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Nonlinear time series analysis of dissolved oxygen in the *Orbetello Lagoon* (Italy)

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ABSTRACT

In this paper, a nonlinear time series analysis of data representing dissolved oxygen collected in the Lagoon of Orbetello (Grosseto, Italy) is performed. A first biological inspection of the data shows that the coastal area is highly eutrophic and subject to unexpected phenomena, like anoxic and distrophic crises. We use the recurrence plots and the recurrence quantification analysis to show that, even if the time series are short and strongly nonstationary, it is possible to characterize the oscillations of dissolved oxygen and the oxygen crises in terms of nonlinear dynamical systems.

1. Introduction

Understanding, modelling, and forecasting the evolution of an aquatic ecosystem is a hard task. In this context, dissolved oxygen (DO) is a highly informative variable which represents reliably important features of the ecosystem. DO is relatively easy to measure using chemical or electrochemical devices. The characterization of DO oscillations is a priority for understanding the functioning of aquatic ecosystems and for planning activities to prevent catastrophic events such anoxic crises. The complex interaction of aquatic ecosystems, based on simultaneous events of chemical, physical, and biological nature makes the DO oscillation extremely irregular, even if, at suitable time scales, oscillations may show regularities.

Characterization and prediction of anoxic crises becomes a particularly important task when dealing with coastal lagoons. Due to their location and physical features, coastal lagoons are very frail ecosystems (Carrada, 1990; Chapelle et al., 2001).

As an example, the *Orbetello Lagoon* has been characterized by large fluctuations in physical and chemical conditions that contribute to growing of the eutrophication processes. Since the beginning of the 1990's, the lagoon was put under the authority of a committee for its protection, and in the last decade it was object of studies aimed at its restoration (Lenzi,

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1992; Bucci et al., 1992) and at modelling and understanding of oxygen oscillations (Buffoni and Cappelletti, 1999).

Eutrophication is related to macroalgae and/or phytoplankton blooms and it usually evolves in anoxic crises. Basically, pollution is due to the organic matter accumulated in the water column produced by sewage and anthropogenetic activities. A large quantity of organic matter in the water column causes an excessive growth of the primary productivity, which increases nutrients presence in the water. Continuous monitoring of oxygen, temperature, wind, nutrients, and other indicators of the ecological status of the lagoon is important for understanding and controlling these periodic phenomena (Viaroli and Christian, 2004).

In this paper, we propose a black box approach for the analysis of the dissolved oxygen in a lagoon, based on techniques related to nonlinear dynamics concepts and deterministic chaos. The main motivation for this approach lies in the well known difficulties generally met in dealing with quantitative physical models of aquatic systems, due to the high complexity of the processes involved and the presence of high level noise in the real data. Here, the objective is to show that performing a black box pre-analysis of data for extracting qualitative information on the system dynamics provides suggestions which can be fruitfully used successively in constructing and estimating a quantitative complex model based on physical and biochemical laws. In fact, mathematical models like those investigated since long time by Masters (1997), Gurney and Nisbet (1998), Scheffer (1998), Murray (1993), successively extended by Marinov et al. (2005), Zaldivar et al. (2004), Chapelle et al. (2000) for distributed processes, and by Garulli et al. (2003), Mocenni and Vicino (2006), Hull et al. (2000) for the parameter identification, can gain much from this qualitative information when dealing with real world applications. For example, the use of nonlinear time series analysis techniques is very important for specifying the level of determinism in the system and for estimating the minimum order of the system that generates the measurements. In the applications, this can be very useful for avoiding problems of order overestimation, which is very common in modelling complex biological processes.

Deterministic chaos as a fundamental concept is, by now, well established and widely described in a rich literature (the reader may refer to Ott, 2002 and Strogatz, 2001). The fact that simple deterministic systems may exhibit complicated temporal behaviors in the presence of nonlinearity has influenced thinking and intuition in many fields. The main question is whether chaos theory can be used to gain a better understanding and interpretation of observed complex dynamical systems and if this theory can give an advantage in predicting such time evolution. The main task of nonlinear time series analysis (NTSA) is to extract information on the dynamical system from the observation of its evolution. This approach is basically different from the statistical one, in the sense that it can overcome typical limits of the traditional linear and statistical tools.

The methods of NTSA based on nonlinear dynamical systems theory are extensively described in two monographs, one by Abarbanel (1996) and one by Kantz and Schreiber (2005). The application of NTSA to real world contexts, where determinism is unlikely to be present in a stronger sense, can be found in Schreiber (1999). Despite its wide range of applica-

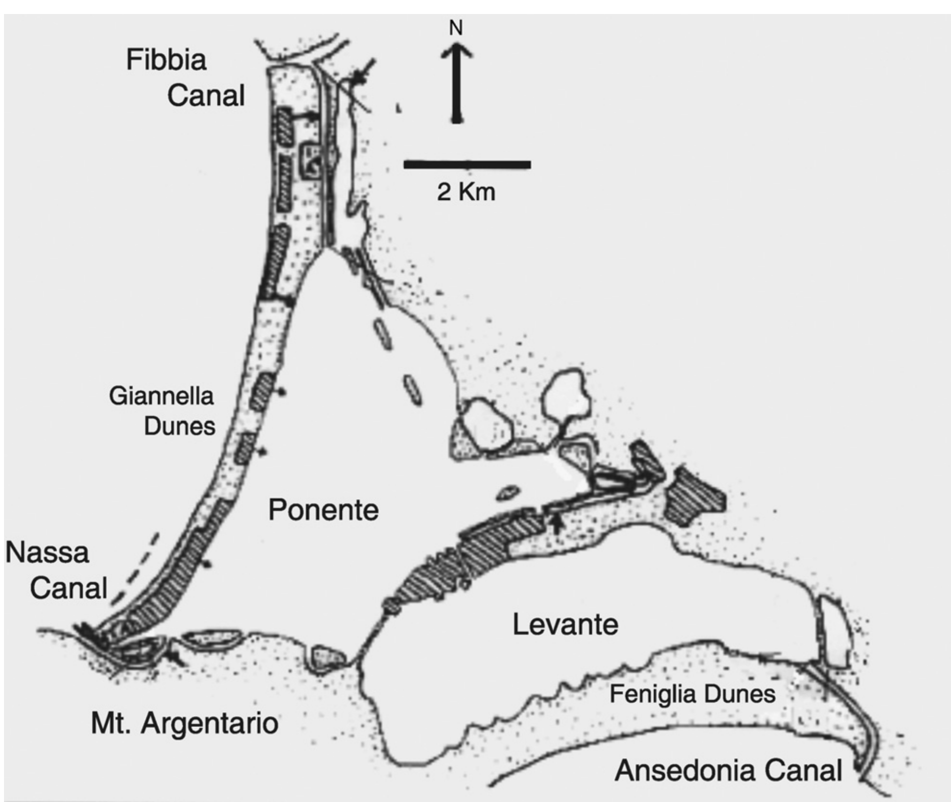

Fig. 1 – View of the Orbetello Lagoon.

tions, NTSA suffers from the problem of nonstationarity of the measured time series, which may lead to pitfalls which invalidate the analysis, as pointed out by Kantz, Schreiber, and Witt (Kantz and Schreiber, 2005; Witt et al., 1998). In order to cope with this problem, we will apply the *recurrence plot* (RP) and the *recurrence quantification analysis* (RQA), which have been developed for the characterization of dynamical systems or the search of transitions even in short and nonstationary time series (Trulla et al., 1996; Marwan et al., 2002). In the next sections, we will introduce the RP as a tool for the visual investigation of spatio-temporal recurrences in the phase-space dynamics and we will illustrate how RP and RQA are useful for the characterization of nonstationary time series in the framework on nonlinear dynamical systems.

Recurrence plots will be computed and recurrence quantification analysis will be performed on the measurements of the dissolved oxygen in the lagoon of Orbetello, showing that the time series exhibits a recurrent behavior typical of chaotic systems.

2. Site description and data acquisition

The Orbetello lagoon is located along the southern coast of Tuscany, near Grosseto (Italian West Coast). It is an important ecosystem from environmental and economical point of view. Very rich in flora and fauna, as well as productive activities, the Orbetello lagoon is divided in two basins (Ponente and Levante) and covers a total area of about 27 km^2. Its extension is limited by two sand dunes, which follow the coastline as far as Monte Argentario, while the two basins are divided by the Orbetello isthmus and by a dam connecting the town of Orbetello to Argentario (Fig. 1). The lagoon runs NW–SW and has three connections to the sea: The Ansedonia canal running east, the Nassa canal running west, and the Fibbia canal running north. The meteorological and environmental situation is strongly influenced by the annual average temperature (about 16 °C), the scarce precipitation, and the limited tides (10–45 cm). Wind intensity is the unique important phenomenon that favors the water movement in summer. The above ecological status of the lagoon, together with the intensive agriculture, aquaculture, and urban activities, causes a strong eutrophication of the lagoon. The excessive concentration of nutrients produces an excessive growth of macroalgae and a decrease in the dissolved oxygen in the water (about 7–8 ppm on average, 5–6 ppm in summer) (Lunardini and Cola, 2000). In this context, a certain amount of hydrogen sulphide is produced by the anaerobic bacteria activity, causing damage to the biological community, see e.g. the death of vegetables and animal organisms (Buffoni and Cappelletti, 1999). The available data consists of a time series recorded in the period 18/07/2001–24/09/2001 by a multiparametric device using a sampling time of 1 h (1657 data samples).

3. Computational techniques

The analysis of ecological time series poses several problems. In particular, standard linear techniques, such as Fourier transform (FT), are not suitable for the investigation of phenomena whose behavior is nonlinear and nonstationary. In fact periodic phenomena show period and amplitude depending directly on the state of the system. In this section, we describe our approach, based on the concepts of the NTSA framework: the attractor reconstruction, the recurrence plot (RP), and the recurrence quantification analysis (RQA).

3.1. *Attractor reconstruction*

The attractor of the underlying dynamics was reconstructed in phase space by the time delay vector method (Takens, 1981; Abarbanel, 1996). Starting from a time series $[s_1, \ldots, s_N]$, where $s_i = s(i\Delta t)$ and Δt is the sampling time, the system dynamics can be reconstructed using the theorem of Takens and Mañe. The reconstructed trajectory $\mathbf{X}$ is expressed as a matrix in which each row is a phase space vector $\mathbf{x}_i = [s_i, s_{i+\tau}, \ldots, s_{i+(D_E-1)\tau}]$ and $i = 1, \ldots, N-(D_E-1)\tau$. The matrix is characterized by two key parameters: the *embedding dimension* D_E and the *delay time* τ. The embedding dimension is the minimum dimension at which the reconstructed attractor can be considered completely unfolded and there is no overlapping of the reconstructed trajectories. If the chosen dimension is lower than D_E, the attractor is not completely unfolded and the underlying dynamics cannot be investigated. A higher dimension should not be used due to the increase in computational effort. The parameter D_E is often estimated by the method *False Nearest Neighbors* (Abarbanel, 1996), looking for the interception points of the trajectories in a poorly reconstructed attractor. As the dimension increases, the attractor unfolds with greater accuracy, and the number of false neighbors decreases to zero. The first dimension with no overlapping points is D_E.

The time difference in number of samples τ (or in time units $\tau\Delta t$) represents a measure of correlation existing between two consecutive components of D_E-dimensional vectors used in the trajectory reconstruction. Following a commonly applied methodology, the time delay τ is usually chosen in correspondence to the first minimum of the autocorrelation function (Abarbanel, 1996).

3.2. *Time series analysis based on recurrence plots*

Recurrent behaviors are typical of natural systems. In the framework of dynamical systems, this implies the recurrence of state vectors, i.e. states with large temporal distances may be close in state space. The *recurrence plot*, proposed for the first time by Eckmann et al. (1987), is a visual tool able to identify temporal recurrences in multidimensional phase spaces. Since phase spaces of more than two dimensions can be only visualized by a projection, it is hard to investigate recurrences in the state space. In the RP, any recurrence of state i with state j is pictured on a boolean matrix expressed by:

$$\mathbf{R}_{i,j}^{D_E} = \Theta(\epsilon - \|\mathbf{x}_i - \mathbf{x}_j\|), \tag{1}$$

where $\mathbf{x}_i, \mathbf{x}_j \in \mathbb{R}^{D_E}$ are the embedded vectors, $i, j \in \mathbb{N}$, $\Theta(\cdot)$ is the Heaviside step function, and ϵ is an arbitrary threshold. In the graphical representation, each nonzero entry of $\mathbf{R}_{i,j}$ is marked by a black dot in the position (i, j). Since any state is recurrent with itself, the RP matrix fulfills $\mathbf{R}_{i,i} = 1$ which, hence, contains a diagonal line, which is called *line of identity* (LOI).

To compute a RP, the norm in Eq. (1) must be defined. We use the maximum norm (L_∞), because it is independent of the phase space dimension and no rescaling is required. Special attention must be paid to the choice of the threshold ϵ. There is not a specific guideline for estimating ϵ, being the noise level of the time series the most important variable to be taken in account. Values suggested are some percentage of the maximum diameter of the attractor (in any case, not more than 10%).

RPs are widely used in searching for deterministic dynamics in highly irregular *stationary* time series, since the characteristic textures of deterministic behaviors are distributions of short lines parallel to the LOI. Recently, RPs were used in the analysis of *nonstationary* time series. In this case, the traditional methods of time series analysis are not adequate for the computation of the characteristic parameters that identify chaotic dynamics, such as Lyapunov exponents, correlation dimension (Kantz and Schreiber, 2005).

3.3. *Structures in RPs*

The initial purpose of the RP was the visual inspection of high dimensional phase space trajectories. The RP is characterized by patterns of two kinds, *Typology* and *Textures* (Eckmann et al., 1987).

Typology offers a global impression and can be characterized as: (a) *Homogeneous*, typical of stationary processes, and usually is associated with white noise. (b) *Periodic*, characterized by diagonal lines parallel to the LOI, which have the same periodic distance from each other. These are typical of periodic systems. (c) *Drifts*, caused by slow varying parameters in the system. (d) *White areas or bands*, indicating nonstationarity and abrupt changes in the dynamics (Marwan, 2003).

The textures are the local structures that can be observed in a RP, which are: (a) *Single points*, if the state does not persist for a long time. Usually a RP made only of single points is related to white noise. (b) *Diagonal lines* of length L, expressed by:

$$\mathbf{R}_{i+k,j+k} = 1|_{k=1}^{L},$$

indicating that the trajectory visits the same region of phase space at different times. (c) *Vertical and horizontal lines* of length L, expressed by:

$$\mathbf{R}_{i,j+k} = 1|_{k=1}^{L} \quad \mathbf{R}_{i+k,j} = 1|_{k=1}^{L},$$

indicating that the state does not change or change slowly in time.

As an example, Fig. 2(a) shows the typical RP of a periodic system, while Fig. 2(b) is the RP of white noise. Fig. 3(a), showing the RP of the $x(t)$ variable of the Lorenz system (Fig. 3(b)), reveals the typical structures of a chaotic signal: a distribution of short lines parallel to the LOI. This structures show one of the main characteristics of chaotic systems, in which the recurrence but not the exact repetition of the states at different times occurs (for a deeper understanding of these structures, the reader may refer to the paper by Gao and Cai (2000)).

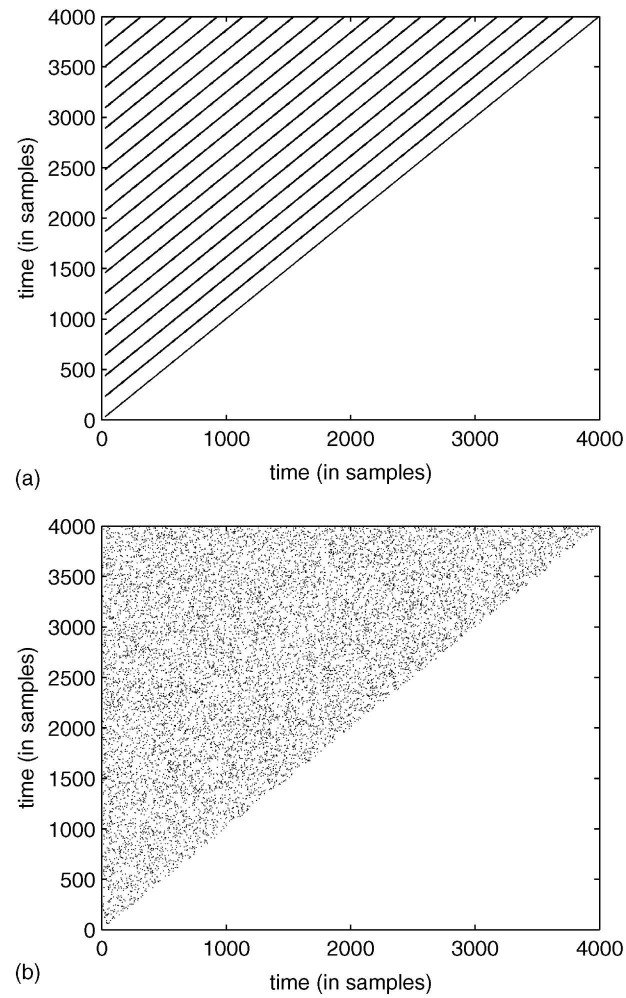

Fig. 2 – (a) Recurrence plot of a periodic and (b) white noise signal. The periodic signal shows a distribution of long lines parallel to the LOI. This indicates that, after a certain amount of time, the state comes back to its original value, and that the orbits visit the same region after the same time, i.e the signal is periodic. On the contrary, the white noise shows a random distribution of points, indicating that the orbits do not visit regularly any region of the phase-space.

3.4. *Recurrence quantification analysis*

The *recurrence quantification analysis* (Webber and Zbilut, 1994) is a tool based on the statistical description of the parallel lines distribution among the RP. It was introduced for the analysis of time series with nonstationarity or high levels of noise.

Measures of complexity are defined using the recurrence point density and diagonal structures in the recurrence plot: the *recurrence rate* (RR), the *determinism* (DET), the *average diagonal line length* (L), and the *entropy* (ENTR). The computation of these measures on moving windows yields the time dependency of these measures. Studies based on RQA measures put in evidence the ability to find bifurcation points and chaotic transitions (especially chaos-order transitions) in stationary and nonstationary signals (Trulla et al., 1996).

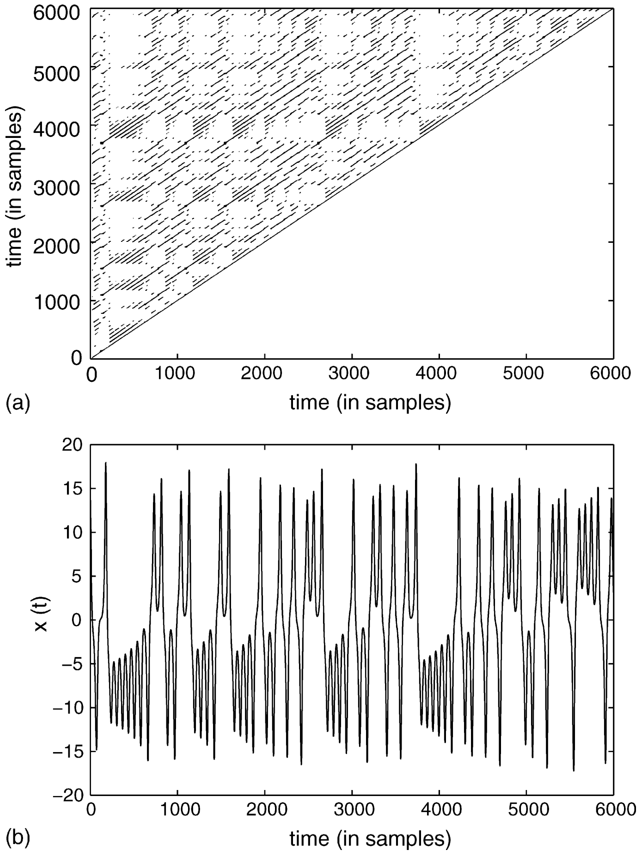

Fig. 3 – (a) Recurrence plot of the Lorenz time series ($x(t)$ component) showing the main characteristic of chaos-looking RPs: a distribution of lines of various length parallel to the LOI. The RP is computed using $D_E = 3, \tau = 10, \epsilon = 5$. The line of identity was removed. (b) The $x(t)$ component of the Lorenz system.

These measures provide a qualitative description of the dynamics underlying the investigated time series, while their significance is endorsed by research in various fields of nonlinear science. For instance, RP and RQA have been used in the analysis of biological systems including neuronal spike trains (Kaluzny and Tarnecki, 1993), electromyographic data (Santo et al., 2006), intercranial EEG recordings (Thomasson et al., 2001), electrocadiograms recording (Marwan et al., 2002), protein folding (Zbilut et al., 2004), and DNA sequences (Wu, 2004).

In contrast to the original definition of Eckmann et al. (1987), where a fixed number of neighbors was used (i.e. a changing threshold for each considered state), we use a fixed threshold ϵ. The recurrence plot is therefore symmetric, and in the following we will introduce the RQA measures within this assumption.

The first measure, the *recurrence rate*, counts the black dots in the RP:

$$\mathrm{RR} = \frac{1}{N^2}\sum_{i,j=1}^{N} \mathbf{R}_{i,j}^{D_E}. \tag{2}$$

It is a measure of the density of recurrence points, and, for the limit $N \to \infty$, corresponds to the definition of the correlation sum introduced by Grassberger and Procaccia (1983). High values mean that the system recurs to a specific state with high probability, while low values indicate a less probability to recur.

The next measures consider the diagonal lines, and can be used for the detection of chaos-period and period-chaos transitions (see Trulla et al., 1996).

For a fixed ϵ, we denote with $P^{\epsilon}(l)$ the histogram of of the lengths l of the diagonal structures, and by l_i the length of the ith equivalence class of diagonal structures. We define the *Determinism*:

$$\mathrm{DET} = \frac{\sum_{l=l_{\min}}^{N} l P^{\epsilon}(l)}{\sum_{i,j}^{N} \mathbf{R}_{i,j}^{D_E}}, \tag{3}$$

which is the fraction of the recurrent points forming diagonal lines. It represents a measure of the predictability (determinism) of the system. Processes with stochastic behaviors cause very few short diagonal lines, while deterministic processes cause longer lines and less single or isolated points. However, the measure does not have the real meaning of the determinism of a process. The choice of the length $l_{\min}$ is critical. For $l_{\min} = 1$ the determinism is equal to the recurrence rate. For larger values $l_{\min}$, $P^{\epsilon}(l)$ contains less elements, therefore there is a tradeoff between the requirement to count as many diagonal lines as possible and to eliminate the short lines due to the tangential motion, i.e. recurrent points belonging to the same part of trajectory but not to different orbits (Theiler, 1986; Marwan, 2003).

Diagonal lines show the range in which a segment of the trajectory is rather close to another segment at different times, giving a hint on how much the trajectories diverge. The *average diagonal line length*

$$L = \frac{\sum_{l=l_{\min}}^{N} l P^{\epsilon}(l)}{\sum_{l=l_{\min}}^{N} P^{\epsilon}(l)}, \tag{4}$$

is the average time in which two segments run close to each other. It can be interpreted as the mean of the prediction time, i.e. the time in which the prediction of the behavior phase space trajectories is reliable. The smaller is L, the higher will be tendency of the trajectory to diverge, which is related to the Lyapunov exponents, as stated by Thiel et al. (2004).

Alternatively, one can choose to measure the *maximum line length* $L_{\max}$ or the *divergence* DIV:

$$L_{\max} = \max_{i=1,\ldots,N}\{l_i\}, \qquad \mathrm{DIV} = \frac{1}{L_{\max}}. \tag{5}$$

As already mentioned, the higher the DIV, the higher the tendency of trajectories to diverge, recalling the typical behavior of a chaotic systems.

The measure *entropy* refers to the Shannon entropy of the distribution probability of the diagonal lines length:

$$\mathrm{ENT} = -\sum_{l=l_{\min}}^{N} p(l)\ln p(l), \quad p(l) = \frac{P^{\epsilon}(l)}{\sum_{l=l_{\min}}^{N} P^{\epsilon}(l)} \tag{6}$$

and reflects the complexity of the RP in respect to the diagonal lines, e.g. for uncorrelated noise or periodic systems its value is rather small (< 0.5), indicating low complexity.

For the detection of chaos–chaos transitions, Marwan et al. (2002) introduced other additional two RQA measures: the *laminarity* (LAM) and the *trapping time* (TT), in which the attention is focused on vertical structures and black patches. Using an analogous formalism as DET, we define the *laminarity*:

$$\mathrm{LAM} = \frac{\sum_{v=v_{\min}}^{N} vP^{\epsilon}(v)}{\sum_{i,j}^{N} \mathbf{R}_{i,j}^{D_E}}, \quad (7)$$

which is the fraction of the vertical lines in respect to all recurrence points. $P^{\epsilon}(v)$ is the histogram of the vertical line lengths in the RP. In order to avoid the influence of points belonging to the tangential motion, LAM is computed starting from $v_{\min}$. Laminarity represents the occurrence of laminar states in the system, i.e. it shows when the state of the system remains on a specific state.

In analogy with L, we define the average length of the vertical structures as the *trapping time*:

$$\mathrm{TT} = \frac{\sum_{v=v_{\min}}^{N} vP^{\epsilon}(v)}{\sum_{v=v_{\min}}^{N} P^{\epsilon}(v)}. \quad (8)$$

It represents the average time in which the system is "trapped" in a specific state, and peaks indicate that the system is undergoing a state transition. In contrast to the other RQA measures, laminarity and trapping time allow the investigation of chaos–chaos transitions in rather short (e.g. 2000 points) and nonstationary time series (Marwan et al., 2002).

In our analysis, we consider further two estimators of *recurrence time* as suggested by Gao and Cai (2000). We denote the set of points of the trajectory $\mathbf{x}$, which fall into the neighborhood of an arbitrarily chosen point at i with

$$\mathcal{R}_i = \{\mathbf{x}_{j_1}, \mathbf{x}_{j_2}, \ldots |\mathbf{R}_{i,j_k}\}. \quad (9)$$

The elements of this set correspond to the *recurrence points* of the *i*th column of an RP. The corresponding recurrence times between these recurrence points (*recurrence times of first type*) are $\{T_k^{(1)} = j_{k+1} - j_k\}_{k\in\mathbb{N}}$. Due to possible tangential motion, some of the recurrence points in $\mathcal{R}_i$ correspond to recurrence times $T_k^{(1)} = 1$. However, in order to obtain the real recurrence times (Poincaré recurrence times), such points must be discarded. One approach is to remove all consecutive recurrence points with $T_k^{(1)} = 1$ from the set $\mathcal{R}_i$. This results in a new set $\mathcal{R}'_i = \{\vec{x}_{j'_1}, \vec{x}_{j'_2}, \ldots\}$. Then, the recurrence times (*recurrence times of second type*) $\{T_k^{(2)} = j'_{k+1} - j'_k\}_{k\in\mathbb{N}}$ are calculated from the remaining recurrence points (i.e. from $\mathcal{R}'_i$). Hence, $T^{(2)}$ measures vertically the time distance between the beginning of (vertically) subsequent recurrence structures in the RP.

4. Results and discussion

The time series of the DO, which covers the period 18/07/2001–24/09/2001 (1657 points), is characterized by almost regular daily oscillations that in some periods become quite evident, while in other time intervals, they break up (refer to Fig. 4). The DO measurements range from 0.2 to 8.65 mg/l. The values are compatible with those typical of the summer period observed in another shallow ecosystem in the central Italy region (D'Autilia et al., 2004). In the considered period, the concentration of DO reached the alarm threshold in two periods: 05/08–14/08 and 01/09–07/09, indicated by boxes in Fig. 4.

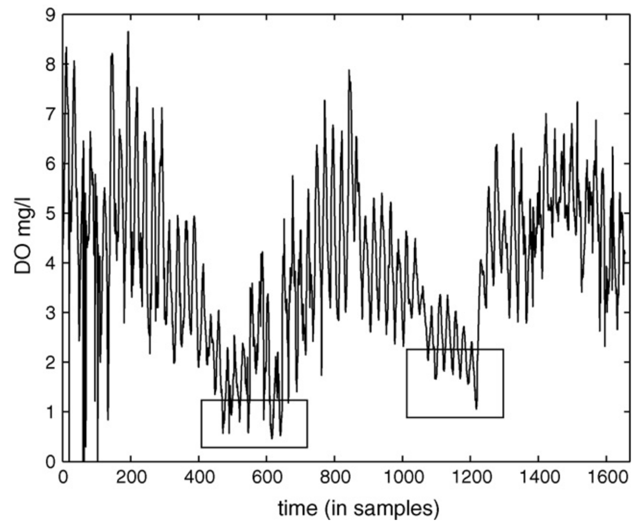

Fig. 4 – Time series of the DO oscillations in the period 18/07/2001–24/9/2001 (1657 points). Here the daily and monthly oscillation is visible. The boxed areas indicate the period in which the alarm threshold was reached.

Under the point of view of the standard linear analysis, the Fourier transform of the signal (Fig. 5) only shows a strong peak corresponding to a frequency of 1.11e−5 (1 day^{-1}), while other lower time scales are compressed on the low frequencies and masked by the continuous component of the signal. The power spectrum was computed using a moving kaiser window of 512 samples, without detrending.

A visual inspection of the recurrence plot ($D_E = 8, \tau = 1, \epsilon = 0.6$) reveals the presence of white bands and white patches indicating the nonstationary nature of the analyzed time series (Fig. 6). A distribution of relatively long lines parallel to

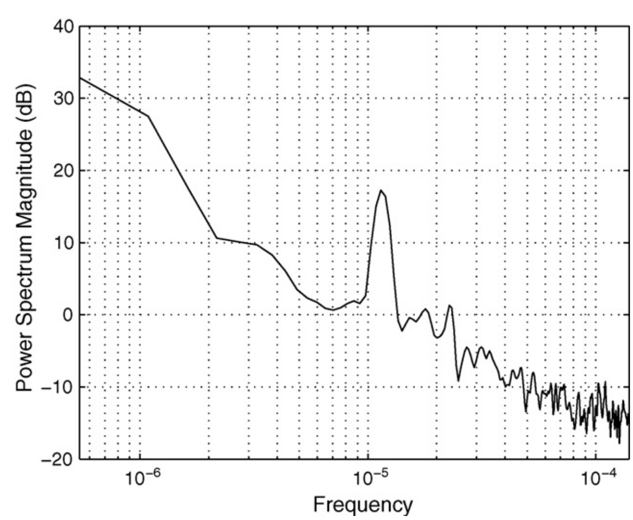

Fig. 5 – Power spectral density of the DO time series. The peak at the frequency 1.15e−5 corresponds to the daily oscillation.

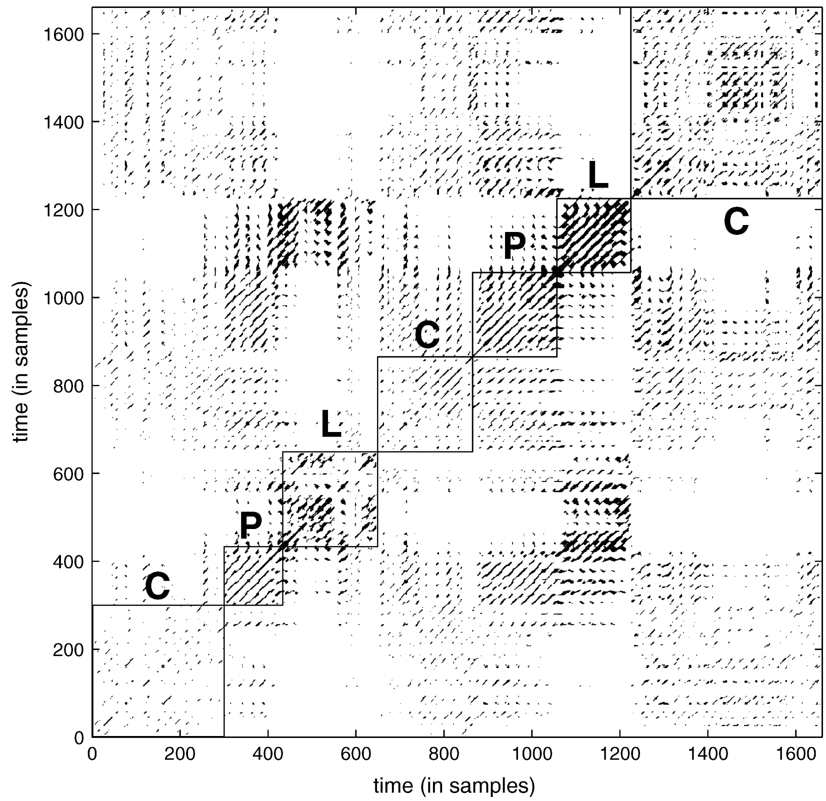

Fig. 6 – Recurrence plot of the analyzed time series of dissolved oxygen. The RP shows an alternate behavior of chaos-like (C), periodic (P), and laminar patterns (L).

the LOI is found in the zone 433–649 and 865–1057. Outside, the RP is characterized by different patterns like distribution of short lines, laminar patches, vertical and horizontal lines. The RP starts with a chaos-looking zone (1–300), after that, a periodic zone arises (300–433) followed by a short distribution of laminar patches (433–649). The same scenario can be observed in the zones 649–865 (chaos looking), 865–1057 (periodicity), and 1057–1225 (laminar patches). The last part of the RP shows again chaos looking patterns (1225–1657).

From the visual inspection of the RP we can conclude that in the period of about 1660 samples, corresponding to 66 days, the dynamics of the DO shows two chaos-periodic transitions; the change in the dynamics is spaced out by a laminar phase.

For a better understanding of this phenomenon, we performed an RQA on the time series, whose results are shown in Fig. 7. We are interested in the trends of the curves, while the fast variation around the profile of the curves is an ordinary effect of the moving window. Using the CRP-Toolbox for Matlab® (available on the web at the address http://www.agnld.uni-potsdam.de/~marwan/toolbox), we have computed the following RQA measures: recurrence rate (RR), determinism (DET), maxline (L_{max}), divergence (DIV), entropy (ENTR), laminarity (LAM), trapping time (TT), and recurrence times of first and second type (T_1, T_2). The results refer to embedding parameters $D_E = 8$, $\tau = 1$ and to a normalization of the time series to zero mean and standard deviation one. The RQA parameters were $\epsilon = 0.6$, l_{min}, $v_{min} = 8$ and a moving window size of 96 samples (4 days) with a shift of 24 points (1 day). Using different larger window sizes and shifts, we have obtained smoother RQA curves, but with a behavior similar to the one showed in the figure. On the contrary, a decrease of the parameters caused an increase of the roughness.

Following the method, l_{min}, v_{min} are chosen as the first zero crossing of the autocorrelation function (Marwan, 2003). We found l_{min}, $v_{min} = 8$. With such choice we look for a duration of recurrences of at least 8 h. The value also reflects the three periods of the typical mediterranean summer day: morning, afternoon, and night.

The RR reflects the nature of the RP, showing two large peaks corresponding to the two periodic and Laminar zones. The peak-to-peak distance is about 28 days, i.e. the moon phase is clearly visible. Higher values of the determinism are found in the zones corresponding to the periodic zone, and a decrease of the measure was found in correspondence to the laminar transition periods. The low values of the DIV correspond to the periodic phase and the high values with the chaotic phase. The values of entropy are greater than zero and range from 0 to 3.2, trapping time ranges from 8 to 15 and the divergence between 0.1 and 0.2. The two peaks of the laminarity curve indicate the existence of a change in the dynamics of the DO. The three DIV peaks correspond to the chaos-looking zones.

The analysis suggests important conclusions under the theoretical and applicative point of view. Theoretically, we have the evidence of chaotic and complex behaviors of the DO oscillations. This agrees with the theoretical models proposed

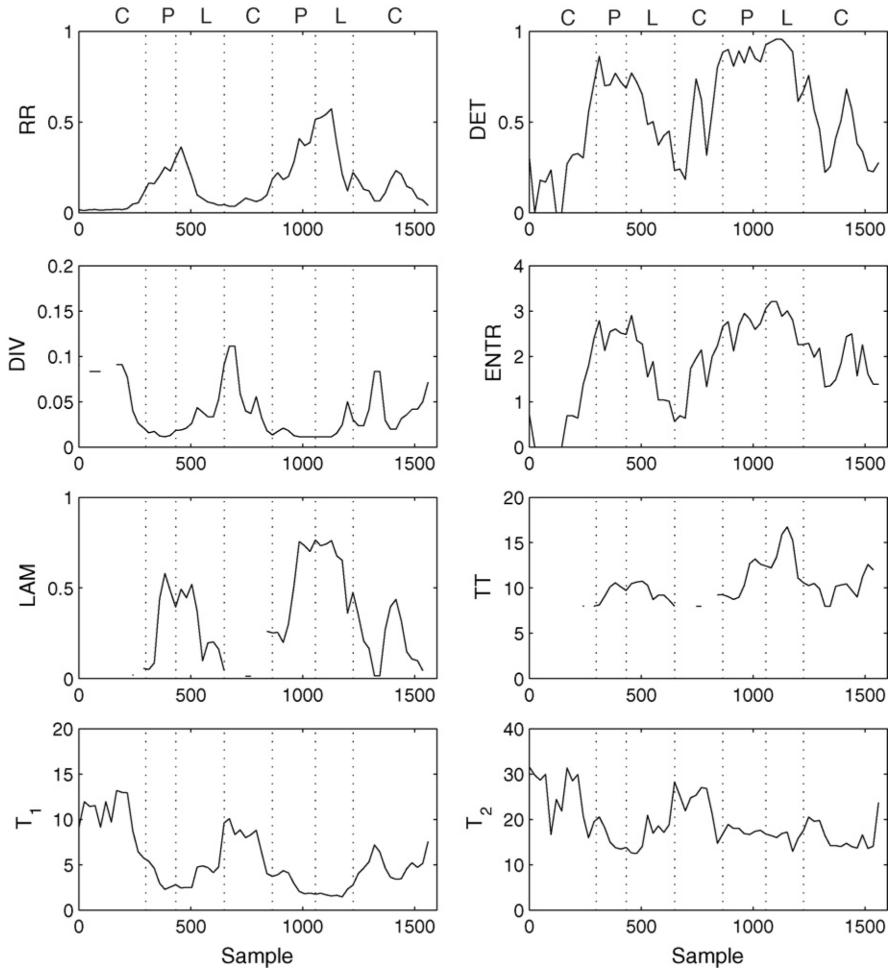

Fig. 7 – Recurrence quantification measures of the DO time series shown in Fig. 6. The analysis was performed using the embedding parameters $D_E = 8$, $\tau = 1$. The RQA parameters were $\epsilon = 0.6$, l_{max}, $v_{max} = 8$, and a window size of 96 samples with a shift of 24. These measures reveal the transitions from chaos (C) to periodicity (P) and then to laminarity (L). Then the cycle is repeated again.

by Jørgensen (1995), in which the chaotic regime corresponds to a high quality status of the ecosystem.

Regarding the applications, we observe that the time series show cyclically different chaos-periodic-laminar regimes. Referring to our data, this happens twice in 2 months (see Figs. 6 and 7). In our analysis, the laminar regimes correspond to the lowest levels of DO, and they systematically occur before the periodic ones. We argue that it may be possible to forecast the onset of an anoxic event by observing the succession of chaotic and periodic oscillations. This fact is confirmed by the analysis of the last part of the RP, where a pure chaotic-like regime is evident, indicating the wealthiness of the DO-related processes.

5. Conclusion

Natural systems are known to be self organized critical systems, and combine the equilibrium concept of criticality with the nonequilibrium concept of self-organization, Kauffman would say at the *Edge of Chaos* (Kauffman, 1993). It had been predicted by theoretical models (Jørgensen, 1995, 2006) that a lake ecosystem lays in this zone, and establishes a relationship between the level of information stored in the system and its evolution toward the edge of chaos.

In this paper, we proposed a method based on nonlinear dynamics concepts and time series analysis through state space embedding: we used the recurrence plots and the recurrence quantification analysis, which enabled us to investigate the dynamics of the dissolved oxygen oscillations in the Lagoon of Orbetello, being the time series short and strongly nonstationary.

The recurrence plot analysis allowed us to identify long temporal scales (28 days) in the signal, showing how the recurrent behavior of the state variables of the system is influenced by the moon cycle.

The proposed method of analysis provides new evidence of the complexity of ecological processes related to the coexistence-succession of different dynamical regimes, making the ecosystem rich and adaptive to the externalities. Further considerations concern the development of tools for managing and controlling the distrophic events in the lagoon.

In fact, we note that a timely detection of the dissolved oxygen decrease is possible by observing the chaos-period transition (see for example Fig. 6, where the periodic regime is about 1 week long).

Even if it is not possible to give a clear indication of the chaotic nature of the investigated time series, the recurrence quantification analysis parameters support our thesis. In particular, the two peaks in the divergence measure correspond to the zones that we indicate as chaotic. The two chaos-period-laminar transitions that we observe in the evolution of the system support our conclusions. Furthermore, two chaos-period transitions are separated by laminar phases corresponding to the two anoxic crises suffered by the lagoon in the period.

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