it was observed in other rivers (Kedra, 2014; Ma, Kang, & Song, 2020). The Hurst exponent revealed a latitudinal gradient from less to more persistence system dynamic. Also, D^2 and maximum Lyapunov exponent were highest in Itatí, intermediate in Corrientes, and lowest in Túnel stations, showing the same decreasing gradient in the chaotic behaviour (Table 2). These parameters might be evidencing the effect of river morphology that has a gradually larger extent of its floodplain from Itatí to Túnel stations. In this regard, floodplain influences hydrological fluctuations by retaining water and could therefore act dampening the chaoticity and increasing the persistence downriver as its development increases. In addition, the floodplain effect on the hydrological fluctuations was also observed since floods with multiple peaks in Corrientes Station tend to lose these characteristic downriver (Cristina & Ramonell, 2018).

On the other hand, the highest complexity shown by the sample entropy values was found at the latitudinally intermediate river station. The confluence of rivers with different regimes might be adding hydrological complexity to this stretch: the Bermejo River originating in the western Andean Mountain flows into the Paraguay River, which upper catchment is in the Brazilian Pantanal and flows into the Paraná (Figure 1). Nevertheless, the tributaries' influence has just a local effect on the water level (Ramonell & Cristina, 2014).

In a general overview, there are many factors influencing the complexity and chaotic dynamic of rivers and they vary in the longitudinal gradient (Ma et al., 2020). Some factors are proper to the configuration of the rivers as geomorphology, topography, sediment transport, inflow composition, and vegetation (Tabacchi et al., 1998; Poff, Olden, Pepin, & Bledsoe, 2006); other factors are external to the river such as meteorological factors (precipitation, temperature, atmospheric pressure) and anthropic interventions (McManamay, Bevelhimer, & Kao, 2014). In the case of the Paraná River, the meteorological component has the main modulating effect on the overall hydrological regime that mainly depends on the precipitation of the upper basin located in Brazil (Berbery & Barros, 2002). They are combined with local conditions that in the case of the stations studied may not contribute to the spatial differences (Amsler, Ramonell, & Toniolo, 2005). Contrarily, the geomorphology and tributary inflows might be important factors influencing the latitudinal differences observed (Ramonell & Cristina, 2014). Vegetation development and sediment transport might also have its effect since both are associated with those characteristics. Additionally, the vegetation has its own influence due its modelling role on hydro-geomorphological features (Ramonell, Marchetti, & Pereira, 2013; Marchetti, Ramonell, Brumnich, Alberdi, & Kandus, 2020). All these denote that the water level behaves in the domain of deterministic chaos and intermediate complexity with variable strength in the longitudinal gradient of the river according to spatial heterogeneity.

Conclusion

In this work we evidenced, by daily time series analyses of water level, that the hydrological regime of the Paraná River has a chaotic deterministic behaviour in the edge of chaos. This dynamic was discovered by evaluating multiple analyses, exposing the robusticity of our results for elucidating the system dynamics. Particularly, the hydrological fluctuations are characterised by non-linear and non-stationary processes. A strange attractor was revealed when the phase space was reconstructed, having a low dimensional chaos, supported by the correlation dimension, Lyapunov exponent, sample entropy, recurrence quantification analysis, and Hurst exponent.

The evidence obtained showed differences from high to low dimensional chaos considering the three different river stations. This changing pattern is associated with the floodplain effect because the stations were in sections of the river with different morphological characteristics and with the effect of Paraná River tributaries.

Considering that the hydrological regime is the main factor governing the functioning of floodplain rivers, knowing the dynamics of hydrology help us to have information at system scale relevant to understand different process, e.g., the dynamic of hydrological events such as floods and droughts, understanding its implication in ecological processes that are associated to the maintenance of biodiversity, among others. Complexity and chaotic behaviour arising from the Paraná hydrological regime may be vital for sustaining biodiversity and system health.

The method employed in this article can be further applied to the analysis of other hydrological systems, evidencing the existence of deterministic chaos in natural environments. We argue that chaos theory offers a better understanding of hydrological systems than the more used deterministic/stochastic paradigm.

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DATA AVAILABILITY STATEMENT

The data used in this study are available upon request. Raw data were obtained from *http://bdhi.hidricosargentina.gob.ar/*).

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest that affected the impartiality of the research reported.

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Figure legends

Figure 1. The Paraná River and tributaries plotted in blue with the location of the gauge stations studied (a: Itatí, b: Corrientes, c: Túnel Subfluvial), and La Plata Basin domain in South America. Landsat images (December 2017) from Google Earth Pro visualizing the Paraná River at each gauge-station. Daily water level fluctuations from 1910 to 2015 for Itatí (a), from 1904 to 1990 for Corrientes (b), and from 1904 to 2015 for Túnel Subfluvial (c) stations.

Figure 2. Power spectrum of temporal daily water level of the Paraná River at three-gauge stations (a: Itatí; b: Corrientes; c: Túnel Subfluvial).

Figure 3. Three-dimensional phase-space reconstructions of the time series of Paraná River water level at three-gauge stations (a: Itatí; b: Corrientes; c: Túnel Subfluvial). The points of trajectories are connected for better visualization of the 'evolution' of the system dynamic.

Figure 4. Correlation dimension of the daily water level time series of the Paraná River at three-gauge stations (a: Itatí; b: Corrientes; c: Túnel Subfluvial). The saturation of the D^2 after an increase of the embedding dimension$m$ reveals that the system is chaotic.

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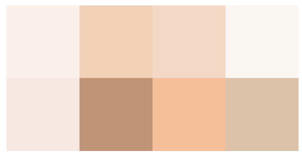
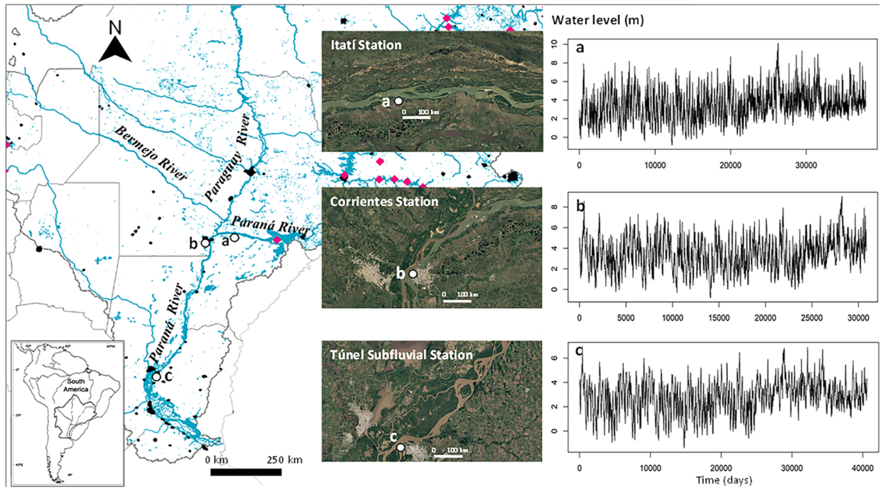


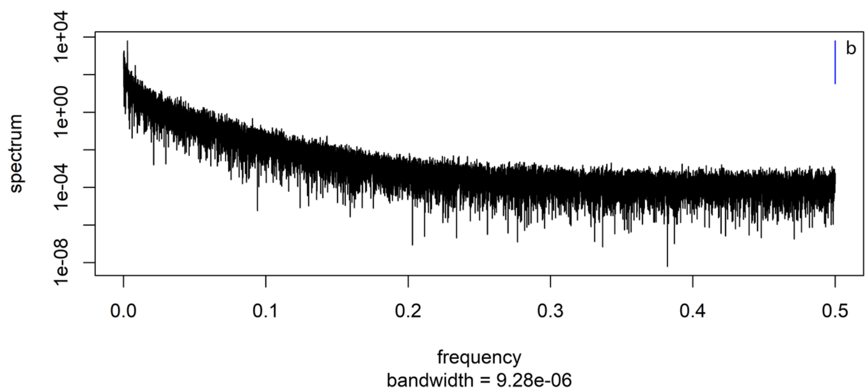
Figure 5. Estimation of maximum Lyapunov exponent on the basis of different embedding dimensions calculated on the water level time series of the Paraná River at three-gauge stations (a: Itatí; b: Corrientes; c: Túnel Subfluvial), for different embedding dimensions m (m =13 to 28 indicated with different line colours).

Figure 6. Recurrence plots as proposed by Eckmann *et al* . (1987), showing the distribution of N_{ij} points represented as black (defined as cero that means minimum distance) and white (defined as one that means maximum distance or major transition) characterizing the trajectory in the state space of our system at the three-gauge stations.

Significance Statement

This work constitutes the first study of the hydrological regime of one of the largest rivers of the world (the Paraná floodplain River) using models that consider chaotic behaviour. We applied several analyses on daily water level during the last century at three-gauge stations. The evidence concludes that the hydrological dynamic behaves at the edge of chaos and presents a non-stationary and intermediate complexity. The study of hydrological processes is fundamental for a proper planning and managing of rivers and for understanding the underlying processes that drive ecological functions and biodiversity assembly.


N
Bermejo River
Paraguay River
Paraná River
Paraná River
South America
0 km
250 km
Itatí Station
Corrientes Station
Túnel Subfluvial Station
Water level (m)
a
b
c
Time (days)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frequency
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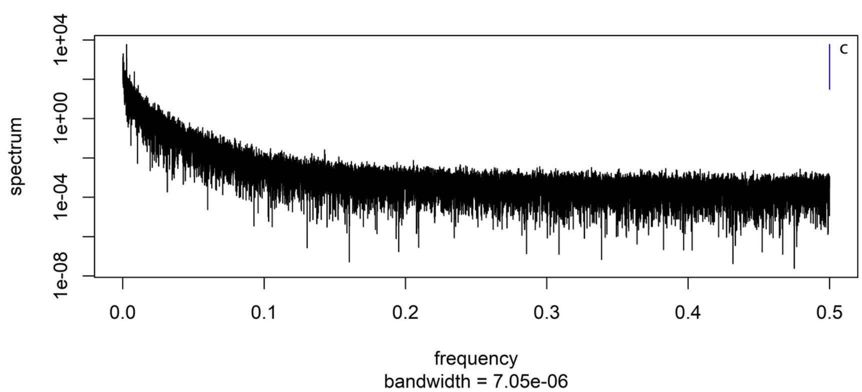
b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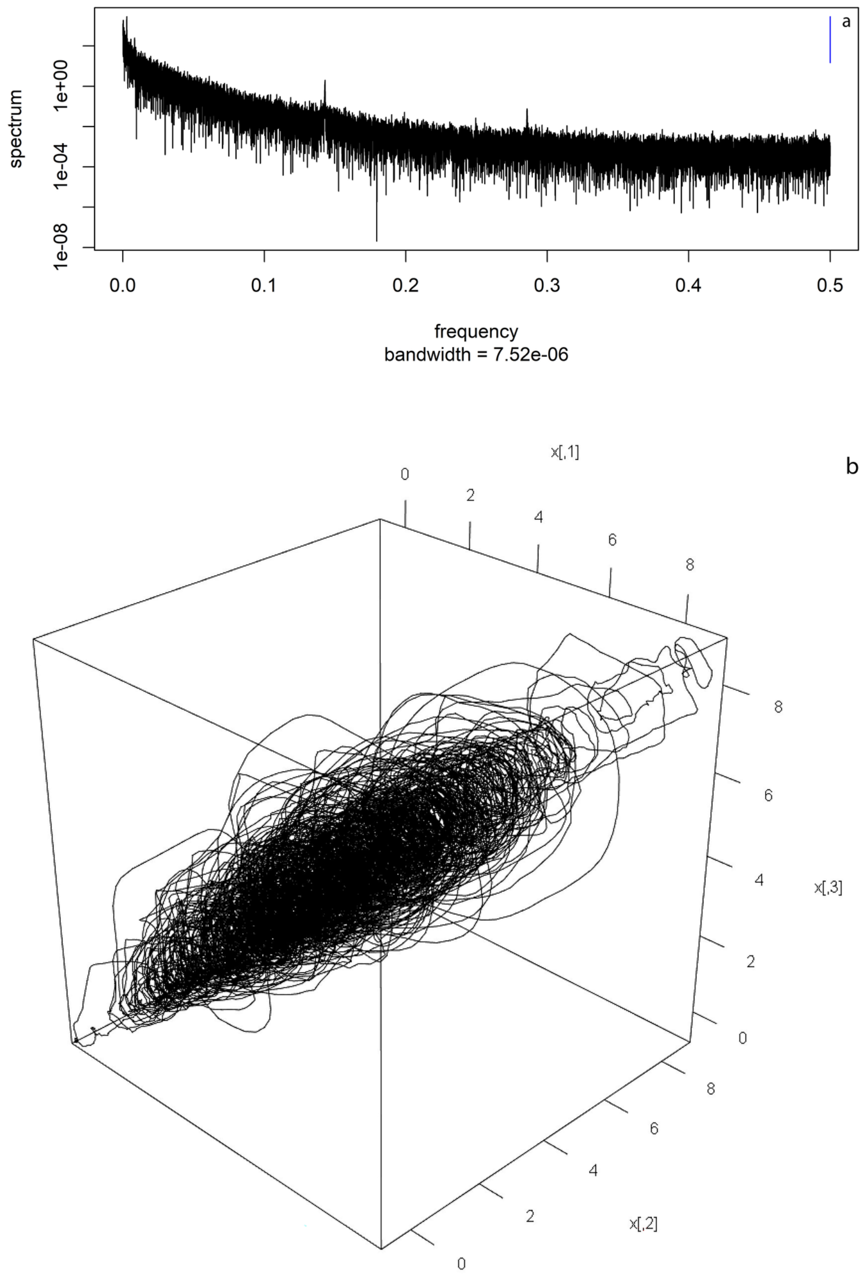
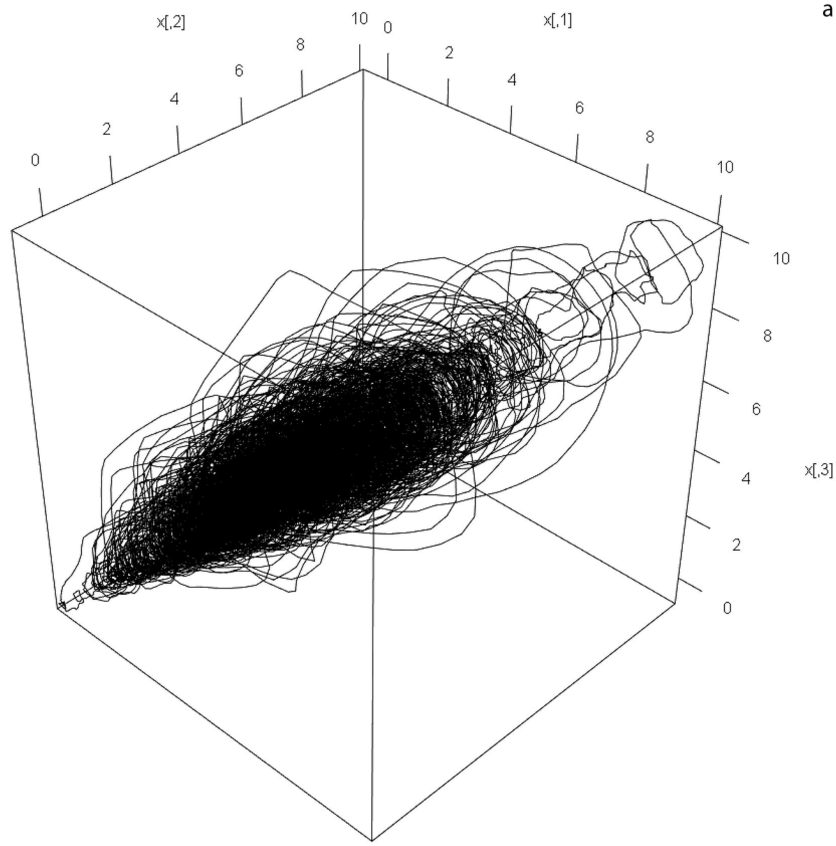


a
spectrum
1e+00
1e-04
1e-08
0.0
0.1
0.2
0.3
0.4
0.5
frequency
bandwidth = 7.52e-06
b
x[,1]
x[,2]
x[,3]
0
2
4
6
8


a
x[,2]
0
2
4
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x[,1]
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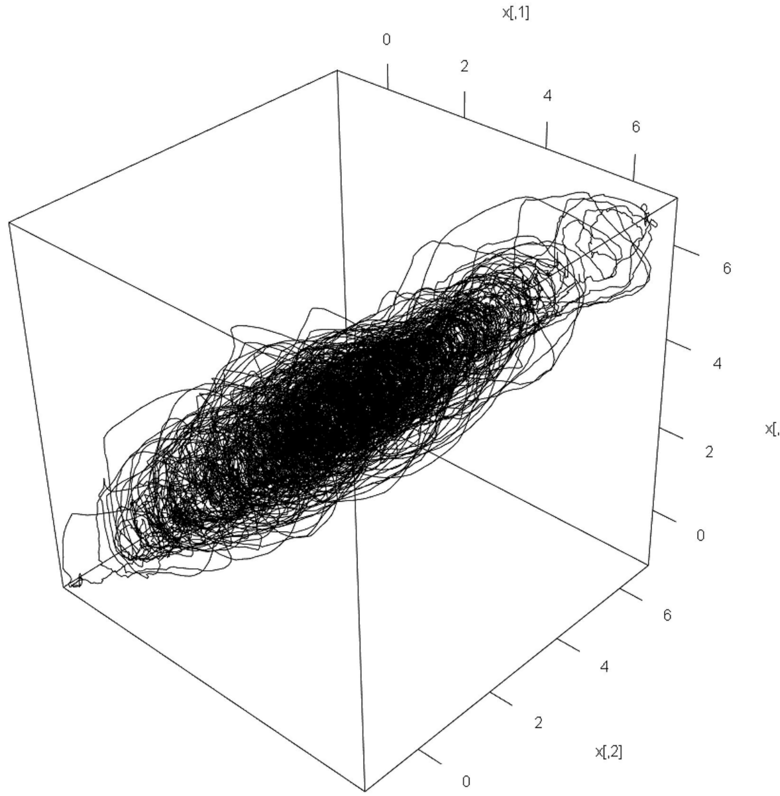
8
10

c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x[,2]
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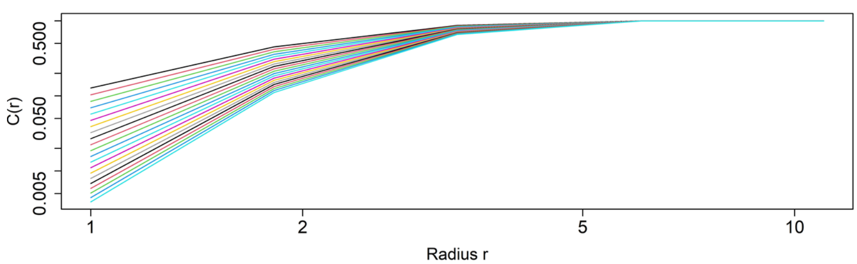
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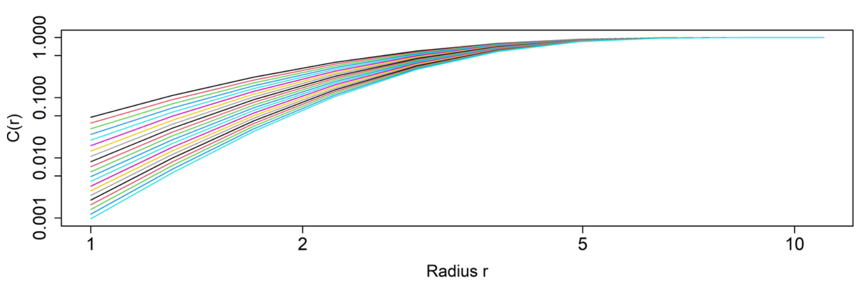
0.050
0.005
1
2
5
10
Radius r

a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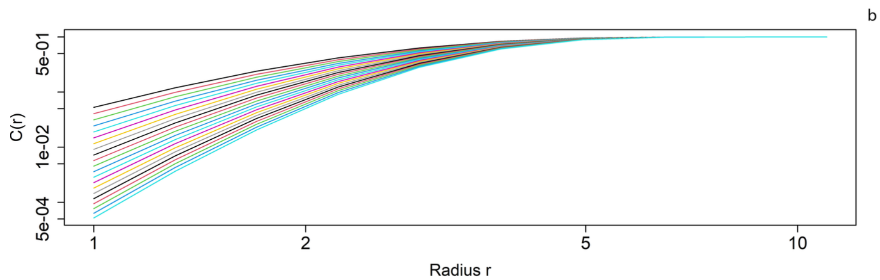
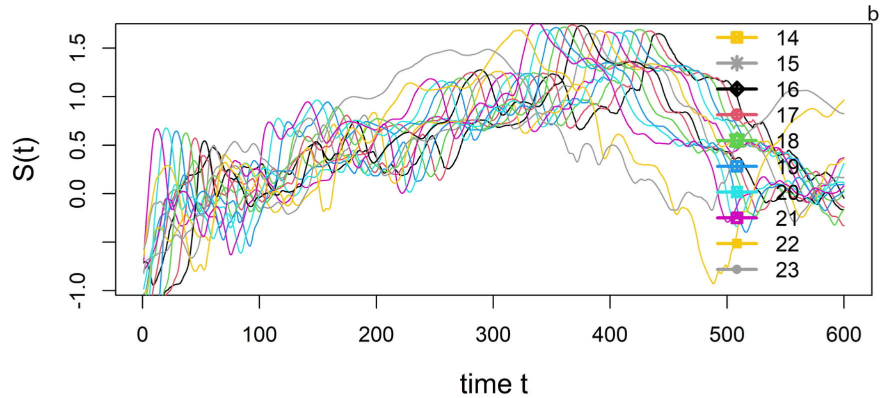
0.100
0.010
0.001
1
2
5
10
Radius r


b
C(r)
5e-01
1e-02
5e-04
1
2
5
10
Radius r


b
S(t)
-1.0
0.0
0.5
1.0
1.5
0
100
200
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400
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time t
14
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16
17
18
19
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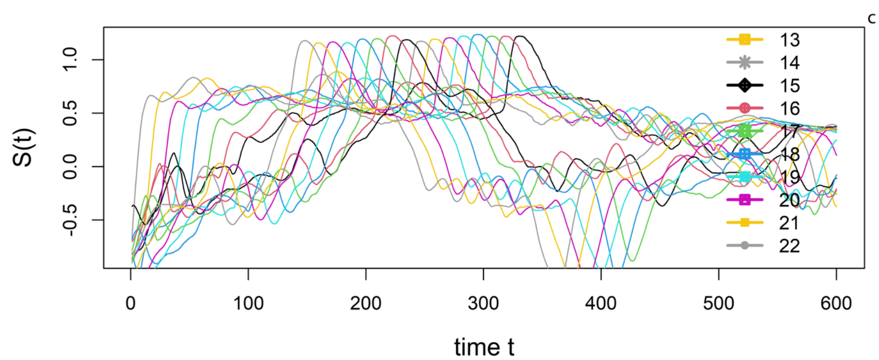
c
S(t)
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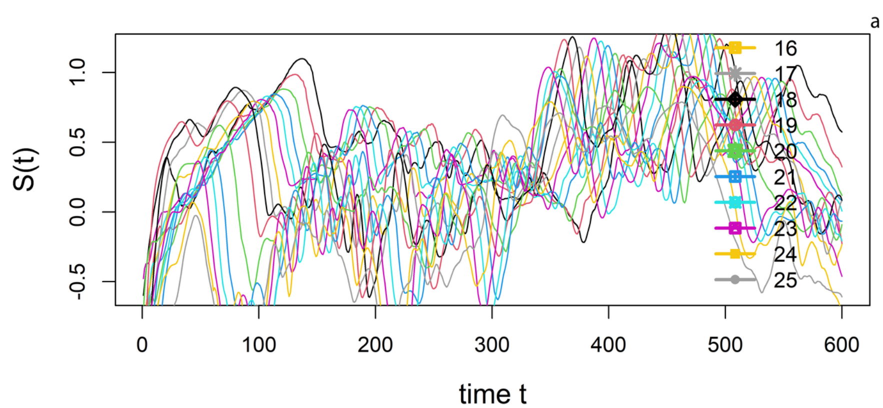
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S(t)
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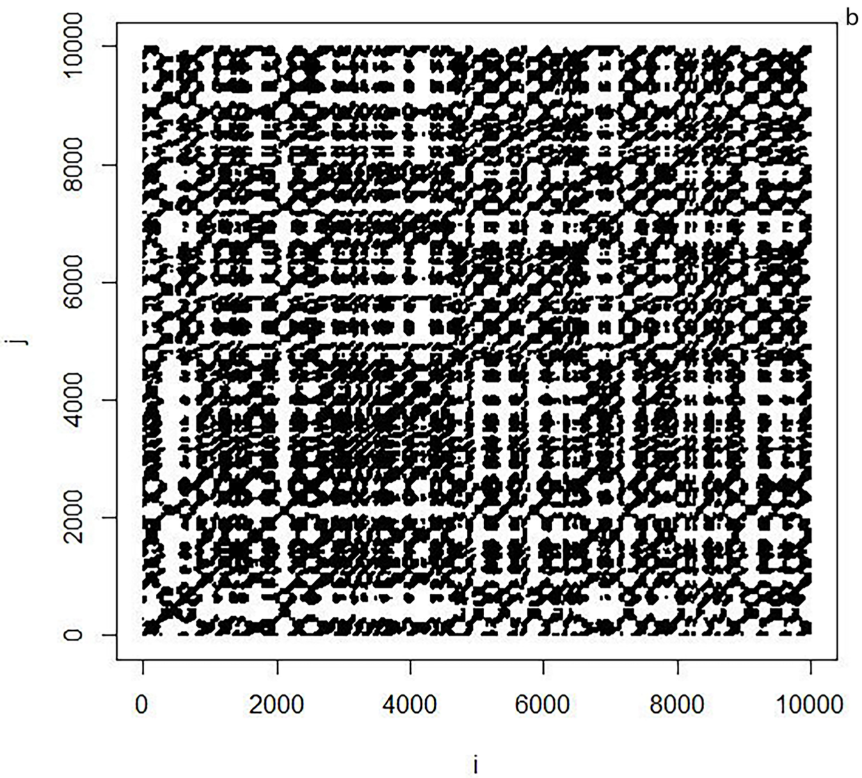
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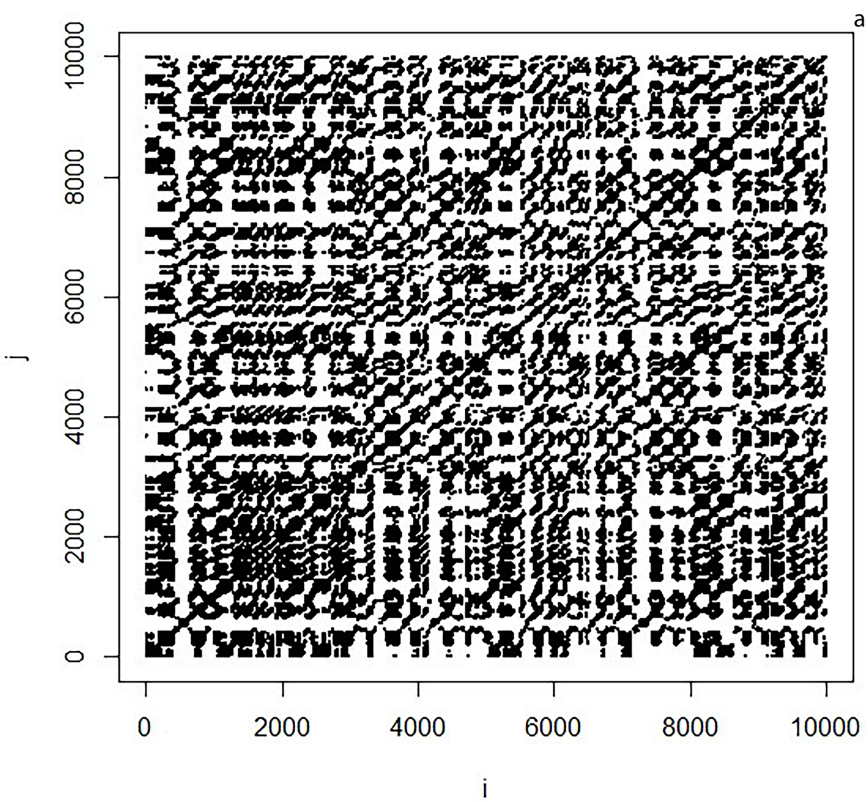
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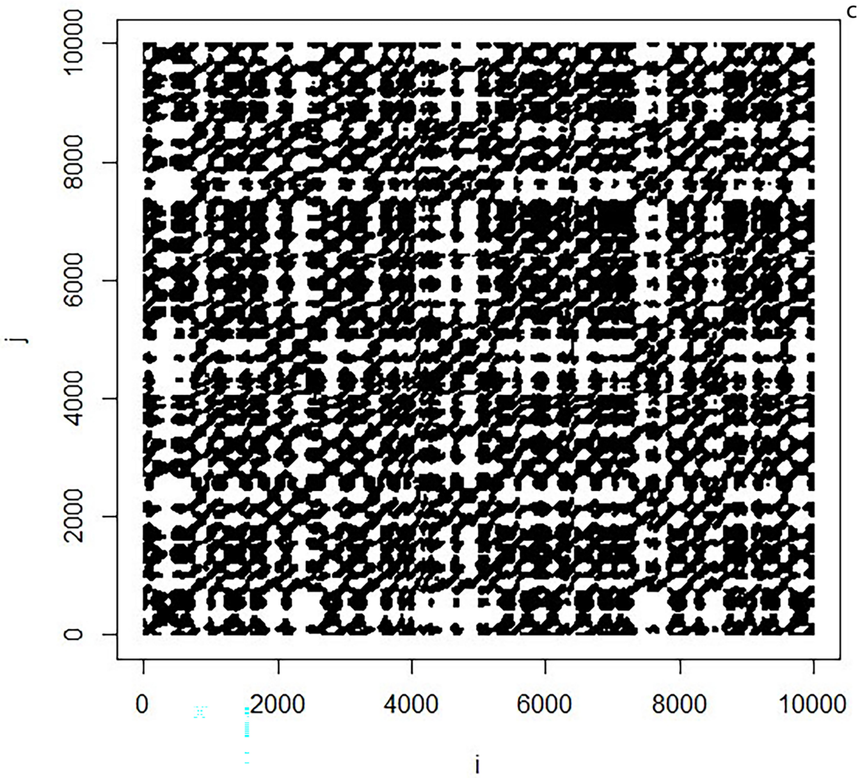

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