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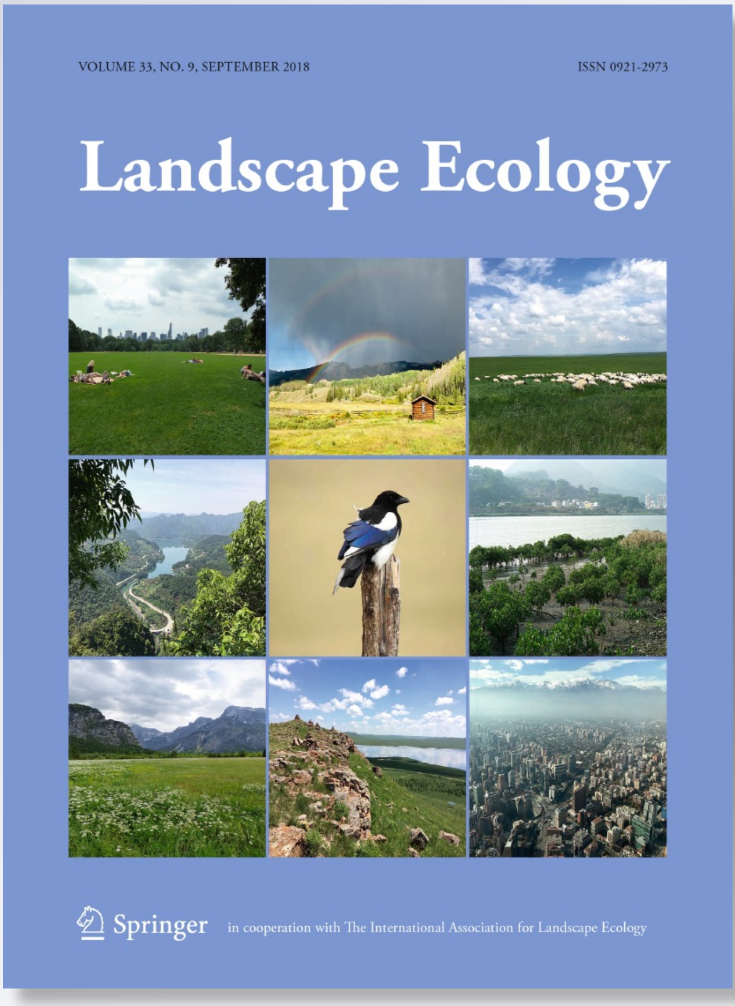

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RESEARCH ARTICLE

Investigating landscape phase transitions in Mediterranean rangelands by recurrence analysis

Giovanni Zurlini · Norbert Marwan · Teodoro Semeraro · K. Bruce Jones · Roberta Aretano · Maria Rita Pasimeni · Donatella Valente · Christian Mulder · Irene Petrosillo

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Abstract

Context Socio-ecological landscapes typically characterized by non-linear dynamics in space and time are difficult to be analyzed using standard quantitative methods, due to multiple processes interacting on different spatial and temporal scales. This poses a challenge to the identification of appropriate approaches for analyzing time series that can evaluate system properties of landscape dynamics in the face of disturbances, such as uncontrolled fires.

Objective The purpose is the application of non-linear methods such as recurrence quantification analysis (RQA) to landscape ecology. The examples concern the time series of burnt and unburnt Mediterranean rangelands, to highlight potential and limits of RQA.

Methods We used RQA together with joint recurrence analysis (JRA) to compare the evolutionary behavior of different land uses.

Results Time series of forests and grasslands in rangelands present both periodic and chaotic components with a rather similar behavior after the fire and clear transitions from less to more regular/predictable dynamics/succession. Results highlight the

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impacts of fire, the recovery capacity of land covers to pre-burnt levels, and the decay of synchronization towards the previous regime associated with vegetation secondary succession consistent with early successional species.

Conclusions RQA and JRA with their set of indices (recurrence rate: RR, laminarity: LAM, determinism: DET, and divergence: DIV) can represent new sensitive measures that may monitor the adaptive capacity and the resilience of landscapes. However, future applications are needed to standardize the analysis by strengthening the accuracy of this approach in describing the ongoing transformations of natural and man-managed landscapes.

Keywords Recurrence quantification analysis (RQA) · Non-linear analysis · Enhanced Vegetation Index (EVI) · Fire disturbance · Predictability · Secondary succession

Introduction

Traditionally, satellite remote sensing has allowed the detection of past land-use dynamics and disturbances at local through regional up to global scales (Goetz et al. 2005; Röder et al. 2008). Time series of vegetation indices derived from big data by remote sensing are broadly recognized as an explicit and robust indicator to gauge social-ecological processes such as habitat-land use conversion or crop rotation. Time series of vegetation are an essential reservoir of past landscape information because they keep track of the disturbances that have occurred. Therefore, through their in-depth investigation, it is possible to reveal the extent of disturbances and the time to return to the normal functionality (resilience) of the landscape (Zaccarelli et al. 2008).

It is noticed that human activity has shaped and sculpted the landscape with a distinctive touch, altering its natural disturbance regime (Moloney and Levin 1996; Millennium Ecosystem Assessment 2005; Mulder et al. 2015), and contributing to its complexity (Levin 1998; Milne 1998; Storch and Gaston 2004). Socio-ecological landscapes show generally a non-stationary and complex behavior due to the interaction of multiple processes driven by nonlinear dynamics in space and time (Proulx and Parrott 2009). The recognition that socio-ecological landscapes behave as complex systems is challenging our ability to derive suitable approaches for analyzing time series data, and identifying possible landscape attractors, able to evaluate changes in landscape dynamics as well as recovery from disturbance. In this respect, resilience is the capacity of a system to absorb disturbance and still retaining essentially the same function, structure, identity, and feedbacks (Walker et al. 2004); it can be measured by the probability that a certain system state will persist (Peterson 2002). Therefore, the identification of recurrent behavior or irregular cycles, tipping points and proximity to transition to alternative states, based on the analysis of time series data (climate conditions, vegetation variation, anthropic pressures or disturbance events), can provide useful indications on past and current landscape dynamics and resilience (Walker et al. 2002; Antrop 2005; Zurlini et al. 2006), and on the possible ways the system might respond in the future (Walker et al. 2002).

The purpose of this research is the application of non-linear time series techniques, such as Recurrence Quantification Analysis (RQA), which is highly effective to detect transitions in the dynamics of any systems from time series (Marwan et al. 2007), to investigate the number and duration of recurrences of spatial–temporal land-cover dynamics in socio-ecological landscapes. In particular, time series of Enhanced Vegetation Index (EVI), which is an ecological functional proxy of the above-ground net primary production (ANPP) (Xiao et al. 2004), are used to better understand inter-annual variability of seasonal vegetation dynamics in relation to fire disturbance, recovery and stability/predictability. In this work, EVI has been preferred to the NDVI (Normalized Difference Vegetation Index), because it is more effective in estimating ANPP in burnt areas (Xiao et al. 2004).

Finally, an example of application of RQA to burnt and unburnt areas in Mediterranean rangelands is presented with the aim to highlight the potential and limits of the methodology in detecting: (1) the impacts of fire and the recovery capacity of land covers to pre-burnt levels; and (2) the changes in functional variability associated with vegetation succession consistent with early successional species.

The theoretical approach of RQA to landscape stability analysis

The RP-RQA approach has been recognized as an efficient strategy for both visualizing and quantifying temporal dynamics. This approach is advantageous compared to other methods for calculating attractor dimensions in systems subjected to external driving forces (Casdagli 1997) because: (1) it provides robust recurrence estimates in the presence of stochastic noise (Thiel et al. 2002; von Bloh et al. 2005); and (2) it works quite well with nonstationary and even short time series often typical of experimental data (Trulla et al. 1996; Zbilut et al. 2000; Marwan et al. 2002; Guimarães-Filho et al. 2010; Donges et al. 2011; Marwan et al. 2015). For these reasons, the practical and powerful use of RQA in the study of complex, time-varying dynamical systems has been demonstrated by multidisciplinary applications, such as for cardiovascular health diagnosis, behavioral, cognitive and neurological studies, studying fluid and plasma dynamics, analyzing optical effects, or palaeoclimate change detection (Marwan et al. 2007; Marwan 2008; Proulx et al. 2009), but the method is still relatively unapplied in landscape ecology. However, the basic idea beyond the recurrence analysis is to consider the dynamics of a landscape system by its states in the phase space. In this manner, a recurrence is deemed as all those times when the state trajectory of the dynamical landscape visits roughly the same area in the phase space and therefore it recurs, driven by an attractor.

In landscape ecology, time series of natural or human-dominated processes can have a distinct recurrent behavior, i.e. periodicities (as seasonal or Milankovitch cycles), but also irregular cyclicities (e.g. El Niño Southern Oscillation). Moreover, the recurrence of states is a fundamental property of deterministic dynamical systems and is typical for non-linear or chaotic systems (Marwan et al. 2007). However, given the often-complex shapes of recurrent cycles, enhanced methods for time series analysis, such as quantifying non-linear dynamics (Marwan 2008) to foster predictability and to identify dynamical transitions (Scheffer et al. 2009) are needed. Such cyclic patterns can provide useful indications on the resilience capacity of landscapes in a retrospective way, exploring the ability of the system to absorb larger shocks occurred in the past without changing its fundamental functions (Zurlini et al. 2006, 2007).

Theoretically, recurrence quantification analysis (RQA) (Marwan et al. 2007) is based on the recurrence plot (RP) that represents an advanced technique of nonlinear data analysis. It is a graphic display of a square matrix, in which the matrix elements correspond to the times at which a state of a dynamical landscape recurs (columns and rows correspond then to a certain pair of times).

Marwan et al. (2007) gave a detailed description of the principle and the algorithm of RPs and RQA. Hence, we give only a brief overview of RPs and RQA in this section.

A landscape state consists of one or more state variables describing all the important properties of a dynamical system, therefore, the state is mathematically a vector $\vec{x}_i = (u_i, u_{i+\tau}, \ldots, u_{i+(m-1)\tau})$ with embedding dimension m and time delay τ. The temporal evolution of the state is expressed by the phase space trajectory of the dynamical system.

The RP is a graphical representation of this recurrence matrix, where black points represent those time points where the spatial distance between two states $\vec{x}_i$ and $\vec{x}_j$ is falling below the threshold ε and, therefore, the system recurs (Eckmann et al. 1987; Marwan et al. 2007, 2015).

Formally, the RP is based on the recurrence matrix:

$$R_{i,j} = \begin{cases} 1 & \text{if } \left\|\vec{X}_i - \vec{X}_j\right\| \le \varepsilon \\ 0 & \text{otherwise} \end{cases} \quad \text{with } \vec{X}_i \in \mathbb{R}^m \text{ and } i,j = 1,\ldots,N \tag{1}$$

where N is the number of measured states $\vec{x}_i$, i.e., the length of the time series reduced by the number $(m-1)\tau$, ε is a threshold distance, and $\|\cdot\|$ is a norm, i.e., the spatial distance between two points $\vec{x}_i$ and $\vec{x}_j$ in the phase space trajectory. The choice of m is usually based on counting false nearest neighbors when increasing m, and choosing the value of m where the number of false nearest neighbors goes to zero (Marwan et al. 2007; Marwan 2010). The delay τ must be selected to minimize the autocorrelations between the time series points, e.g., by using mutual information. ε is a crucial parameter and special attention has to be put on its choice, because if it is chosen too small or too large, it is possible that there are no recurrence points, or every point is a neighbor of every other point, respectively (Marwan et al.

2007). As systems often do not recur exactly but just approximately to a formerly visited state, therefore following three methods, mean or maximum phase space diameter, recurrence point density, and standard deviation of the observational noise, the appropriate threshold ε can be selected (Marwan et al. 2007).

For illustrative purposes, the RPs of three typical synthetic time series (A, B, C) are presented (Fig. 1). The trajectory with regular oscillations (Fig. 1c) is the least common in nature, and the possibility given by RQA to analyze more complex but recurrent oscillation trends represents the strength of the RQA approach.

Diagonal lines in the RP indicate that the temporal evolution of states is similar at different times and, thus, can point to deterministic processes; vertical or horizontal lines in the RP indicate that some states do not change or change very slowly for some time and can suggest laminar or persistent states (Fig. 1).

The RQA is using line structures within the RP to derive several measures of dynamical transitions (Marwan et al. 2007):

- Recurrence rate (RR): the percentage of recurrence points in the RP:

$$RR = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{ij} \tag{2}$$

- Determinism (DET): the percentage of temporally aggregated recurrence points which form diagonal lines in the RP:

$$DET = x = \frac{\sum_{l=lmin}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)} \tag{3}$$

where P(l) is the histogram of the length l of the diagonal lines. Processes with stochastic behavior will render a DET value close to 0, while it will be close to 1 for purely periodic processes.

- Laminarity (LAM): the percentage of temporally aggregated recurrence points which form vertical lines in the RP:

$$LAM = \frac{\sum_{v=vmin}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \tag{4}$$

where P(v) is the histogram of the length v of vertical lines.

High values of LAM are an indication of dynamics that are trapped more often to certain states.

RR and DET can be interpreted in terms of predictability as well as LAM that can be interpreted in terms of no change of the system.

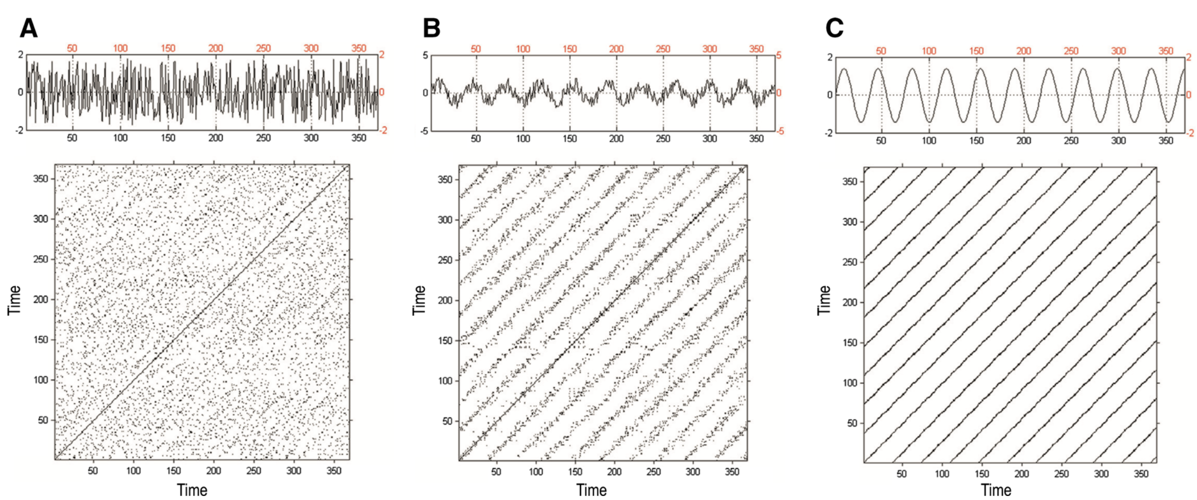


Fig. 1 Recurrence Plots (RPs) of three typical synthetic time series. **a** the homogeneous RPs' structure of stochastic series mainly characterized by single points. **b** RPs' structure of a sinusoidal sequence (with white noise). **c** RPs' structure of a sine function (i.e., a circle in phase space) (modified by Zhao et al. 2015)

- Divergence (DIV): the inverse of the longest diagonal line. It is an indicator of the divergence rate (chaoticity) of the dynamics.

$$DIV = \frac{1}{Lmax} \tag{5}$$

where *Lmax* is the longest diagonal line: $Lmax = max(\{l_i; \text{i} = 1,\ldots,N_l\})$.

The higher the DIV, the more chaotic (less stable) is the system under study, since *Lmax* depends on the type of its dynamics (Marwan 2010) with effects on its complexity.

In DET and DIV formulas the trivial longest diagonal (when i = j) are excluded from the calculation.

The embedding dimension, i.e., the minimum dimension of the space in which the trajectory does not cross itself, and the time delay for reconstructing the phase space trajectory are derived from time series like those of EVI.

In addition, we used the joint recurrence analysis (JRA) (Marwan et al. 2007) to compare the evolutionary behavior of different time series profiles in their respective phase spaces separately and look for the times of phase synchronization when both of them recur simultaneously, i.e. when a joint recurrence occurs. By means of this approach, the individual phase spaces of both systems are preserved.

Formally, the joint recurrence plot (JRP) is the element-wise product of two (or more) recurrence matrices, derived separately from single time series (Romano et al. 2004; Marwan et al. 2007). Thus, for instance, for the time series of two different land covers like grasslands and forests:

$$JR_{i,j} = R_{i,j}^{\text{forests}} \cdot R_{i,j}^{\text{grasslands}} \tag{6}$$

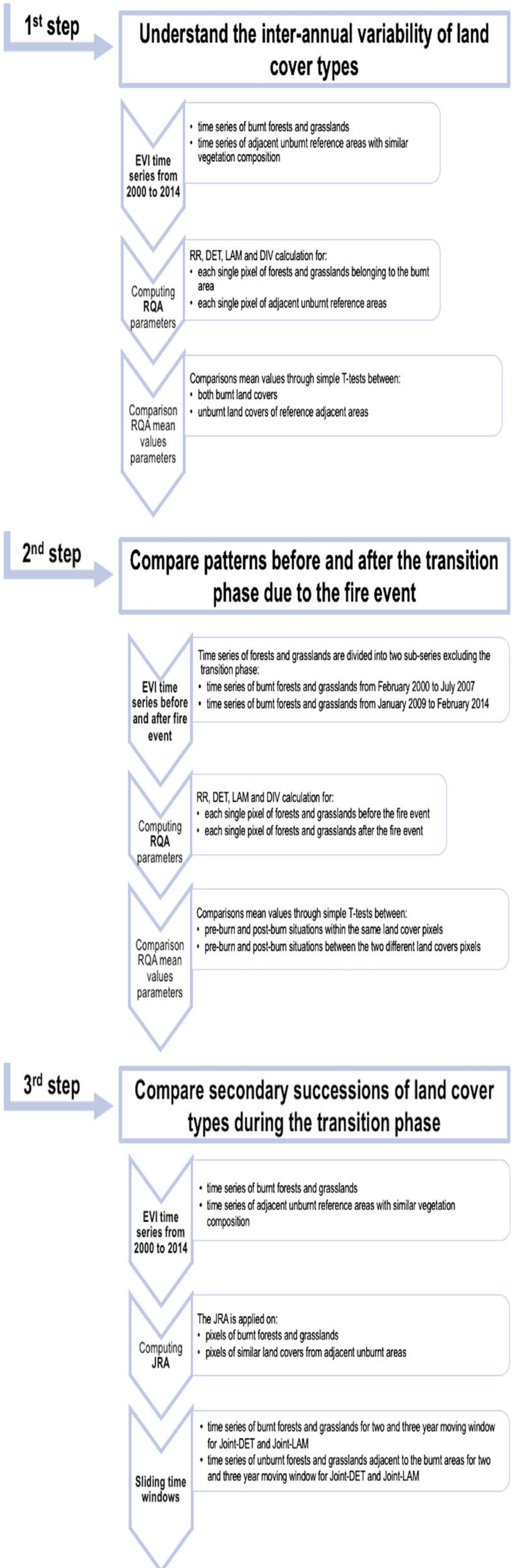
where $R_{i,j}^{\text{forests}}$ and $R_{i,j}^{\text{grasslands}}$ are the entries at (i, j) in the recurrence matrices of forests and grasslands. The JRA reveals all those times when a recurrence in a dynamic system occurs simultaneously (phase synchronization) with a recurrence in the second dynamic system. The JRA has the advantage to compare original data coming from different observations that can have different variability. It has been successfully used for the detection of phase synchronization and general synchronization as well as for the detection of coupling directions (Marwan et al. 2007; Ramos et al. 2017).

Example of the application of RQA to Mediterranean rangelands

The step-by-step procedure of RQA application to Mediterranean rangelands within the municipality of Vieste, inside the Gargano National Park, SE Italy, is reported in Fig. 2. Rangelands are lands supporting vegetation that can be grazed by domestic livestock and is not dedicated to others uses. It can be dominated by herbaceous vegetation, dense woody vegetation, or any of the intermediate gradations between the two (Kolars 1966; Naveh and Dan 1973; Avi and No'am 1998). In particular, Mediterranean rangelands are characterized by pinewood (*Pinus halepensis* Mill) mixed with Mediterranean xeric grasslands (Thero-Brachypodietea) (Biondi et al. 2010), and in the study area they have been disturbed by a large fire in July 2007. Pine forests are autochthonous and naturally occurring in the area where there is no harvest of trees and a long history of grazing and local fires. The area belongs to a typical Mediterranean semi-arid region (Pueyo and Alados 2007). Unfavorable biophysical factors include erratic precipitation (mainly during the winter), high summer temperature with frequent drought events, poor and erodible soils, extensive deforestation with frequent fires and land abandonment (Ladisa et al. 2012). After the fire event, the vegetation grew spontaneously (i.e. secondary succession) as the study area was not subjected to interventions of environmental restoration.

We applied recurrence quantification analysis (Marwan et al. 2007) to the time series of EVI, extracted from MODIS imagery from 2000 to 2014, totaling 323 16-day composite MODIS images (Terra MOD13Q,1), where one point of time is equal to 16 days, with 250 m resolution (USGS 2014). Ten MODIS pixels, covering an overall area of approximately 60 ha, have been analyzed: five pixels (30 ha) have been characterized by pinewood vegetation when the relative cover was higher than 70%, and five pixels (30 ha) by grassland vegetation. The ten pixels refer to the rangeland area affected by the fire in 2007, through a video interpretation of historical ortho-images of 2006 based on the Corine Land Cover Map of the Apulia Region (http://www.sit.puglia.it).

In this example of RQA application, the embedding dimension and the time delay for reconstructing the phase space trajectory, were derived from the EVI time series of two different land covers, e.g., forests



◂**Fig. 2** The step-by-step procedure of RQA application to Mediterranean rangelands within the municipality of Vieste, Gargano National Park, SE Italy

and grasslands. The choice of $m = 3$ and $\tau = 1$ are based on standard methods. For m, the false-nearest neighbors method is used choosing the value for m where the number of false nearest neighbors vanishes. The value for time delay τ is selected with the mutual information method to minimize autocorrelations between points of the time series (Marwan et al., 2007). For the recurrence threshold, we used an empirically derived fixed threshold with the maximum norm $\varepsilon = 0.1$, however, the value selected does not significantly affect RQA measures (Marwan et al. 2015).

In the first step of RQA procedure (Fig. 2), to better understand the inter-annual variability of land cover types in the investigated area, we applied RQA to the EVI time series of burnt forests and grasslands as well as to the time series of adjacent unburnt reference areas with similar vegetation composition. RPs were derived from the mean EVI profiles of burnt forests and grasslands. RR, DET, LAM and DIV were calculated for each single pixel of forests and grasslands belonging to the burnt area considering the time series from 2000 to 2014. Each measurement was then spatially averaged, thus providing an average value of RR, DET, LAM and DIV. Comparisons between mean values were conducted through simple T-tests.

In the second step (Fig. 2), to compare patterns before and after the phase transition due to the burning, the EVI time series of forests and grasslands of burnt areas were divided into two sub-series: before (from February 2000 to July 2007) and after (from January 2009 to February 2014) the fire event excluding the transition phase. For each pixel of the satellite image we calculated the RQA measurements and their average values for both land covers to provide insights on the different dynamic behavior between burnt and unburnt areas.

The third final step (Fig. 2) aimed at comparing the secondary successions of grasslands and forests during the transition phase (from July 2007 to January 2009) in their respective phase spaces separately, and at analyzing if and when both of them recur simultaneously (joint recurrence). Therefore, transition phases from forests to grasslands and from old to new states of grasslands caused by the fire were highlighted using joint recurrence analysis (JRA) to compare synchronization of system properties for burnt and unburnt forests and grasslands. The JRA was performed to study large-scale temporal trends of the joint recurrence and was also applied on pixels of similar land covers from adjacent unburnt areas. For this purpose, we applied sliding time windows of 2 and 3 years to the original time series. RP, DET and LAM were also calculated from the JRP. All the analyses were carried out in MATLAB using the CRP Toolbox available at http://tocsy.pik-potsdam.de/CRPtoolbox/.

Results

Overall, the EVI time series for burnt and unburnt forests and grasslands of the investigated area are characterized by both periodic and chaotic components (Figs. 3, 4). For burnt areas, the phase transition related to the fire event and the subsequent recovery process are evident. After the fire in July 2007, the periodic component prevails for both forests and grasslands (Fig. 3a, b) likely because of the binding of primary productivity of post-fire land cover to seasonal climatic variations.

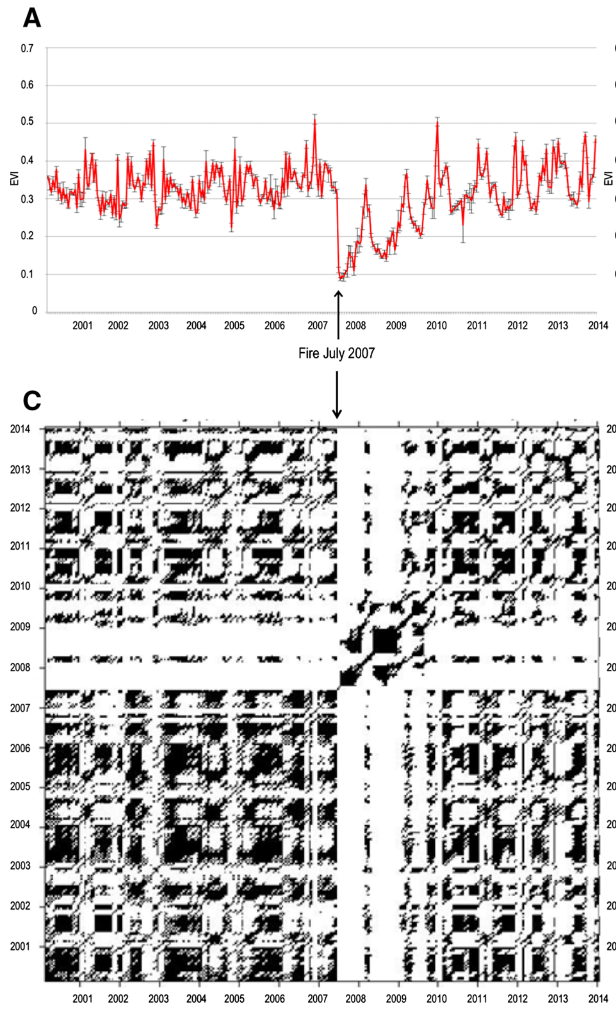


Fig. 3 Mean time series of the Enhanced Vegetation Index (EVI) for burnt forests (**a**) and grasslands (**b**) from 2000 to 2014 in the Gargano National Park rangelands showing the fire event and the recovery processes. Standard error bars are shown. Recurrence plot (years vs. years) of forests (**c**) and grasslands (**d**) time series for the burnt areas in the Gargano National Park. Phase transitions between July 2007 and January 2009 are identified by "disruptions" (white bands)

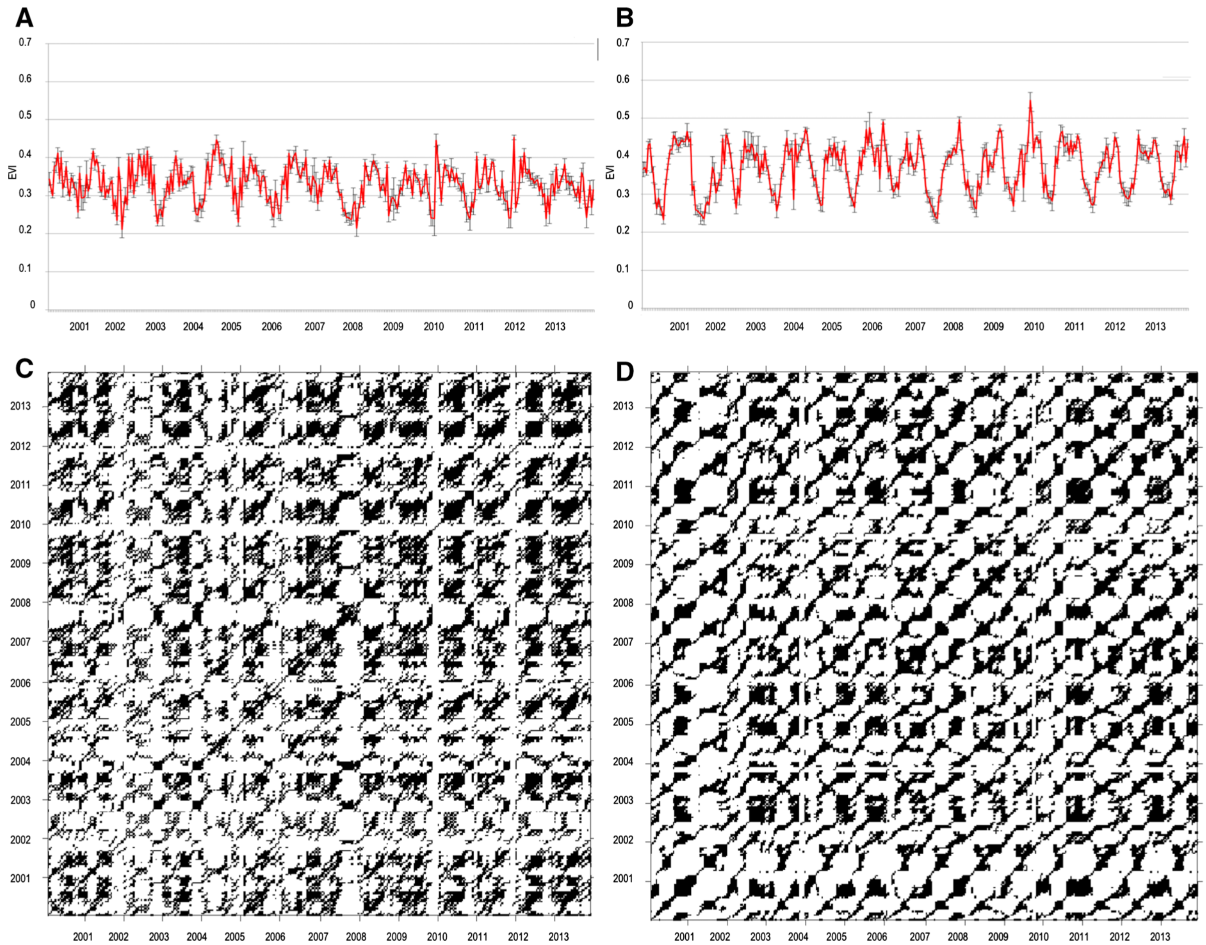


Fig. 4 Mean time series of the Enhanced Vegetation Index (EVI) for unburnt forests (**a**) and grasslands (**b**) from 2000 to 2014 in the Gargano National Park rangelands. Standard error bars are shown. Recurrence plot (years vs. years) for time series of unburnt forests (**c**) and grasslands (**d**) adjacent to the burnt areas in the Gargano National Park

Correspondingly, patterns in the RPs for burnt forests and grasslands reveal phase transitions between July 2007 and January 2009 (Fig. 3c, d) identified by "disruptions" (white bands) in all RPs in correspondence to the fire event. For the two land uses different patterns are found, however, the periodic patterns in the RPs before and after the destructive event are mainly related to the seasonal variability. In addition, as expected, the RPs of forests and grasslands show more similar patterns after the fire event.

The relevant recurrence measures for forests and grasslands in burnt areas are given in Tables 1 and 2 for the two sub-series before and after the fire, while Table 3 reports the overall time series. All RQA parameters for forests and grasslands are statistically different before and after the fire, except for DIV in grasslands (Table 1). In particular, LAM is higher and DIV is lower after the fire, therefore, forests and grasslands can be assumed to have a more predictable and less chaotic behavior after the fire. Before the fire, forests and grasslands have different values for DET and LAM but with higher values for grasslands (Table 2).

Interestingly, after the fire, RR, DET, LAM and DIV for forests and grasslands are not significantly different (Table 2). There is also a marked increase in DET and LAM for forests and grasslands and a slight decrease in DIV compared to the situation before the fire. Therefore, forests and grasslands have a rather similar behavior after the fire event, with a clear transition from more complex to more regular dynamics and hence to a better predictable succession.

Table 1 Mean recurrence rate (RR), determinism (DET), laminarity (LAM) and divergence (DIV) before and after the fire within the same land cover pixels

Parameters	Forest pixels					Grassland pixels				
	Before fire		After fire		T-Test	Before fire		After fire		T-Test
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
RR	0.2954	0.0001	0.2947	0.0002	*	0.2954	0.0001	0.2948	0.0001	*
DET	0.515	0.010	0.720	0.028	*	0.600	0.037	0.721	0.045	*
LAM	0.599	0.046	0.823	0.022	*	0.719	0.038	0.824	0.036	*
DIV	0.110	0.014	0.072	0.073	*	0.102	0.014	0.082	0.021	n.s.

*P-value < 0.05

Table 2 Mean determinism (DET), laminarity (LAM) and divergence (DIV) before and after the fire between the two land cover pixels

Parameters	Before fire					After fire				
	Forests		Grasslands		T-Test	Forests		Grasslands		T-Test
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
RR	0.2954	0.0001	0.2954	0.0001	n.s.	0.2947	0.0002	0.2948	0.0001	n.s.
DET	0.515	0.010	0.600	0.037	*	0.720	0.028	0.721	0.045	n.s.
LAM	0.599	0.046	0.719	0.038	*	0.823	0.022	0.824	0.036	n.s.
DIV	0.110	0.014	0.102	0.014	n.s.	0.072	0.073	0.082	0.021	n.s.

*P-value < 0.05

Table 3 Mean recurrence rate (RR), determinism (DET), laminarity (LAM) and divergence (DIV) for the overall time series of both burnt land covers

Parameters	Forests		Grasslands		T-test
	Mean	SD	Mean	SD	
RR	0.2977	0.0001	0.2972	0.0002	n.s.
DET	0.913	0.006	0.926	0.008	*
LAM	0.818	0.019	0.864	0.016	*
DIV	0.0299	0.005	0.029	0.004	n.s.

*P-value < 0.05

For the overall time series (Table 3), RR and DIV for forests and grasslands are not significantly different, whereas DET and LAM show significant differences. In the case of grasslands DET and LAM are higher than forests, indicating that grasslands present more predictable dynamics and lower variability than forests.

Considering the overall time series of unburnt grassland and forest (Fig. 4), RPs of forests (Fig. 4c) and grasslands (Fig. 4d) are relatively homogeneous throughout the temporal profile while the RP of grasslands (Fig. 4d) shows a more regular pattern. Only in the case of forests there is a small disruption between 2007 and 2008 (Fig. 4c). This probably might be due to the general extreme dry conditions that occurred in 2007 with a drastic positive feedback on the fire intensity with possible local effects on EVI values. This climatic stress is, however, without long-term effects on the functional activity of ANPP for forests, which recovers suddenly with the same pattern as before 2007. Calculation of RQA parameters for the total time series for adjacent unburnt areas (Table 4) shows that grasslands have higher DET and LAM but lower DIV than forests.

By applying JRA, the joint collapse of both systems can be identified in correspondence of the burning (Fig. 5a). Joint-LAM and Joint-DET for

Table 4 Mean recurrence rate (RR), determinism (DET), laminarity (LAM) and divergence (DIV) for the overall time series of unburnt land covers of reference adjacent to the burnt areas

Parameters	Forests		Grasslands		T-test
	Mean	SD	Mean	SD	
RR	0.2977	0.0001	0.2977	0.0001	n.s.
DET	0.900	0.006	0.923	0.003	*
LAM	0.746	0.008	0.893	0.006	*
DIV	0.039	0.004	0.019	0.002	*

*P-value < 0.05

burnt areas reveal transitions from less to higher synchronization of forests and grasslands in correspondence to the fire event followed by a gradual decrease towards the previous synchronization regime. Joint-DET (Fig. 5b, d) and Joint-LAM (Fig. 5c, e) decade similarly after the fire. We also applied JRA to time series of forests and grasslands from adjacent unburnt reference areas. In this case, JRA shows no evidence of collapse/transition (Fig. 6a), as well as the profiles of Joint-DET (Fig. 6b, d) and Joint-LAM (Fig. 6c, e) that do not show relevant variation, indicating that each land cover maintains its proper functional dynamical traits.

Discussion

The frequency of fires in Mediterranean rangelands has historically promoted the adaptation of evergreen trees like *Pinus halepensis* and grasses like *Hyparrhenia hirta* and *Brachypodium ramosum* whose resilience to fire depends on adaptive protective mechanisms as well as life-history and recovery traits (e.g., Noble and Slatyer 1980; Keeley 1986; Quinn 1994).

Recurrence analysis represents an exploratory approach to provide useful information to unveil the dynamics of the landscape after a fire. Transitions observed in RPs (Fig. 3) are due to the destruction of the original vegetation cover during the fire in both forests and grasslands. There is a clear simplification of vegetation structures as well as of landscape dynamics that is more regular and predictable after the burning (i.e., higher DET and LAM) and less chaotic (lower DIV).

In particular, the analyzed RPs of forests and grasslands are based on structural transitions that underlie functional transitions, given that EVI represents an ecological functional proxy of the aboveground net primary production (ANPP). The RQA discloses functional transitions of ANPP because RQA measurements are significantly different between unburnt and burnt pixels in both land-covers,

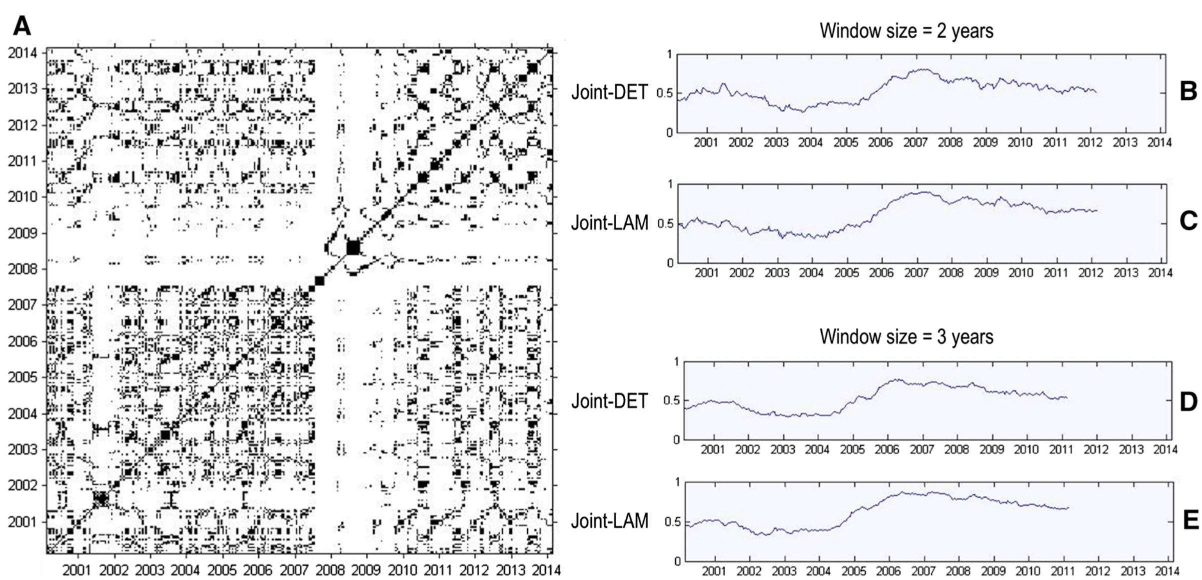


Fig. 5 Joint Recurrence Analysis (JRA) for the time series of burnt forests and grasslands. Joint recurrence plot (**a**); time series for 2 and 3 year moving window for Joint-DET (**b**, **d**) and Joint-LAM (**c**, **e**). Joint phase transitions are identified by white bands (**a**)

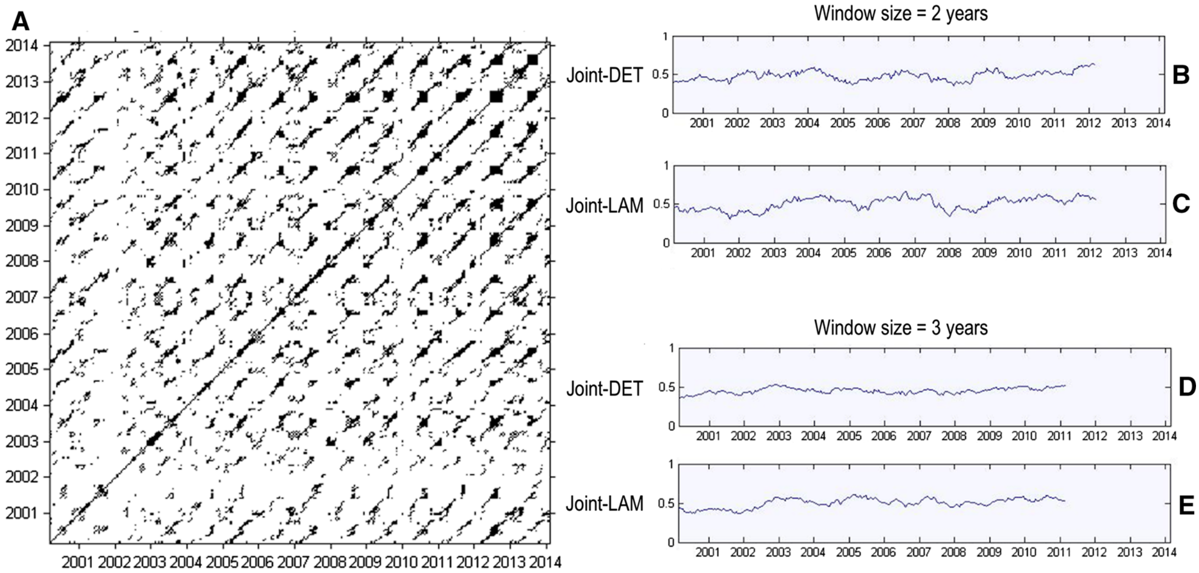


Fig. 6 Joint Recurrence Analysis (JRA) for the time series of unburnt forests and grasslands adjacent to the burnt areas. Joint recurrence plot (**a**); time series for 2 and 3 year moving window for Joint-DET (**b**, **d**) and Joint-LAM (**c**, **e**)

but without significant differences between burnt grasslands and forests. Comparing EVI profiles before and after the burning for forests and grasslands, and following few field surveys, forest vegetation is replaced by new grassland vegetation with coniferous seedlings (a kind of ecological memory of forests), while grasslands preserve the same structure after the burning with similar xeric vegetation because of the resistance to fire of the structuring (herbs and grass) species. RR, DET, LAM and DIV for forests and grasslands are not significantly different after the fire event (Table 2), since understory vegetation abundance usually increase rapidly after fire in response to abundant resources and an influx of disturbance adapted species in early successional forest areas (Hart and Chen 2007). Due to frequent local fires in such Mediterranean rangelands countering the onset of shrubs and promoting grazing, no phase transition of forest to scrubland or grassland to scrubland occurred that could greatly reduce ANPP, representing a supporting ecosystem service (Millennium Ecosystem Assessment 2005). This represents a guarantee of the overall delivery of ecosystem services in the landscape (Petrosillo et al. 2013).

JRA can provide useful insights on landscape evolutionary behavior during the transition phase, even if the temporal extent of the analysis could be too short for an exhaustive knowledge of the dynamics of vegetation covers after the burning (secondary succession). High values of Joint-DET and Joint-LAM at the time of fire indicate high synchronization of system properties in terms of predictability/stability. After the burning, such synchronization gradually decays towards the previous synchronization regime of vegetation covers.

Nonlinear analysis of spatial–temporal dynamics of socio-ecological landscapes helps gauge landscape adaptability (Walker and Salt 2006), that is the capacity of any landscape to activate balancing feedback loops to adjust its responses to changing external drivers and internal processes and continue developing within the current stability domain or basin of attraction (Berkes et al. 2003). A three-dimensional reconstruction of NDVI signal in phase space for Forest (2000–2012) shows that phase space trajectories have been visiting for 12 years approximately the same area all the times showing a high recurrence (adaptability) (Fig. 7).

Other valuable non-linear methods like Entropy-based indices like Shannon's H or contagion are among the most commonly used metrics in landscape ecology to analyze time series in order to represent landscape dynamics (Zaccarelli et al. 2013). Entropy and information theory have been extensively applied

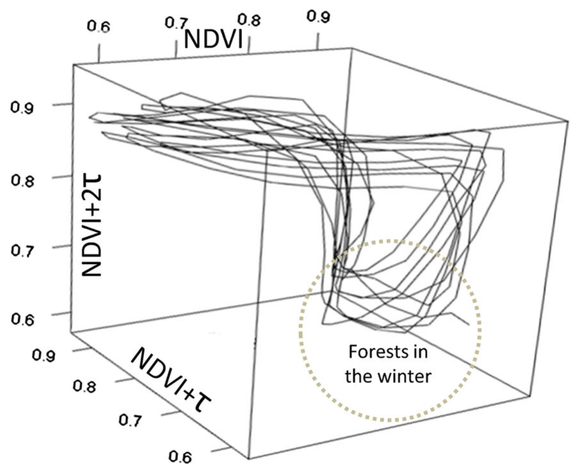


Fig. 7 Three-dimensional reconstruction of Normalized Difference Vegetation Index signal in phase space for the land cover class of Forest (2000–2012) by the method of time delays, with phase space trajectories visiting approximately the same area all the times (modified form Zurlini et al. 2014a)

in ecology (Ulanowicz 2001), including environmental assessments (Ekström 2003; Magurran 2004), dynamics (Avery 2003), and species coexistence (Chen et al. 2005; Parrott 2005). In particular, the "normalized spectral entropy" (H_{sn}) is an entropy-related index able to describe the degree of regularity (orderliness) within an ecological time series based on a power spectrum obtained by its Fourier transformation (Zaccarelli et al. 2013). Normalized spectral entropy can also provide indices related to the degree of temporal disorder. The main difference between normalized spectral entropy and RQA is that the first approach focuses on probabilities and not the timing of events, while the second has its focus on the timing. However, spectral entropy involves some types of transformation of the original time series designed to isolate dominant components of periodic variation of imagery across the multi-temporal spectral space. The RQA reduces the time series to a matrix t x t that contains all the information of the original series without transformations or simplifications of the reality as in the case of spectral entropy through time series Fourier transformation. In addition, the comparisons among different time series or multitemporal scale analysis performed by JRA are not possible with the normalized spectral entropy approach.

The present application of RQA to landscape ecology shows the strength of this method in terms of graphical rendering of the recurrence and joint recurrence, together with advanced numerical parameters that offer insights on the behavior of the landscape. However, further researches are needed on several case studies to additionally test the potentiality for RP and JRP in describing landscape dynamics together with the ability to respond to disturbances.

Finally, the limiting aspects of RQA could be that it is very demanding for the time series data, and the threshold ε is empirically set. However, for the purpose of studying dynamical transitions, threshold selection is not of fundamental importance since the relative change of RQA measures does not substantially depend on it (Marwan 2010; Marwan et al. 2015).

Conclusions

Socio-ecological landscapes typically characterized by non-linear dynamics in space and time that are difficult to be analyzed using standard quantitative methods (Parrot 2010). Our ability to evaluate with accuracy the complexity of natural and human-controlled processes from reliable dynamical measures is crucial from the perspective of landscape management and restoration in the face of climate change. We have shown the efficacy of recurrence quantification analysis (RQA) and joint recurrence analysis (JRA) to track depletion and regrowth of vegetation cover in Mediterranean rangelands, and to assess spatial and temporal variability changes both before and after the disturbance represented by a fire event. The RQA and JRA can visualize and quantify temporal dynamics and gauge phase transition like those observed from forests to grasslands providing accurate and novel quantitative insights also on secondary succession. It is potentially capable of describing both gradual and abrupt transitions in land covers and provides an effective alternative way to study several aspects linked to landscape level properties like the resilience and adaptive capacity for specific disturbances.

Recent research has focused on developing methods to characterize the temporal, spatial or structural signatures of complex systems along a gradient of order to disorder. In particular, ordered systems can be characterized by periodic cycles with high predictably in time and in space (Fig. 1c). On the other hand, disordered systems show random dynamics and spatial structure (Fig. 1a, b). Generally, when time series result relatively predictable, the adaptive responses of socio-ecological landscape have been effective either because of human and/or natural balancing feedback loops that result in landscape trajectories within current preferred bounds. Thus, the more adaptive capacity within a landscape, the greater the likelihood that the landscape will be resilient to induced stress (Zurlini et al. 2014b). In this context, RQA and JRA with their set of indices (RR, LAM, DET, and DIV) can represent new sensitive measures that may monitor the adaptive capacity and the resilience of landscapes (Parrot 2010). Even if both methods are very demanding for data, in the last decade, automated ecological monitoring systems have been progressively installed (e.g., the FluxNET network—https://fluxnet.ornl.gov/), national and international networks for long-term ecological research have been established (e.g., ILTER—https://www.ilter.network/, Müller et al. 2016) and the number of ecological time series databases with public access has increased. All these advancements should greatly contribute to the application of complexity measure in general, and the use of RQA in particular, especially in the perspective of climate change assessment and ecosystem's service evaluation.

However, although we can understand ecological regime shifts retrospectively, it is difficult to predict them in advance. Forecastable landscape attributes are those for which uncertainty (chaoticity) can be reduced to the point where a forecast contains a valuable amount of information. To evaluate that amount, RQA could represent a very useful tool. Future applications are needed to better identify the RQA parameter sets useful for standardizing the analysis by strengthening the accuracy of this approach in describing the ongoing transformations of natural and man-managed landscapes.

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