Complex and chaotic tourism systems: towards a quantitative approach

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Abstract

Purpose: Tourism systems have been considered more and more in the light of complexity and chaos theories. Most of the work done in this area has highlighted the reasons and the issues for this approach. A steadily growing strand of the recent literature uses it to overcome the problems of a reductionist and mechanicistic view considered unable to provide a full understanding of the structural and dynamic characteristics of tourism systems and specifically of tourism destinations. This paper continues this approach and provides a series of quantitative methods to assess the dynamics of nonlinear complex tourism systems.

Design/methodology/Approach: The time series used in the paper contains data collected from a sample of 23 large (four star) hotels located in Milan, Italy. For each structure daily data of occupancy, average room rate and RevPAR (Revenue Per Available Room) were recorded for the period 2006-2009. The daily distributions of these observations are highly skewed, therefore the median of the daily values were considered. This results in three series of 1461 points per type (occupancy, room rate and RevPAR).

Findings: The data confirm the complex nature of the destination system and its tendency towards a chaotic state. Additionally, high stability and long memory effects are detected. The outcomes and the implications of this analysis are examined.

Research implications: A comparison of the values obtained leads to the conclusion that the series under study has a detectable level of nonlinearity, even if it does not reach the pure chaoticity of the Lorenz attractor. A first conclusion is that, as qualitatively assessed in many similar studies, the tourism destination is a complex system with a tendency to become chaotic.

Originality/value: The picture obtained with the analyses conducted can be summarized by saying that the system under study exhibits an unequivocal complex nature. It tends towards a chaotic stage but does so at a slow pace. The stability of the system is quite high: it might be able to resist well transient shocks, but once led into one direction, its long memory characteristics tend to keep it on the resulting path.

Keywords: tourism systems; tourism destinations; complexity and chaos theory; quantitative methods

1. Introduction

In the last few years a scant but steadily growing strand of literature has started to consider tourism systems, and mainly a tourism destination, from a ‘complex systems science’ perspective. A destination has been recognized to be an unstable system, subject to non-linear relationships, where triggering events, both internal or external, natural or human (Laws & Prideaux, 2005) can challenge the existing structure, habitual operations or the existence of the organization and can displace the system “from its steady state condition” (Russell & Faulkner, 2004: 557) and move it along new dynamic paths, and possibly to a new order, which is not permanent.

The essential idea is that a destination cannot be seen as a ‘simple’ (linear) composition of the entities composing it. Its complexity cannot be reduced using a mechanistic approach, typical of a Newtonian perspective, anchored on equilibrium and stability (Farrell & Twining-Ward, 2004; Faulkner & Valerio, 1995; Leiper, 1979; McKercher, 1999; Russell & Faulkner, 1999; Zahra & Ryan, 2007). Rather, exploring a tourism system needs a more realistic, organic approach (Edgar & Nisbet, 1996; Russell & Faulkner, 1999), in which the system is considered to have ‘life-like’ characteristics (Flower, 1993; Russell & Faulkner, 2004). This approach has been sponsored in several studies investigating different aspects such as the analysis of destination development (Cole, 2009; Faulkner, 2000, 2002; Russell & Faulkner, 1998; Warnken et al., 2003; Zahra & Ryan, 2007), the management of crises and disasters (Crandall et. al., 2010; Faulkner & Vikulov, 2001; Laws & Prideaux, 2005; Prideaux et al., 2003; Ritchie, 2004; Scott & Laws, 2005), the forecast of demand (Faulkner & Russell, 2001; Faulkner & Valerio, 1995), the development of entrepreneurship (Russell & Faulkner, 1999, 2004), the networks among tourism companies (Tinsley & Lynch, 2001), or the management of hospitality businesses (Edgar & Nisbet, 1996).

This field of research is a small one, but increasing and promising. In many cases it has rejuvenated well known models such as Butler’s (1980) destination life cycle concept built around the idea that the system moves along evolutionary paths in which it undergoes a series of different phases. This systemic approach has been developed, explicitly or implicitly, around some premises underlying the complexity theory (Russell & Faulkner, 2004) and has already provided a number of interesting empirical evidences. The approach used in many of these works is a qualitative one, and the outcomes originate generally from the observation and interpretation of historical evolutions or case studies descriptions. Although the ‘complexity’ interpretation seems to be gaining momentum, the attitude of most scholars in the tourism field is similar to that expressed quite recently by Stevenson et al. (2009: 219):

> “To date the main contribution of complexity theory to understanding social phenomena in tourism has been the challenge to linear thinking and positivism and the criticism of the emphasis of much research on the ordered, and more easily defined aspects of systems. This has progressed thinking at a conceptual level. It is now time to take that challenge further and to draw upon some of the wider debates about the application of complexity to social phenomena and explicitly engage in discussion about its methodological implications.”

While agreeing with these statements, it must be noted that in the last few years a wide number of researchers from many disciplines have developed and applied a wealth of methods for the analysis of complex systems and many of these have been employed in the study of social and economic systems. They have shown not only their relevance, but also the usefulness of this approach in several cases (Castellano et al., 2009).

The goal of this paper is to present some of these methods, those deemed the most reliable and 'usable' for the assessment of some critical premises underlying chaos and complexity theory. They are then applied to an empirical case: the city of Milan, Italy, observed during the period 2006-2009. The city is considered to be the economic Italian capital. Located in the Lombardy region (northern Italy), it accounts for 20% of the national GDP. Milan is also the second most important Italian destination in terms of overnight stays (after Rome), with a tourism capacity superior to the stars of Italian heritage tourism such as Florence and Venice (Istat, 2010). Furthermore, the city is the second European destination for exhibition facilities. This competitive position assures a relatively good stability to firms' performance. The rest of the paper is organized as follows. The next section contains a brief introduction to the main concepts of complexity and chaos theories and a concise survey of the most relevant studies conducted in tourism. The methods and the data for the empirical study are examined in section 3. Finally a discussion of the outcomes and the implications along with the limitations and possible future developments are presented.

2. Complexity, chaos and tourism

Although not well defined, the field of complexity sciences with its rigorous quantitative approaches to the study of a complex system, has proved to be able to provide interesting theoretical and practical outcomes. Many of these methods have a long history but, due to their characteristics (Shalizi, 2006) only the modern technological advancements in computing capabilities and in the possibility to collect reasonable amounts of data have allowed a full and practical implementation. This situation is common to many areas of investigation, but it has not restrained scientists from obtaining important results.

A complex system is difficult to label and no common agreement exists on a rigorous definition, but its characteristics can be well described and a general consensus on some basic features exists. A large number of elements composes such systems. Their well defined, and often very simple relationships and interactions at a local level are typically nonlinear. This nonlinearity causes the dynamic generation of behaviors and structures unpredictable by a mere straightforward composition. These complex adaptive systems, furthermore, continually interact with the external environment, adjusting both their structure and their behaviors. The visible effects can be traced in the system's ability to sometimes withstand large shocks without apparently modifying itself or their evolutionary path in dramatic ways, while, in other situations, a seemingly irrelevant event can produce an avalanche which completely destroys it. During its life a complex system gives birth to several intermediate structures which appear spontaneously without any given external guidance. This self-organization has the objective of optimizing the available resources and renders the system better suited to face external or internal burdens. If examined at different scales the system appears to have similar forms and characteristics: it is self-similar (Pavard & Dugdale, 2000; Procaccia, 1988; Waldrop, 1992).

Complex systems' dynamic behaviors are usually described by examining their trajectory in a phase space. This is a mathematical abstraction, a multidimensional space in which all possible states of a system are represented. The degrees of freedom (or parameters) of the system constitute the axes and every possible state of the system (allowing a combination of the parameters' values) is depicted as a point in the n-dimensional space. A succession of plotted points (a trajectory) corresponds to the evolution of the system over time. In its evolution a system can undergo a number of different states (configurations). It is possible for a system to pass from a completely ordered phase to one in which its behavior is so strongly dependent on very small variations of the initial conditions as to appear completely unpredictable: a 'chaotic' phase. In this, governed by deterministic laws, the system may tend to certain specific configurations. These, the *attractors* and the regions close to them (their basins), can be fixed to equilibrium points, or follow orbits or more complicated patterns. It is also possible to have a system that never returns to the same place (in these cases we speak of strange attractors).

The region at the boundary of these phases, known as the 'edge of chaos', is a region of complexity (Crutchfield & Young, 1990; Waldrop, 1992). Chaos theory, today considered by many researchers as part of the wider 'complexity science' field (Lewin, 1999) essentially studies non-linear effects in deterministic systems, while complexity theories study definite patterns in non-deterministic systems (Gleick, 1987; Kauffman, 1995).

In all cases, the characteristics of these systems, composed of hundreds of interdependent elements (organizations, people, objects etc), frequently creatively 'disturbed' by new entrants or disrupted by external or internal shocks make it impossible to forecast accurately any long-term future evolution, above all when the system dwells on an 'edge of chaos' region or moves from one phase to another (Doran, 1999; Linstone, 1999). Nonetheless, large scale behaviors at system level might still be predictable if it is possible to identify some attractors and their basins. Close to these, a system may follow a relatively steady path and a limited (in time) forecast is possible (Andersen & Sornette, 2005; Boffetta et al., 2002; Hansell et al., 1997). This justifies the many 'linear' forecasting methods and their (at times) relatively successful outcomes.

2.1. The chaos and complexity approach in tourism studies

Even if not always explicitly defined as such, the idea that tourism is a complex adaptive system has been with us for a long time (see for example Leiper, 1979). Despite the lack of a clear and rigorous definition, a large number of researchers and practitioners has set several models, methods and approaches that have helped (and still do so) to understand structures and dynamic evolutions, and provided means to manage systems, to predict their effects or to optimize their functioning. Many authors have employed complexity and chaos based approaches to tourism starting from the realization of the 'complexity' and instability of these systems (Edgar & Nisbet, 1996; McKercher, 1999). In fact "tourism is new enough, chaotic enough, and in the past unregulated enough to be a very attractive field" (Russell & Faulkner, 2004: 562).

Few studies have explicitly identified the principles of complexity theory. A notable exception is the work carried out by Russell and Faulkner. The authors suggest that (2004: 557): "the more pertinent features of chaotic system that are particularly relevant to the examination of destination development are: i) 'edge-of-chaos' phenomena, ii) 'self-organizing behavior', iii) the 'butterfly effect', iv) 'lock-in effect', v) 'self-similarity' and vi) 'bifurcation'.

Self-organization is a characteristic of tourism systems able to bottom-up create new structures (Baggio, 2008), especially when a triggering event or a 'rogue' occurs. This capacity assures a "tremendous adaptive ability" to the system (McKercher, 1999: 428), and it is generated not by the system itself, but rather by its entities, as suggested by Russell and Faulkner (2004).

The butterfly effect (Lorenz, 1963), perhaps an icon of these theories, refers to a major change in the system caused (triggered) by apparently small changes. The butterfly effect is related to the initial conditions of the system (Russell & Faulkner, 1999) and it helps to explain "how seemingly similar destination areas can evolve in completely different manners. It also explains the unpredictable nature of tourism development, where even slight changes in initial conditions can lead to profoundly different outcomes" (McKercher, 1999: 429).

Tourism complex systems can show a high sensitivity to apparently unrelated events which, even despite their low significance, may trigger major changes. These triggering events are what Taleb (2007) names 'black swans'. A black swan event: i) is a surprise (to the observer), ii) has a major impact on the system, iii) after the event is rationalized by hindsight, as if it had been expected. A recent example, affecting demand (Laws & Prideaux, 2005) can be the negative publicity generated by several high profile business conventions in the United States in 2009. The US administration strongly criticized companies engaging in such activities during periods in which profits were low and layoffs occurring. As a consequence, many firms cancelled their planned conventions, resulting in significant losses in some resort areas such as Las Vegas (Friess, 2009).

The lock-in effect is related to the pervasiveness of some initial conditions that create a sustainable head-start (Russell & Faulkner, 2004), explaining "why accidents of history are still current today" (McKercher, 1999: 429). At a tourism destination, "the lock-in effect might be evident in the continuing concentration of tourist accommodation capacity and attractions around a location, which was originally advantaged by access to rail transport. With the passage of time, rail transport might have become less relevant as a means of access for tourists, but the original location might retain its dominance owing to agglomeration effects" (Russell & Faulkner, 1999: 415).

Self-similarity is both a characteristics of the way the different elements form a system and a result of the functioning of the system itself. Focusing on the parts, each entity could be similar to others but not identical (Komulainen, 2004), focusing on the process, the chaotic functioning of the system tends to produce similar but not identical effects, as "the pounding of the ocean on the shoreline leaves a fractal coast" (Legge, 1990: 132) cited in (Zahra & Ryan, 2007).

Finally, bifurcation is closely related to the edge of chaos. When the system overcomes a critical point (or region) of the space phase and enters into a new phase. Here, the values of the system's parameters undergo abrupt changes (Langton, 1990), and alternatives emerge that tend to create Y-shaped junction bifurcations (Gleick, 1987; Wolfram, 2002).

The purpose of this paper, as stated, is to examine quantitative methods in order to test some premises of complexity and chaos theories in a tourism setting. Previous works have dealt with this issue in two ways: theoretically and empirically. The majority of theoretical papers focus on new insights that the application of these theories can provide on specific themes. A general overview containing an initial proposal for a quantitative approach to the analysis of a complex system with a specific focus on tourism destinations is provided by Baggio (2008). McKercher (1999) proposes an alternative model of tourism system based on the principles embodied in complexity theory. Significantly, at the centre of the model there are 'rogues' which can push the system beyond the edge of chaos. Edgar and Nisbet (1996) reflect on the limits of long-term strategic planning for small businesses operating in the hospitality industry. Hospitality firms (especially if small) "should not try and overcome their environment by predicting future outcomes but instead should change and adapt with the environment" (1996: 8). Cole (2009) explores the sensitivity and variability of tourism systems to initial conditions (butterfly effect), using a logistic tourism model. "The approach used is to show that the generating processes of resort tourism can be formalized as a discrete logistic equation, a well-researched 'chaos' model that gives rise to innumerable possible trajectories, including the familiar S-shaped curve" (Cole, 2009: 690). This essentially theoretical work also uses some empirical data from Aruba and Barbados destinations.

Amongst specific issues, crisis and disaster management is one of the most discussed topics. Following the view that complexity and chaos theories offer a means for enriching the comprehension of these events and improve the ability to manage their effects (see for example Crandall, 2010), many authors have used such models for their analyses. Faulkner (2001) distinguishes between crises and disasters and proposes a framework to manage disasters in tourism destinations. Ritchie (2004) deals with strategic and holistic approaches to crisis management, proposing a framework in three stages: i) crisis and disaster prevention and planning, ii) strategic implementation, iii) resolution, evaluation and feedback. Scott and Laws (2005) propose an analysis of crises and disasters from a systems theory perspective, starting from the complex structure of tourism activity. Laws and Prideaux (2005) focus on crisis management and propose a typology, based on a definition of some key words. Empirical works are mainly based on case studies, built using documentation and interviews (Yin, 1994) as a primary source of qualitative evidences.

Faulkner and Vikulov (2001) and Hystad and Keller (2008) are interested in crisis and disaster management. The first paper "aims to refine a previously developed model for tourism disaster management plans (companion paper) by examining the case of the 1998 Australia Day flood at Katherine" (Faulkner & Vikulov, 2001: 331). The second is "a follow-up study investigating the long-term experience of a tourism industry affected by a major forest fire disaster that occurred during the summer of 2003 near Kelowna, British Columbia, Canada" (Hystad & Keller, 2008: 151). Both papers are based on interviews.

A second stream of research applies the chaos theory to demand forecasting. Faulkner and Valerio (1995), starting from the Australian Tourist Commission approach, argue the necessity to combine different techniques in order to facilitate a more meaningful dialogue between analysts and those responsible for tourist management decisions. Otherwise, forecasting tends to "become an end in itself, resulting in its alienation from the planning process" (1995: 30). Prideaux, Laws and Faulkner (2003) find that "current methods of forecasting are not able to cope with unexpected crises and other disasters and that alternative methods need to be examined including scenarios, political risk and application of chaos theory" (2003: 475). Both articles are qualitative in nature, even if they report some quantitative data.

Russell and Faulkner (1999) explore the role of entrepreneurs in destination development, using the Gold Coast in Australia case study as illustrative purposes. These seminal ideas have been examined in greater depth in subsequent works (Russell & Faulkner, 1998, 2004) applying the chaos theory to Coolangatta and Surfers Paradise, two Australian destinations. The findings illustrate "how entrepreneurs took advantage of chaos and turbulence, and applied their creativity in a manner that gave one destination a competitive advantage over the other" (Russell & Faulkner, 2004: 556). Warnken, Russell and Faulkner investigate "the impacts of the growth of condominium developments and their potential for inhibiting destination rejuvenation" (2003: 155). Evidences are taken from the Gold Coast, mixing qualitative and quantitative data. Zahra and Ryan use complexity theory to explain the functioning of New Zealand's regional tourism organizations, during a period characterized by instability. Empirical findings suggest a possible "re-emergence of past oscillations of changing relationships between the centre and the periphery" (Zahra & Ryan, 2007: 861). Tinsley and Lynch (2001) explore the relationships between networks of small tourism businesses and their contribution to destination development. Evidences are taken from a peripheral rural location (west coast of Scotland), using in-depth interviews.

3. Materials and methods

When a system is well known and the *physical* laws governing it are clear, a system of differential equations can be used to describe it (a physicist would call this the *equations of motion*). The solutions, when it is possible to find them, will give all the possible means to fully understand its structure and its evolution. However, for the majority of systems, and certainly for a tourism system, this is not possible. The only available *tool* is a series of observations of some characteristics. These observations form a time series, a widely used and well-known object in tourism studies. It consists of a sequence of measurable observables in which the measurements refer to a certain period of time and are taken usually (but not necessarily) at constant intervals. A series provides a wealth of information on the dynamic behavior of a system and is used essentially for the purpose of predicting a future state of the system. This usage is well established in the tourism field and has been object of innumerable studies from both a theoretical and a 'practical' point of view. The techniques for deriving forecasts and the assessment of their reliability are an essential part of the toolbox of tourism researchers and practitioners.

Less known is a second usage. For a real complex system a time series is one of the very few possibilities to assess a number of characteristics about the nature and the extent of the complexity or chaoticity of the system. Obviously, by examining a time series it is not possible to fully understand the physical laws governing the system (Sprott, 2003), but a good analysis can unveil a number of properties and make it possible to infer the type of dynamics that generates the observable behavior and, at least in principle, provide suggestions on how to control the system and the effects small perturbations may have in the improvement of system's performance (Sainaghi, 2006).

Before proceeding, a warning is in order. Most of the methods described in what follows are *data hungry* and they start to give reliable and meaningful results only with relatively long-term series (typically more than 1000 values) which may be problematic in a field such as tourism, where this type of datasets is not very common. Another sensitive issue regards the frequency with which data are collected. If it is too high, the number of values risks overly increasing the computational time needed, but if it is too low an interesting dynamic pattern may be lost. As often happens, only experience will guide the researcher towards the 'ideal' set to study: "this is more an art than a science, and there are few sure-fire methods. You need a battery of tests, and conclusions are seldom definitive" (Sprott, 2003: 211). However, an accurate usage of the techniques available has shown to provide a wealth of interesting insights into the structural and dynamic patterns of complex and chaotic systems.

3.1. Nonlinear time series analysis

With these premises in mind, the first operation to perform on the series is its filtering to remove trend and seasonal components. What is needed is a series of values which can clearly represent the internal dynamics of the system under study, not too much disturbed by components such as trend, seasonality or other, which may conceal the properties we are looking for. While this procedure might weaken the precision of a traditional analysis, it becomes essential for the purpose of the investigations discussed here. As extensively noted by the literature (see for example Clegg, 2006), trend and seasonality components may corrupt the outcomes of the measurements by superimposing too strong effects on the recording of system's internal dynamics.

The classical techniques to filter a time series make some fundamental 'linear' assumptions, which may be too strong when examining a highly nonlinear system. Therefore it is better to use some method which draws the filtering directly from the data without any 'external' intervention (such as, for example, the decision on the length of a season). One such method is the Hodrick-Prescott filter (named after its proponents Hodrick & Prescott, 1997). It is a nonparametric, nonlinear algorithm which acts as a tunable bandpass filter controlled by a parameter λ. The effect is the identification of a smooth long-term trend component without affecting too much the short term fluctuations. Essentially, the series is split into a stationary and a nonstationary component (the trend) in such a way that the squared deviation of actual values from trend is minimized subject to a smoothness constraint weighted by λ. Higher values for λ lead to a smoother long-term component (in the extreme cases: $\lambda = \infty$ produces a line, $\lambda = 0$ leaves intact the observed values). The literature suggests as optimal choice λ the value $\lambda = (10 \cdot FREQ)^2$ where $FREQ$ is the frequency of observations (number of observations per year). Typical values suggested and used in literature are: 14 400, 260 100, and 6 250 000 for monthly, weekly, and daily data, respectively. Even if criticized (Ravn & Uhlig, 2002), the filter is widely used in the economics literature and has received some attention in the tourism literature (Gouveia & Rodrigues, 2005; Guizzardi & Mazzocchi, 2009). Once filtered, the series can be examined to assess whether it originates from a linear or a nonlinear or chaotic process. The most common procedure is the Brock, Dechert and Scheinkman (BDS) test (Brock et al., 1996). It checks whether a given signal is deterministic or stochastic by comparing it with the correlation integral.

As described in section 2, the instantaneous state of a dynamic system is characterized by a point in phase space. A sequence of such states subsequent in time defines the phase space trajectory. If the system is governed by deterministic laws then, after a while, it will arrive at a permanent state regime. This fact is reflected by the convergence of ensembles of phase space trajectories towards an invariant subset of phase space, the attractor of the system. One difference between a chaotic signal from a strange attractor and a signal from a noisy random process is that points on the chaotic attractor are spatially organized. The dimension of an attractor can be estimated by calculating the probability that the states at two different times are close (Grassberger & Procaccia, 1983; Takens, 1985). This probability is called the correlation integral and depends on the sizes of the attractor's neighborhood and the phase space dimension. This dimension can be estimated from the time series data by using a time-delay technique (Kantz & Schreiber, 1997; Schreiber, 1999). In essence, a time series can be plotted versus a time-delayed version of itself. The lag used corresponds to the dimension of the phase space (it is called embedding dimension). The optimal lag can be chosen in different ways. Usually, the computerized procedures that make use of this quantity offer a series of alternative solutions and the researcher compares the outcomes choosing the smallest value able to provide the information required. The theoretical basis for these calculations were given by Takens (1980; 1985). His theorem states that a dynamic system can be reconstructed from a sequence of observations of its state, and, in the general case, the dynamics of a system recovered by 'time-lagging' this series of observations is the same as the dynamics of the original system. The BDS test examines whether the correlation integral from a given signal (time series) is significantly different from the one given by a random series. If a significant difference exists, the given signal is deterministic (and thus chaotic).

Stationarity is a desired feature in a time series and a prerequisite for the most used analysis methods and for the possibility of forecasting future outcomes (Chatfield, 1996). In the context of the present work, this property assumes a more important physical meaning; it can make it possible to measure the resilience of a system, that is its capability to resist events which could spoil its normal functioning. In other words, if the time series under examination shows substantial stationarity (at least in some reasonably long time periods), the system can be considered able to recover relatively well from the effects of external or internal shocks. When considerable changes in the trend or the level of a series exist (they are called structural breaks), it is important to assess whether they heavily affect the resilience (series stationarity) or they have only a limited influence and the system is able to recover quickly and return onto its previous evolutionary path. The econometric literature offers a number of procedures whose aim is to check for stationarity when structural breaks are present. The most commonly used are those due to Dickey and Fuller (1979), both in the simple (DF) and the augmented (ADF) version, the variations suggested by Phillips and Perron (PP test: Phillips & Perron, 1988), by Zivot and Andrews (ZA test: Zivot & Andrews, 1992), or by Lee and Strazicich (LS test: Lee & Strazicich, 2003). These tests also provide an estimate of the period where a major structural break occurs. As Metes (2005) notes in his review, it is advisable to use more than one test to obtain a reliable outcome, as they have different applicability, limitations and power. Several examples of use of these tests can be found in the recent tourism literature (Hooi Lean & Smyth, 2008; Narayan, 2005; Sen, 2003).

A chaotic system is characterized by a great sensitivity to the initial conditions, in other words it has a long memory. This attribute can be assessed by adopting an approach originally due to Harold Edwin Hurst. His work as a hydrologist in Egypt led him to study the long-term behavior of the River Nile's rain and drought conditions in order to devise an optimal size for a dam (Hurst, 1951). The mathematical definition of long memory processes calls for the evaluation of the autocorrelation function *p(k)* of the time series (*k* is the lag). When long memory is present, *p(k)* decays following a power law: $p(k) \sim k^{-\alpha}$. The quantity $H = 1-\alpha/2$ is called Hurst exponent and its value range between *0* and *1*. If $H=0.5$, the behavior of the time series is similar to a random walk; when $H<0.5$, the time series is antipersistent (i.e., if the time series increases, it is more probable that it will decrease in subsequent periods, and vice versa); if $H>0.5$, the time series is persistent (if the time series increases, it is more probable that it will continue to increase). Values higher than *0.5* therefore characterize systems with a long memory and thus show a tendency to be chaotic. The calculation of H can be performed by using a number of different methods, again, all having their specificities, power and reliability in different conditions (Clegg, 2006; Mielniczuk & Wojdyłło, 2007; Taqqu et al., 1995).

This measure has been introduced in the chaos theory by Mandelbrot (see Mandelbrot & Hudson, 2004) as a measure of fractality for financial time series, the fractal dimension *D* is related to H by the expression: $H = E + 1 - D$ (where E is the Euclidean dimension, i.e. 0 for a point, 1 for a line, 2 for a surface; for a one-dimensional signal such as a time series: H=2-D). The Hurst exponent has also been used as a measure of complexity, with the indication that the lower its value, the higher the complexity of the system (Giuliani et al., 2001; Yu & Chen, 2000).

An attractor in the phase space is, as discussed above, a trajectory of stability for a complex system. The assessment of the extent to which a system, in its dynamic evolution, tends to follow one of these paths can therefore clearly show how it behaves and what its tendencies are, and provide one more measure of the sensitive dependence on initial conditions, that is of its chaotic (or potentially chaotic) behavior. In the study of the stability of motion of a low dimensional physical system, Aleksandr Mikhailovich Lyapunov (1892) proposed a method to assess the rate of convergence between two orbits when one of them had been perturbed. The quantities calculated, called Lyapunov exponents, depend on the equations of the orbits (e.g. the system's path and a reference orbit) and on the dimension of the phase space in which the system is embedded. The largest exponent (LCE: Lyapunov characteristic exponent) gives the most important information on the system's motion. Simplifying, it is possible to say that LCE is the time constant in the expression for the distance between two nearby orbits $e^{\mathrm{LCE}\cdot t}$. When $LCE<0$, orbits converge in time and the system is insensitive to initial conditions. If $LCE>0$, the distance grows exponentially in time, and the system tends to go away from the stable attractor and exhibits sensitive dependence on initial conditions. If the equations governing the system are known, LCE can be derived from them. However, this happens only in very few cases and mostly for simple *didactic* examples. In the case of a real system, for which we have a time series as a representation, a possible computational method is the one proposed by some authors (Rosenstein et al., 1993; Wolf et al., 1985).

The outcomes of all the methods described here, obviously, need an interpretation of a qualitative nature. In many cases we do not deal with a standard statistical test for which a critical value or a p-value are sufficient to answer an initial question (a null hypothesis). When using these methods it is important to have available a *null model*, a well known system with which to compare the results of the analyses in order to assess the characteristics of the one under study. In chaos theory, probably the most known system of such kind is the one described by Lorenz (1963), that is commonly referred to as an archetypical chaotic (and thus complex) system. In what follows, as in many other studies of this type, the Lorenz equations in the 3-dimensional space have been used to provide a series of values taken at constant time intervals. This can be seen as a time series representing the system (one realization of such series is shown in Figure 1 where the X component has been drawn).

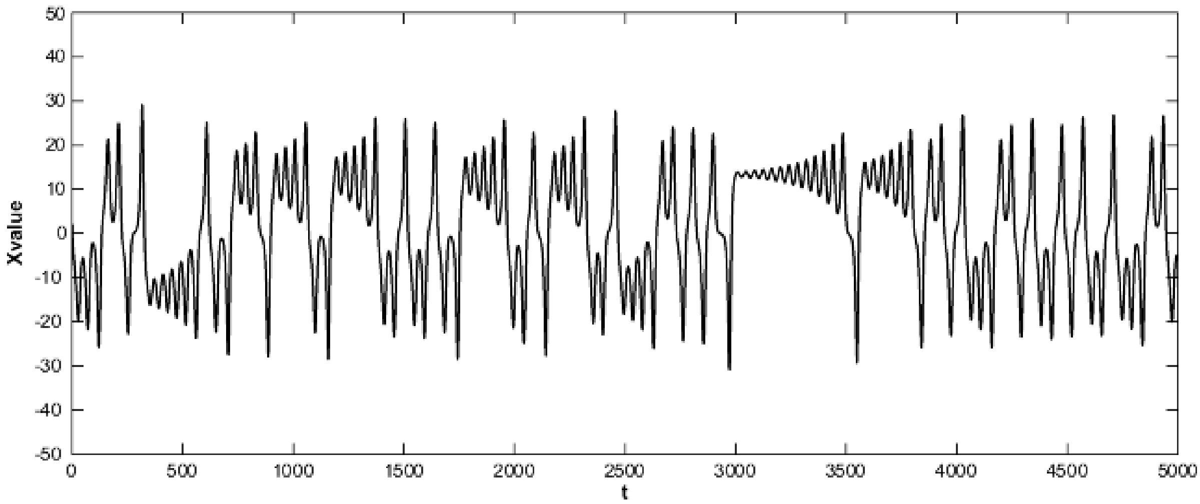

Figure 1 A time series (X component) generated from the Lorenz system of equations

In summary, the quantitative methodological approach proposed here consists of the following steps: data representing the evolution of a tourism system are collected; the series obtained is filtered in order to remove strong trend or seasonality effects and retrieve a representation of the system's dynamics. A series of treatments and tests makes it possible to examine the extent to which complex or chaotic features affect the system: the BDS test checks whether the correlation integral gives evidence of a chaotic signal, unit root tests allow to determine the resilience of the system, the Hurts exponent constitutes a measure of the fractality and the tendency to chaoticity, and LCE provides the degree of divergence from a stable attractors measuring how sensitive the dependence on initial conditions is. These measurements combined with a good qualitative knowledge of the system's behavior will provide an assessment of the desired characteristics.

3.2. Computational tools

The references provided in the previous section will allow the reader to appreciate all the nuances and the implications of the methods described. From a practical point of view, they require a relatively significant computational effort and well tested software procedure. The programs used for this work are listed here (specific instructions are normally provided in the script comments in the accompanying documentation):

- Hodrick-Prescott filter: Matlab script by W. Henao, available at: http://www.mathworks.com/matlabcentral/fileexchange/3972-hodrick-prescott-filter

- BDS test: Matlab script by L. Kanzler, available at: http://econpapers.repec.org/software/bocbocode/t871803.htm

- Unit root tests: Gauss/Ox scripts by J. Lee, available at: http://www.cba.ua.edu/~jlee/gauss

- Hurst exponent: Matlab scripts by C. Chen, available at: http://www.mathworks.com/matlabcentral/fileexchange/19148-hurst-parameter-estimate

- Lyapunov characteristic exponent: Matlab script by S. Mohammadi, available at: http://ideas.repec.org/c/boc/bocode/t741502.html

- Lorenz time series: Matlab scripts by E. A. Wan , available at: http://www.bme.ogi.edu/~ericwan/data.html

3.3. Sample data

The time series used here contains data collected from a sample of 23 large (four star) hotels located in Milan, Italy. For each structure daily data of occupancy, average room rate and RevPAR (Revenue Per Available Room) were recorded for the period 2006-2009. Attempts were made to collect data also from three-star or two-star hotels, but these proved to be unable to record data with the constancy needed. The daily distributions of these observations are highly skewed, therefore the median of the daily values were considered. This results in three series of 1 461 points per type (occupancy, room rate and RevPAR). The rooms measured constitute almost 42.6% of the Milan city accommodation endowment and therefore are a highly reliable sample. Also, if we consider the role played by the accommodation industry in the tourism business of a destination, and the power and control they exert over the tourism (and not only) economy of the area, the sample can be considered a good candidate for representing the whole destination (Butler, 2005a, 2005b; Song & Li, 2008; Vanhove, 2005).

The data collected are in line with the ideas of Venkatraman & Ramanujam (1986). Regarding performance, the authors propose a tri-partition of dimensions considering a financial, an operational and an organizational dimension. The financial dimension includes mainly accounting measurements able to appreciate the margins and company profitability. The operating dimension is not clearly defined by the authors except in negative (non-financial) terms and through a few examples of indicators. The operational dimension includes the main determinants of the financial results; therefore the authors maintain that in the absence of an operational success, it is impossible to achieve satisfactory financial performances. Lastly, the organizational dimension measures the satisfaction achieved by the various company stakeholders, usually employees and shareholders. Operating performance appears to be the most relevant dimension for this study, because it is strongly connected with daily activities and processes, it can be measured at a daily level and it is very sensitive to the evolution of both environment and firm strategy. This category is operationalized using indices representing occupancy, prices and RevPAR (Chung, 2000; Enz et al., 2001; Israeli, 2002).

For the purpose of this study, the authors focus their attention on RevPAR, primarily due to the ‘double’ nature of this indicator which includes both the occupancy and the average price (Sainaghi, 2010). Moreover, a limited series of calculations performed on occupancy and price time series show no large differences from the results obtained by using the RevPAR series for what concerns the objectives of this work.

4. Results and discussion

The data series obtained as described in the previous section is shown in Figure 2 (panel A), along with the Hodrick-Prescott filtered component (panel B) and the resulting smoothed trend (panel C).

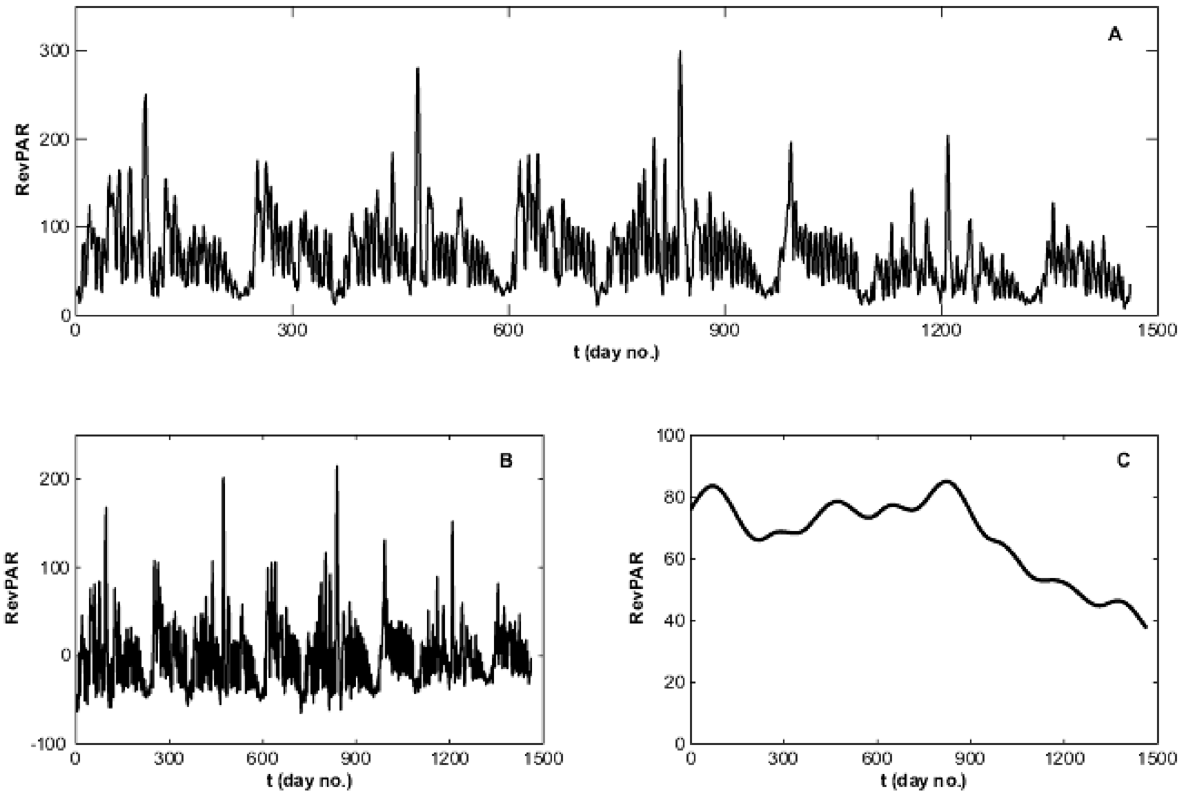

Figure 2 The time series of RevPAR (A), its filtered component (B) and the resulting smoothed behavior (C). The time axis shows the day number (1 = 1 January 2006)

The inspection of the latter provides a clear picture of the evolution in the time frame considered (2006-2009). After a relatively stable period, the destination exhibits a marked decline. The last peak (day no. circa 820) corresponds to the end of March 2008 and after the beginning of September 2008 (day no. circa 980), the descent appears irreversible. The economic recession has a very big impact, and in the case of Milan the effects have been even worse than in other destinations due to the strong characterization of the city as a business tourism destination.

Table 1 reports the results of the BDS test calculated for different dimensions of the reconstructed phase space (embedding dimension). The Milan series is judged against a pure random series and the one derived from the Lorenz equations. The values are all highly significant ($p < 0.005$). A comparison of the values obtained leads to the conclusion that the series under study has a detectable level of nonlinearity, even if it does not reach the pure chaoticity of the Lorenz attractor. A first conclusion is that, as qualitatively assessed in many similar studies, the tourism destination is a complex system with a tendency to become chaotic.

Table1 BDS test statistic values for the series considered. All the quantities reported have $p < 0.005$. The Milan series is compared with a pure random series (BDS_Rnd) and with the one obtained for a Lorenz attractor (BDS_Lorenz)

Embedding dimension	*BDS_Milan*	*BDS_Rnd*	*BDS_Lorenz*
2	52.32	1.56	488.40
3	50.03	1.03	524.26
4	48.02	0.60	568.99
5	47.57	0.49	633.14

The Hurst exponent calculated (actually an average of those calculated with different methods) is H = 0.788 ± 0.05. As a comparison, Yalçınkaya & Lai (1997) report a value H = 0.74 for the Lorenz series. Thus we have a confirmation of the long memory characteristics for the system and that its complexity, although present, is not excessively high. A four-year period of data series (forse dovrebbe essere A four-year period of data series?) may seem not fully able to show a long memory effect, and this is a limitation of the example discussed here. It must be noted, however, that definition and the method are more concerned with the number of observations in the series than with the time interval covered.

The unit root tests (Table 2) provide a consistent result by rejecting the null hypothesis of nonstationarity at $p < 0.01$. The large distance between all the values and the critical values stresses this result even more, suggesting a considerable, firm stability of the system. The test that it provides (PP, ZA, LS) substantially agrees in finding a structural break around period 820, which corresponds to the end of March 2008. This is a confirmation of the observation made when visually inspecting the smoothed trend of the series (Figure 2).

Table 2 Unit root test outcomes along with the critical values at $p = 0.01$

Test	*Test Statistic*	*Critical Value (p=0.01)*
ADF	-9.139	-4.07
PP	-9.482	-4.03
ZA	-9.936	-5.57
LS	-9.751	-5.15

The calculation for the Lyapunov characteristic exponent gives LCE = 0.0036. The value for the Lorenz time series is 1.50 (Wolf et al., 1985). Being positive, LCE indicates a tendency to go away from a stable attractor orbit. However, its value is small compare to the one obtainable when analyzing a Lorenz system. In other words, it can be concluded that the system has a definite tendency towards a chaotic state, but this tendency is not too accentuated.

4.1. Implications of the analysis for tourism governance

The picture obtained with the analyses conducted can be summarized by saying that the system under study exhibits an unequivocal complex nature. It tends towards a chaotic stage but does so at a slow pace. The stability of the system is quite high; it might be able to well resist transient shocks, but once led in one direction, its long memory characteristics tend to keep it on the resulting path.

When considering possible models for guiding a destination's development, the realization that it might possess *complex* or *chaotic* characteristics is crucial. It is well known, in fact, that forced evolutions, when dealing with a complex adaptive system are destined to fail in the long term. The intrinsic system's characteristics will tend to prevail and the system will return to its original, natural evolutionary path (Kauffman, 1995; Nicolis & Prigogine, 1977). It is very much like forcing a river into a different, artificially created path. In many cases, for having experienced devastating events, it has been experienced that sooner or later the river will go back to its original track. In our case the strong long memory effect detected and the high stability of the system suggest an adaptive governance approach rather than a decisionist management attitude, which would inevitably come into collision with the system characteristics (Chhotray & Stoker, 2009; Erkus-Ozturk & Eraydin, 2010; Nordin & Svensson, 2007).

According to the common knowledge on the methods to control complex and chaotic systems (Boccaletti et al., 2000; Poon & Grebogi, 1995; Shinbrot et al., 1993), the most effective way seems the adoption of plans that make provisions for a series of small *perturbations* whose effects will be, from time to time, assessed regarding their real outcomes and effectiveness in order to inform the subsequent steps. Therefore, the governance approach defined by Chhotray and Stoker (2009: 3) as: "rules of collective decision-making in settings where there are a plurality of actors or organizations and where no formal control system can dictate the terms of the relationships between these actors and organizations" looks the most appropriate for a tourism destination such as the one studied here. The long memory and the high stability discovered definitely call for a long term strategy. This strong inertia inhibits the system from reacting swiftly and, when it is forced with too strong shocks, risks inducing a disruptive process or firmly putting the system onto an unpredictable evolutionary path.

We may here make one more observation. The over-stability assessed read through the lenses of complexity science, is a dangerous situation. Seeking a stable equilibrium, although desirable by many, is highly disadvantageous for the development of a system. Positive evolution and growth are possible only in regions of the phase space at the boundary between order and chaos (Rosenhead, 1998: 3.1):

> "Rather than trying to consolidate stable equilibrium, the organization should aim to position itself in a region of bounded instability, to seek the edge of chaos. The organization should welcome disorder as a partner, use instability positively. In this way new possible futures for the organization will emerge, arising out of the (controlled) ferment of ideas which it should try to provoke. Instead of a perfectly planned corporate death, the released creativity leads to an organization which continuously re-invents itself. Members of an organization in equilibrium with its environment are locked into stable work patterns and attitudes; far from equilibrium, behavior can be changed more easily."

Governing a complex system requires, therefore, an adaptive attitude, rather than rigid deterministic, authoritarian styles. The proposal of using adaptive management to deal with complex systems originates from the work of 1970s ecologists (Holling, 1978). It consists of an experimental path to governance, built on the idea of exploring different scenarios, enforcing one or more actions, monitoring the outcomes, testing the predictions and learning what are the most effective for the achievement of the desired objectives. Some applications to tourism systems, with encouraging results, exist (Agostinho & Teixeira de Castro, 2003; Farrell & Twining-Ward, 2004; Patterson et al., 2008). Obviously, rules and actions are needed, but it is important to ensure a capability to change them dynamically, reacting in short times to the changes that may occur in the system or in the external environment.

The methods and the analysis presented here concern a destination, but they can be easily used at a single stakeholder level. An individual organization is a complex entity (Lissack, 1999; Rosenhead, 1998), and, as subsystem of a wider complex or chaotic system, might share some common structural or dynamic attributes. With very little adaptation, all the techniques described, along with the possible interpretations of their outcomes, can be employed to provide better insights into the nature of the organization and indications for an effective management of its operations.

5. Concluding remarks

Tourism scholars have long recognized the complex nature of their object of study, but, so far and with very few exceptions, have limited their analysis to the qualitative characteristics of such systems. In the last few years, scientists from a wide range of disciplines have assembled a numerous and powerful toolbox for the analysis of complex and chaotic systems. Even if not always decisive, when coupled with a sound knowledge of the main aspects of a system, they can provide quite important insights into its structure and dynamics. The availability of powerful computer systems and tested software procedures makes this toolbox relatively straightforward to use.

This paper has shown a possible methodological approach to a quantitative study in this field, by employing a series of well known techniques and by using available data, and has provided reference to well grounded usable tools. Obviously, much is still to be done to improve and to refine the methods presented here and their applicability to the specific setting. Also, a wider collection of samples will make it possible to better focus on the most important and effective ways to characterize the complexity traits of a tourism system. Moreover, the promising area of network science, whose initial applications to this field have already provided interesting outcomes (Baggio et al., 2010), needs to be harmonized with these methods. In this way, it will be possible to come to a more complete quantitative assessment, able to consider a wider range of the peculiarities of the study area.

The sample includes large (four star) hotels located in the city of Milan, Italy. They are mainly specialized in serving business and trade fair clients. Despite large variations in daily values during the period examined, these firms tend to show a positive evolution of operational results in the long run. The empirical work shows the complex behavior of the system, even if it does not reach a pure chaoticity such as the one of a Lorenz attractor. The stability of the system is found to be quite high. This strong inertia inhibits the system from reacting swiftly. Therefore, if forced with too strong shocks, there is a risk to induce a disruptive process or to put the system into an unpredictable evolutionary path. These conclusions are precious indications for informing plans aiming at improving the strategic positioning of the destination, without disrupting the system's performance.

The approach taken in this study is obviously susceptible to improvements and the limitations noted in the paper may orient future efforts. For example, long memory effects can be better assessed by collecting not only a high number of observations (as in the present study), but considering a longer time interval as well. Also, a longer period of observation could provide a more substantial confirmation of the outcomes obtained here concerning the complexity characteristics of the system examined. In any case, the usage of a combination of tests having different null hypotheses and based on different algorithms allows the researcher, when results agree as in the present case, to draw a general picture and remain confident in its validity at least for the period observed. A second factor which may limit the reliability of the analyses presented here is the requirement for large quantities of observations. It must be noted, however, that not all the techniques described are so demanding and useful indications can be obtained by using only those viable with the data at hand.

A major future development of the approach discussed here concerns the governance of a complex tourism system. As noted previously, such a system cannot be directed too strongly, but must be steered in an adaptive fashion, by inducing small perturbations on the system with the objective of pushing it along a certain trajectory. The technique is well known in other fields (Andrievskii & Fradkov, 2003, 2004; Boccaletti et al., 2000). In order to be successful it requires a good understanding and assessment of the characteristics of the system of interest which can be obtained with methods such as those described in this work. Future work, already under way, is moving in this direction.

Practitioners in the area of destination governance can enrich their toolsets with the techniques described in this work and find ways to improve their strategy and policy formulations. On the other hand, the tools and methods presented here will allow scholars to better assess the characteristics of their objects of study in their endeavors to analyze and explain the phenomena relating to the behavior and development of tourism systems.

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