MPRA
Munich Personal RePEc Archive

Looking into the future of complex dynamic systems

Baggio, Rodolfo

Bocconi University

30 June 2015

Online at https://mpra.ub.uni-muenchen.de/65549/
MPRA Paper No. 65549, posted 14 Jul 2015 06:48 UTC

Looking into the future of complex dynamic systems

Rodolfo Baggio

Master in Economics and Tourism,
and Dondena Centre for Research on Social Dynamics
Bocconi University, Milan, Italy
rodolfo.baggio@unibocconi.it

====================

Working paper: June, 2015

Abstract

The desire to know and foresee the future is naturally bound to human nature. Traditional forecasting methods have looked after reductionist linear approaches: variables and relationships are monitored in order to foresee future outcomes with simplified models and to derive theoretical and practical implications. The limitations of this attitude have become apparent in many cases, mainly when dealing with dynamic evolving complex systems, that encompass numerous factors and activities which are interdependent and whose relationships might be highly nonlinear, resulting in an inherent unpredictability of their long-term behavior. Complexity science ideas are important interdisciplinary research themes emerged in the last few decades that allow to tackle the issue, at least partially. This paper presents a brief overview of the complexity framework as a means to understand structures, characteristics, relationships, and explores the most important implications and contributions of the literature on the predictability of a complex system. The objective is to allow the reader to gain a deeper appreciation of this approach.

Keywords

forecasting, predictability, complex systems, nonlinear analysis, time series

1. Introduction: the desire to know and foresee

The desire to know is a specific trait of human beings, well recognized by historians, philosophers and many other scholars of any age. It is not by chance that one of the most influential books ever, Aristotle's Metaphysics, starts with the words "*All men by nature desire to know*", and Maslow, in his renown, and debated, hierarchy of needs assigns it a great importance to the *desire to know and to understand*: *"We must guard ourselves against the too easy tendency to separate these desires (the desire to know and to understand) from the basic needs we have discussed above (five basic needs in vogue hierarchy), i.e., to make sharp dichotomy between cognitive and co-native needs"* (Maslow, 1970: 50-51).

Naturally and inseparably coupled with the need to know and to understand how things work, and what their functioning mechanisms are, there is a strong wish to figure out, as much as possible, their future state. This is true for any *object of study* we may call a system, that is: *a set* [even small] *of elements* [of any kind] *standing in interrelations* (von Bertalanffy, 1968: 55).

This thrust has been recognized for a long time, as Cicero puts it in his De divinatione, probably the first technical book ever written on forecasting: *"There is an ancient belief, handed down to us even* *from mythical times and firmly established by the general agreement of the Roman people and of all nations, that divination of some kind exists among men; this the Greeks call μαντική—that is, the foresight and knowledge of future events"*.

The very basics of what today we identify with 'science', and most of the techniques used for the description, the analysis and the comprehending of natural and artificial systems, come from this ancestral need to uncover the future. Mathematics, the most important tool we have, was born out of two needs, counting objects and counting time. After that, roughly five thousand years ago, the first written records, Sumerian and Babylonian clay tablets, document an incredibly sophisticated series of techniques aimed at solving practical problems tied to human survival: computing areas and quantity of goods and, more importantly, guess good times for agricultural activities. Some centuries later, the same impulse led Egyptian to forecast harvests from the level the Nile reached in the flood season. Then, the natural abstraction of the idea of predicting the future resulted in the attempts to foresee personal fates and brought prophetic phenomena such as the Oracle of Delphi, Zoroaster or Nostradamus. As McHale states: *"The future is an integral aspect of the human condition. Man survives, uniquely, by his capacity to act in the present on the basis of past experience considered in terms of future consequences"* (McHale, 1969: 3).

The contemporary idea of forecasting, however, is relatively recent and might be reputed to originate from the work of the XVII century scholars, that put the bases to what is known today as scientific method. Physicists, astronomers, meteorologists, economists or social scientists started in that period to consider the systems they were investigating as made of a certain number of parts that could be examined individually and studied in order to understand their intrinsic dynamic characteristic. From the record of system activities they thought possible the derivation of universal laws that govern the evolution of the system and foresee its future behavior.

This *reductionist* idea is well expressed by the words of the man who formalized the idea: René Descartes. In the Discourse on Method he states that it is necessary *"to divide each of the difficulties under examination into as many parts as possible, and as might be necessary for its adequate solution"* (Descartes, 1637: part II). Our approach to the issue of understanding and forecasting, which is founded on the pre-Socratic, consists of an attempt to disclose the universal principles that would explain nature and was elaborated and rigorously formulated as a method by thinkers such as Copernicus, Galileo, Bacon, Kepler.

This work reached its highest point with Isaac Newton and his Philosophiae Naturalis Principia Mathematica (1687). Newton's effort was so successful that specialists of any discipline struggled to tackle their own field of enquiry in the same way, especially when no strong empirical tradition existed, such as in the study of human societies and actions. Simplicity, coherence and a seeming completeness of the proposal, along with a substantial agreement with intuition and common-sense, pushed scholars such as Thomas Hobbes, David Hume, Adolphe Quetelet, Auguste Comte (to cite only a few), to try to explain aggregate human behaviors by using analogies from the world of physics and employing its mechanicistic laws. The same did Vilfredo Pareto or Adam Smith in the field of economics.

The recent history of forecasting mainly revolves around the idea of studying the past behavior of a system as observable through the periodic measurements of some of its characterizing parameters. The analysis of these *time series*, started at the beginning of XX century with the works of George

Yule (Yule, 1921, 1927), and has evolved producing an incredible array of sophisticated methods and techniques (Klein, 1997; Mills, 2011).

These methods are all based on the idea of a deterministic world, as stated by Laplace: *"An intelligence which, for one given instant, would know all the forces by which nature is animated and the respective situation of the entities which compose it, if besides it were sufficiently vast to submit all these data to mathematical analysis, would encompass in the same formula the movements of the largest bodies in the universe and those of the lightest atom; for it, nothing would be uncertain and the future, as the past, would be present to its eyes"* (Laplace, 1814: 2). In this world phenomena are of a substantial linear nature (or can be easily linearized), and we can postulate that the series is the realization of a stochastic process.

However, when examining a *real* system such as the economy, the weather, or any other phenomena involving a large number of elements whose relationships are not linear or not simply foreseeable, all these methods, although partially successful in some cases, show strong limitations, mainly in their predictive power which tends to decline very rapidly as the forecast horizon increases, revealing a limited maximum interval beyond which forecasts can provide no reliable information about the quantities examined (Galbraith & Tkacz, 2007). In other words, complex dynamic systems are inherently unpredictable. Nonetheless, the desire to know about the systems and their evolution has provided a number of possibilities that give, at least partially, an answer to the question.

In the rest of this paper, after a brief elucidation of what we know about complex systems, we concisely describe these methods.

2. Simple, complicated and complex systems

The ideal Newtonian world in which one could have examined any system by taking it into smaller parts and describe analytically deriving the general laws of its present and future behavior lasted a very short time. People started soon realizing that having more than simple individual objects introduced a number of additional variables, due to the mutual interactions, that made quite difficult, if not impossible, finding a 'simple' solution unless by ignoring higher order terms in the analytical formulations and restraining the description to a simplified and linearized picture.

In 1883 Poincaré finally realized that even a small three-body system can be the source of such complicated outcomes that the equations describing it become practically unsolvable. In the same period Lyapunov (1892) studied the conditions for a stable equilibrium in the motion of a system. This work provided the first indication that even minor changes in initial conditions of relatively simple systems, when expressed by deterministic relationships, could give rise, in some cases, to widely differing trajectories. It is what today we identify with chaos, that is the instability due to a heavy sensitivity to initial conditions.

Large and nonlinear systems (those characterized by nonlinear relationships between components) were the subject of an increasing number of studies, that, in the second half of XIX century brought to a strong theoretical formalization, mainly due to James Clerk Maxwell, Ludwig Boltzmann and Josiah Willard Gibbs (Gibbs, 1902), of what today is known as statistical physics. The idea is that ensembles of many objects could not be studied by writing a large number of analytical relationships and solve them, but a resort to statistical methods was necessary. This happens, for example, if we consider a gas in which a very large number of particles interact (just to give an idea, one liter of air contains about $3 \cdot 10^{22}$ molecules).

In the second half of last century (Solomon & Shir, 2003) we became fully aware that there are at least three broad classes of systems: simple, complicated and complex. They can be briefly characterized as follows (Amaral & Ottino, 2004; Baggio, 2008; Lewin, 1999; Procaccia, 1988; Wolfram, 2002).

Simple systems: composed of a limited (often one) number of elements, and in which we can easily identify cause and effect due to the linearity of the relationships that bind the parts. Examples are a billiard ball and the stick that strikes it, a body sliding down an inclined plane, or a simple pendulum (provided oscillations are small). On the other hand, a simple object made of only two elements, a double pendulum, a pendulum hanging from another pendulum, is well known to any physics student for its chaotic and totally unpredictable behavior.

Complicated system: collections of a number, often very high, of elements systems, whose collective behavior is the cumulative sum of the individual ones. This system can be decomposed in different parts and understood by analyzing each of them. There are clear cause-effect relationship, but it may be difficult to detect them. These are usually static systems or systems that are not really vulnerable to changes (if there is a change, it can be easily predicted and analyzed). Examples of such systems are a watch, a car, an airplane or a house.

Complex systems: while practically no common definition exists for such systems, we can characterize them as entities made of a large number of elements that have well defined, and often very simple relationships and interactions at a local level whose nature is typically nonlinear. This causes a dynamic generation of behaviors and structures that is unpredictable by a simple composition. These systems, moreover, continually interact with the external environment, tweaking both their structure and their behaviors. The visible effects can be seen in the ability to sometimes resist large shocks without apparent large modifications, while, in other circumstances, seemingly irrelevant events can produce dramatic transitions and disruptions. During its life a complex system may form several intermediate structures that appear spontaneously. This self-organization aims at optimizing available resources and rendering the system more capable to face external or internal problems. Also, when surveyed at different (time or spatial) scales the system appears to have similar structure and characteristics: it is self-similar. Most natural and artificial systems can be labeled as complex: the weather, an economy, tourism destinations, a biological organism.

The dynamic behavior of a system is usually described by observing its trajectory in a phase space (or state space), the multidimensional space of all the possible states. The parameters (degrees of freedom) of the system are the axes and each state of the system (a set of parameters' values) is a point in the n-dimensional space. Over time, a system can assume many different configurations (states); the succession of points corresponding to this evolution is a trajectory in the phase space.

Depending on some parameters (order parameters) a system may pass from a completely ordered phase to one in which it is so strongly dependent on very small variations of the initial conditions that it appears completely unpredictable: a 'chaotic' phase. In this, which is still governed by deterministic laws, the system may tend to follow certain specific patterns. These are termed attractors and the regions close to them their basins of attraction. An attractor can be a fixed equilibrium point, or a closed path or have more complicated patterns. It is also possible to have a system that never returns to the same state (strange attractors). The region at the boundary of these phases (between stable and chaotic behaviors) is known as the ‘edge of chaos’, a region of complexity (Lewin, 1999; Waldrop, 1992).

For what interests us here, the most striking characteristics of these systems, composed of hundreds of interdependent elements (organizations, people, objects etc.), frequently ‘intruded’ by new entrants or affected by external or internal shocks, is the impossibility to forecast accurately any long-term future development. This is mainly true when the system settles on an ‘edge of chaos’ region or travels through different phases (Linstone, 1999).

However, some behaviors at system level might still be predictable when an attractor and its basin can be identified. In these conditions the system may follow a relatively stable path, showing some kind of inertial motion that allows limited (in time) forecasts (Andersen & Sornette, 2005; Boffetta et al., 2002). This justifies the many traditional forecasting methods and their (at times) relatively successful outcomes.

One important point, for the success of forecasting activities, is the necessity to assess the general conditions of the system in a certain time frame or spatial scale in order to guess what are the possible windows of predictability and to choose the best prediction method. This is a crucial activity that any forecaster should embrace, and that can rely on well-established techniques, developed and tuned by a large array of scholars in many different disciplines. The importance is not only a theoretical one, but, as easily comprehensible, also a practical one, for virtually any management decision (both strategic and tactical) expects as input a reliable assessment of the future behaviors of the system of interest.

3. Assessing system characteristics

The most commonly used object for the analysis of a system (i.e. assessment of its complexity or chaoticity levels) that can affect the possibility of a trustworthy forecast is a time series of some observable quantity related to the system. As said, the inherently complex nature of many artificial and natural systems make impossible (mostly theoretically, but often practically) to have analytical representations (Lansing, 2003). The only possibility is to record, along a certain time interval, a number of observable quantities that can provide a depiction of the system’s behavior and derive from these insights into the structural and dynamic features (Kurtz & Snowden, 2003). Examples are time series of GDPs, prices, demand, tourist arrivals, temperatures, water levels.

In all cases it is advisable to choose quantities that in some way consider endogenous elements and not only external features. For example, let us consider a tourism destination, the goal of a trip, as a system whose components (organizations, environmental resources, and people) are linked by different business (institutional, commercial, ownership) and personal relationships (family, friendship, trust) (Baggio, 2008). When dealing with such an ‘object’ the number of tourist arrivals, the nights they spend at destination or their expenditures are common quantities used for planning and forecasting purposes (Frechtling, 1996). Among these, the number of nights spent in a destination by tourists is an interesting candidate for investigating the general dynamics of the destination system (Barros & Machado, 2010). In fact, overnight stays, besides being obviously related to the demand side, are influenced by the perceived image of the destination and strongly related to tourists' expenditures (Sainaghi, 2012). Similarly when studying a socio-economic system, such as a whole country or an industrial sector, its overall production expressed by the GDP is an ideal aggregate measure.

3.1. Nonlinear analysis of time series

Clearly, no full comprehension of the laws governing the system can be attained by only examining a time series (Sprott, 2003), but the analysis can reveal a number of properties and allow inferring the type of dynamics that generates the observable behavior. as a consequence, such an analysis can, at least in principle, provide insights into the possibility to control the system and highlight the effects that small perturbations may have in changing its behavior (Sainaghi, 2006).

Many techniques have been proposed for this task, and a common feature is that most of the methods are *data hungry*, i.e. they give meaningful results only with relatively long-term series (typically more than some thousand values). Another sensitive issue regards the frequency with which data are collected. If it is too high, the number of values risks to overly increase the computational time needed, but if it is too low dynamic patterns may be lost.

Finally, we want to make sure to have values clearly representing the internal dynamics of the system under study. These values should be not excessively disturbed by mechanisms such as trend or seasonality that may disguise the properties we are looking for. Unless we are sure that these are important features of the system, trend and seasonality components may corrupt the outcomes of the measurements by adding too strong effects on the recording of the internal dynamics (Clegg, 2006).

In any case, experience will guide the researcher towards the best 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). As much literature shows, many of the techniques available have shown the capacity to provide interesting insights into the structural and dynamic patterns of complex and chaotic systems (Baggio, 2008; Baggio & Sainaghi, 2011; Schreiber, 1999; Small, 2005).

The rest of this section will describe some of the most used and important methods that can help identifying the dynamics of a system and therefore giving a better idea of its predictability. The items discussed are: stationarity, Hurst and Lyapunov exponents, and the visibility graph algorithms[1].

3.1.1. Series filtering

A preliminary step, when needed, to any analysis is the filtering of unwanted components, typically trend and seasonality that can, as said, confuse the visibility of important features. The time series analysis literature is quite vast on this topic, as it is the most common procedure for any analysis. Here we note that most of the known and used methods have 'linear' assumptions at the basis and do not seem quite appropriate here. A better idea is to use some method that filters the data without the need of exogenous hypotheses (such as, for example, the decision on the length of a season).

[1] All the methods described in this section can be exploited by using scripts available in many of the most known programming environments: Matlab, R, Stata, Python etc. A Google search will allow locating the scripts for the environment of interest.

The Hodrick-Prescott filter is one such possible choice (Hodrick & Prescott, 1997). It is a nonparametric, nonlinear algorithm that functions as a tunable bandpass filter. It aims at identifying a smooth long-term trend component without affecting too much the short term fluctuations. The algorithm is controlled by a parameter λ. In short, the series is split into a stationary and a nonstationary component (the trend) so as to minimize the squared deviations from the trend subject to a smoothness constraint weighted by λ. High values for λ lead to smoother long-term components ($\lambda = \infty$ produces a line, $\lambda = 0$ leaves intact the observed values). The literature provides a number of suggestions for optimally selecting λ (Baggio & Klobas, 2011; Ravn & Uhlig, 2002). Even if criticized, the filter is widely used in the economics literature and has received some attention in the tourism literature (Guizzardi & Mazzocchi, 2010).

3.1.2. Stationarity

The ability of a system to adapt its configuration to events or shocks of internal or external origins is an important feature of a complex system. This resilience (Holling, 1973), and the connected capacity to independently reorganize can be evaluated by examining the stationarity of the time series (Baggio, 2008; Olmedo & Mateos, 2015). That is: if the time series exhibit a substantial stationarity, at least in some time periods of reasonable length, it is possible to argue that the system is able to recover relatively well from the effects of external or internal shocks.

Standard procedures can be used to assess this characteristic (Box & Jenkins, 1976; Hamilton, 1994). However, one warning is in order. There may be sizeable changes in the trend or the level of the series exist, these structural breaks must be scrutinized to see whether they can affect, more or less heavily, the stationarity, or they have only small influence.

A number of different tests (with many variations) have been proposed in the econometric literature for this purpose, they test the presence of a so-called unit root which signals the non-stationarity of the series . The most frequently used are those due to Dickey and Fuller (Dickey & Fuller, 1979), both in the simple and the augmented version, to Phillips and Perron (Phillips & Perron, 1988), Zivot and Andrews (Zivot & Andrews, 1992), Kwiatkowski et al. (Kwiatkowski et al., 1992) or Lee and Strazicich (Lee & Strazicich, 2003). Along with the significance of the hypothesized stationarity, some of these tests can provide an estimate of the period where a major structural break (if present) occurs. The unit root tests, as happens for many other statistical tests, have different applicability, limitations and power. It is therefore advisable to run more than one test and compare their results in order to obtain a reliable outcome (Glynn et al., 2007; Metes, 2005).

3.1.3. Hurst exponent

Great sensitivity to the initial conditions, one of the features of complex and chaotic systems means long-term memory. This aspect can be assessed by adopting the approach originally proposed by Harold Edwin Hurst. Work as a hydrologist in Egypt Hurst studied the behavior of the River Nile's rain and drought conditions with the objective to optimally size a dam (Hurst, 1951). He found that when a long memory is present, the autocorrelation function p(k) of the time series (k is the lag) decays following a power law: $p(k) \sim k^{-\alpha}$. He was also able to use the exponent α to characterize the process generating the time series. We can define $H = 1-\alpha/2$ (called the Hurst exponent), whose values lie in the range $0<H<1$. For $H=0.5$, 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). Therefore, when H>0.5 the 'memory' of the system is long and we have a tendency to be chaotic. This allowed Mandelbrot (Mandelbrot & Hudson, 2004) to tie the Hurst exponent to the fractal dimension D of the series: H = 2 – D (for a univariate series), which is a statistical index of complexity that comparing how details in a pattern (a fractal pattern) change with the scale used for the measurements. Other authors have used Hurst exponent as a measure of complexity, with the indication that the lower its value, the higher the complexity of the system (Giuliani et al., 2001).

Different methods have been employed to calculate the Hurst exponent, all having their specificities, power and reliability in different conditions (Clegg, 2006; Mielniczuk & Wojdyłło, 2007). Here too, employing different methods and comparing the results is advisable.

3.1.4. Lyapunov stability

Aleksandr Mikhailovich Lyapunov (1892) proposed a method to assess the rate of convergence between two orbits when one of them had been subject to some kind of perturbation. This can be found by calculating a series of quantities, called Lyapunov exponents, that depend on the equations of the orbits and on the dimension of the space in which the system is embedded. The largest one (LCE: Lyapunov characteristic exponent) gives an important information: when LCE<0, orbits converge in time and the system is insensitive to initial conditions; when LCE>0, the distance grows exponentially in time. If we use this idea to assess the difference between the system's trajectory in the phase space and a stable attractor, we find a way to measure the sensitivity on initial conditions, and hence the complexity or the chaoticity of the system under study. A time series of observables can be used, as proposed by a number of authors, to perform this task (Rosenstein et al., 1993; Wolf, 1986; Wolf et al., 1985).

3.1.5. Visibility graph algorithms

As stated above, the methods of nonlinear analysis of time series require large sets of observations that, in usual cases, are not so common. One recent proposal allows, at least partially, to overcome this issue. The idea is to transform the time series into a different mathematical object: a network (graph). Then, when it is possible to show that the network structure inherits the most important characteristics of the series, we can use the powerful techniques of network analysis to assess the complexity of the system. There are different proposals for accomplishing this task, that satisfy the requirement stated (Campanharo et al., 2011; Strozzi et al., 2009; Yang & Yang, 2008). One relatively simple, conceptually and computationally series of methods, termed visibility graph algorithms, have been proposed by Lacasa (Lacasa et al., 2008) (Nuñez et al., 2012). The main features of a time series (periodicity, fractality or chaoticity) are captured by the algorithms and translated into different topologies of the associated network. One of the algorithms, the horizontal visibility graph is of particular interest. In fact, Lacasa and Toral (2010) derive analytically the shape of the degree distribution of the network obtained that allows distinguishing between a stochastic (correlated or uncorrelated) and a chaotic time series and specify the threshold value of the exponent of the distribution that separates systems having a chaotic behavior from those whose dynamics is a correlated stochastic process. Moreover, it can be shown that the size of the series used does not affect heavily the reliability of the outcomes, making it possible the use of relatively short series (some hundreds of points) that are common in many environments such as regional economies or tourism destinations (Baggio, 2013, 2014).

4. Complex systems and predictability

All the different methods described so far are classifiable as diagnostic methods. They provide the researcher with a way to assess, at least qualitatively, the degree of complexity of a system and to infer the possibility to predict its behavior. The higher the complexity, or even the chaoticity, the smaller the predictability window. Qualitatively, as it is extremely difficult, if not impossible, to give a 'measure of complexity', given the substantial disagreement among scientists on a formal definition of a complex system (Bar-Yam, 1997; Lewin, 1999; Wolfram, 2002). For a reasonably understandable assessment, the absence of absolute metrics compels to run (a number of) the tests described above and to compare their outcomes with some known chaotic or complex system. One such example is the one studied by Edward Lorenz (Lorenz, 1963), whose equations can be solved numerically to provide a time series representing his famous butterfly chaotic attractor.

The 'complexity' diagnosis is extremely important when dealing with social and economic systems, where the capability to forecast accurately is closely connected to the capacity to put in place adequate styles for their governance, and steer the system along an evolutionary path able to guarantee the achievement of the strategic objectives set. (Folke et al., 2005; Gharajedaghi, 2006; Kopel, 1997). When in presence of stable dynamics, traditional management styles can be successfully employed. However, when long-term planning is almost impossible, good outcomes may stem only from being part of a self-adapting process, and radical or incremental changes should be enforced only after careful consideration of their possible effects which can be guessed by building and evaluating different scenarios (Lindgren & Bandhold, 2003). Governing a complex system requires, in fact, an adaptive attitude, more than a rigid deterministic, authoritarian style. A an experimental path is needed, where exploring alternative possibilities, implementing one or more of them, monitoring the outcomes, testing the predictions and learning which one most effectively allows to meet the objectives is the strong suggestion coming from the studies in complexity science (Baggio et al., 2010; Folke et al., 2005; Holling, 1978; Voß & Bornemann, 2011).

4.1. Empirical applications: tourism system

Before closing this paper it may be worth mentioning some of the most interesting applications of the methods and the techniques discussed in this contribution. To do that, given the wide variety of environments in which they have been used, let us consider a single field of research: tourism.

The choice is justified by the fact that tourism is one of the most important economic activities in the world, whose revenue has become a very important resource and a key factor in the balance of payment for many countries and regions and is a major contributor to their economic growth. Tourism is an archetypal complex system sharing many of the characteristics previously mentioned.

It is difficult to measure and analyze since it is an 'industry' with no traditional production functions, no consistently measurable outputs and no common structure or organization across countries or even within the same country (OECD, 2000). Tourism activities traverse a number of traditional economic sectors and are generally not considered, as a whole, in national accounts. The tourism system has also a marked hierarchical and modular structure, with many ensembles of actors, typically, but not always necessarily, organized into geographically delimited settings.

A tourism destination, the unit of analysis for tourism studies, is a spatially localized system made of many different companies, associations, and organizations having mutual relationships that are typically dynamic and nonlinear (Framke, 2002; Michael, 2003) that renders the response of individual stakeholders to inputs from the external world or from within the destination largely unpredictable (Faulkner & Russell, 2001).

One important stream of research concerns the forecast of the demand side. This stream has recognized the complexity of tourism systems in several ways, typically by trying to combine different qualitative and quantitative methods for the formulation of realistic predictions or scenarios (Baggio & Antonioli Corigliano, 2008; Faulkner & Valerio, 1995; Michailidis & Chatzitheodoridis, 2006).

A more direct analysis of the nonlinear complex nature of tourism destinations has been the objective of a number of authors (Abraham et al., 2011; Baggio, 2008; Baggio & Sainaghi, 2011; Cole, 2009; Olmedo & Mateos, 2015; Sriboonchitta et al., 2011). By using one or more of the methods described above and by applying them to different cases they have been able to perform a diagnosis of the dynamics of the systems examined so as to highlight the different degrees of complexity and chaoticity present in the destinations studied or in some of their subsystems.

Finally, some initial attempts to use the visibility graph algorithms (Baggio, 2013, 2014) using the same data of other studies have confirmed both the previous conclusions and the easier and more effective possibilities that this method offers.

5. Concluding remarks: future developments

Forecasting is a difficult art, that can rely on an incredibly vast number of methods that have shown different levels of success. However, most of them have considered, so far, no more than a simplified view of the phenomena and the systems studied. The complexity, or even the chaotic characteristics, that make phenomena and systems so difficult to foresee, are almost disregarded in the normal practice, with the exception of some primarily qualitative reference to their importance and their effects on good and reliable predictions.

As shown in this paper, however, many techniques exist that take into account the nonlinearities responsible for these issues that can be used to arrive to a good diagnosis of the object of study and set reasonable limits for the effectiveness of those traditional methods (Boffetta et al., 2002; DelSole & Tippett, 2009a, 2009b; Galbraith & Tkacz, 2007).

From a certain point of view we might say that *complexity* may also depend on our knowledge and our capabilities to understand, and on the sophistication and accuracy of the methods we employ. Actually the refinement of these methods and the collection of a wider number of cases is the challenging task in which many researchers are heavily involved.

This effort begins to provide some interesting results. For example, a very recent strand of literature has started to examine a partial problem, that of predicting not the full behavior of a system but those extreme or critical events that may have a big impact on the smooth functioning of the system, or create dangerous critical unexpected transitions (Sornette & Ouillon, 2012; Taleb, 2007), above all in areas where this can be of high interest for obvious reasons. From these studies it seems that even if not fully predictable, it may be possible to detect some early warning signals for the increased probability of black swans (rare, unforeseen and extremely large events) and dragon kings (meaningful outliers), so that these symptoms can be helpfully diagnosed (Scheffer et al., 2009). Scholars have worked on stock markets and financial bubbles (Sornette, 2003), brain diseases

(Sornette & Osorio, 2010), tornados (Schielicke & Nevir, 2013), earthquakes or other catastrophic events (Sornette, 2002).

Although still with many uncertainties, forecasting is entering a new era and we should sincerely hope that this art transforms into a well-grounded *science*, since, as Galileo would have said (Letter to Orso d'Elci, Florence, 25 December 1617): *"this is a complete art, although just born, based on principles and means that are new, but noble and commendable, and needs to be embraced, cultivated and promoted, so that with exercise and time it will be possible to benefit from the fruits of which it has in itself the seeds and the roots."*

6. References

Abraham, B. J., Ricardo, T. P., Oswaldo, M. M., & Isaias, B. P. A. (2011). Fractal behavior of the sales restaurant in a great tourism hotel. *International Journal of Physical Sciences, 6*(10), 2422-2431.

Amaral, L. A. N., & Ottino, J. M. (2004). Complex networks - Augmenting the framework for the study of complex systems. *The European Physical Journal B, 38*, 147-162.

Andersen, J. V., & Sornette, D. (2005). A mechanism for pockets of predictability in complex adaptive systems. *Europhysics Letters, 70*(5), 697-703.

Aristotle. (IV century B.C.E.). *Metaphysics* (W. D. Ross, Trans.). Internet Classics Archive: http://classics.mit.edu/Aristotle/metaphysics.html.

Baggio, R. (2008). Symptoms of complexity in a tourism system. *Tourism Analysis, 13*(1), 1-20.

Baggio, R. (2013). Studying complex tourism systems: a novel approach based on networks derived from a time series. *Proceedings of the XIV April International Academic Conference on Economic and Social Development, Moscow, April 2-5*.

Baggio, R. (2014). Complex tourism systems: a visibility graph approach. *Kybernetes, 43*(3/4), 445-461.

Baggio, R., & Antonioli Corigliano, M. (2008). A practical forecasting method for a tourism organization. *Proceedings of the International Conference: Knowledge as Value Advantage of Tourism Destinations, Malaga, 29-31 October*.

Baggio, R., & Klobas, J. (2011). *Quantitative Methods in Tourism: A Handbook*. Bristol, UK: Channel View.

Baggio, R., & Sainaghi, R. (2011). Complex and chaotic tourism systems: towards a quantitative approach. *International Journal of Contemporary Hospitality Management, 23*(6), 840-861.

Baggio, R., Scott, N., & Cooper, C. (2010). Improving tourism destination governance: a complexity science approach. *Tourism Review, 65*(4), 51-60.

Bar-Yam, Y. (1997). *Dynamics of Complex Systems*. Reading, MA: Addison-Wesley.

Barros, C. P., & Machado, L. P. (2010). The length of stay in tourism. *Annals of Tourism Research, 37*(3), 692-706.

Boffetta, G., Cencini, M., Falcioni, M., & Vulpiani, A. (2002). Predictability: a way to characterize complexity. *Physics Reports*, 367-474.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis. Forecasting and control (revised edition)*. San Francisco: Holden-Day.

Campanharo, A. S. L. O., Sirer, M. I., Malmgren, R. D., Ramos, F. M., & Amaral, L. A. N. (2011). Duality between Time Series and Networks. *PLoS ONE, 6*(8), art. e23378.

Cicero, M. T. (44 B.C.E.). *De Divinatione* (W. E. Falconer, Trans.). Perseus Digital Library: http://www.perseus.tufts.edu/hopper/text?doc=urn:cts:latinLit:phi0474.phi053.perseus-lat2:1.1.

Clegg, R. G. (2006). A practical guide to measuring the Hurst parameter. *International Journal of Simulation, 7*(2), 3-14.

Cole, S. (2009). A Logistic Tourism Model: Resort Cycles, Globalization, and Chaos. *Annals of Tourism Research, 36*(4), 689-714.

DelSole, T., & Tippett, M. K. (2009a). Average predictability time. part I: Theory. *Journal of the Atmospheric Sciences, 66*(5), 1172-1187.

DelSole, T., & Tippett, M. K. (2009b). Average predictability time. Part II: Seamless diagnoses of predictability on multiple time scales. *Journal of the Atmospheric Sciences, 66*(5), 1188-1204.

Descartes, R. (1637). *Discours de la méthode pour bien conduire sa raison, et chercher la verité dans les sciences*. Leiden: De l'imprimerie de Ian Maire.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association, 74*, 427-431.

Faulkner, B., & Russell, R. (2001). Turbulence, chaos and complexity in tourism systems: a research direction for the new millennium. In B. Faulkner, G. Moscardo & E. Laws (Eds.), *Tourism in the 21st century: lessons from experience* (pp. 328-349). London: Continuum.

Faulkner, B., & Valerio, P. (1995). An integrative approach to tourism demand forecasting. *Tourism Management, 16*(1), 29-37.

Folke, C., Hahn, T., Olsson, P., & Norberg, J. (2005). Adaptive governance of social-ecological systems. *Annual Review of Environment and Resources, 30*, 441-473.

Framke, W. (2002). The Destination as a Concept: A Discussion of the Business-related Perspective versus the Socio-cultural Approach in Tourism Theory. *Scandinavian Journal of Hospitality and Tourism, 2*(2), 92-108.

Frechtling, D. C. (1996). *Practical Tourism Forecasting*. Oxford: Butterworth-Heinemann.

Galbraith, J. W., & Tkacz, G. (2007). Forecast content and content horizons for some important macroeconomic time series. *Canadian Journal of Economics, 40*(3), 935-953.

Gharajedaghi, J. (2006). *Systems Thinking: Managing Chaos and Complexity - A Platform for Designing Business Architecture* (2nd ed.). Amsterdam: Elsevier.

Gibbs, J. W. (1902). *Elementary Principles in Statistical Mechanics*. New York: Scribner.

Giuliani, A., Colafranceschi, M., Webber, C. L. J., & Zbilut, J. P. (2001). A complexity score derived from principal components analysis of nonlinear order measures. *Physica A 301*, 567-588.

Glynn, J., Perera, N., & Verma, R. (2007). Unit root tests and structural breaks: a survey with applications. *Journal of Quantitative Methods for Economics and Business Administration, 3*(1), 63-79.

Guizzardi, A., & Mazzocchi, M. (2010). Tourism demand for Italy and the business cycle. *Tourism Management, 31*(3), 367-377.

Hamilton, J. D. (1994). *Time series analysis*. Princeton: Princeton University Press.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking, 29*(1), 1-16.

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics, 4*, 1-23.

Holling, C. S. (Ed.). (1978). *Adaptive Environmental Assessment and Management*. New York: John Wiley and Sons.

Hurst, H. E. (1951). Long-term storage of reservoirs: an experimental study. *Transactions of the American Society of Civil Engineers, 116*, 770-799.

Klein, J. L. (1997). *Statistical visions in time: a history of time series analysis, 1662-1938*. Cambridge: Cambridge University Press.

Kopel, M. (1997). Improving the performance of an economic system: Controlling chaos. *Journal of Evolutionary Economics, 7*, 269-289.

Kurtz, C. F., & Snowden, D. J. (2003). The new dynamics of strategy: Sense-making in a complex and complicated world. *IBM Systems Journal, 42*(3), 462-483.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54*, 159-178.

Lacasa, L., Luque, B., Ballesteros, F., Luque, J., & Nuño, J. C. (2008). From time series to complex networks: the visibility graph. *Proceedings of the National Academy of Sciences of the United States of America, 105*(13), 4972-4975.

Lacasa, L., & Toral, R. (2010). Description of stochastic and chaotic series using visibility graphs. *Physical Review E, 82*, art. 036120.

Lansing, J. S. (2003). Complex Adaptive Systems. *Annual Review of Anthropology, 32*, 183-204.

Laplace, P. S. (1814). *Essai philosophique sur les probabilités*. Paris: Courcier.

Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks. *The Review of Economics and Statistics, 85*(4), 1082-1089.

Lewin, R. (1999). *Complexity, life on the edge of chaos* (2nd ed.). Chicago The University of Chicago Press.

Lindgren, M., & Bandhold, H. (2003). *Scenario planning: the link between future and strategy*. New York: Palgrave McMillan.

Linstone, H. A. (1999). Complexity Science: Implications for Forecasting. *Technological Forecasting and Social Change, 62*, 79-90.

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of Atmospheric Sciences, 20*, 130-141.

Lyapunov, A. M. (1892). *General problem on motion stability*. Kharkov: Kharkovskoye Matematicheskoe Obshchestvo, vol. 11 [in Russian].

Mandelbrot, B., & Hudson, R. L. (2004). *The (Mis)Behavior of Markets, A Fractal View of Risk, Ruin and Reward*. New York: Basic Books.

Maslow, A. (1970). *Motivation and personality* (2nd ed.). New York: Harper & Row.

McHale, J. (1969). *The Future of the Future: Where the New Technology Is Taking Us and What We Can Do About*. New York: G. Braziller.

Metes, D. V. (2005). *Visual, Unit Root and Stationarity Tests and Their Power and Accuracy*. Summer NSERC student report. Retrieved December, 2009, from http://www.stat.ualberta.ca/~wiens/pubs/metes.pdf.

Michael, E. J. (2003). Tourism micro-clusters. *Tourism Economics, 9*(2), 133-145.

Michailidis, A., & Chatzitheodoridis, F. (2006). Scenarios Analysis of Tourism Destinations. *Journal of Social Sciences, 2*(2), 41-47.

Mielniczuk, J., & Wojdyłło, P. (2007). Estimation of Hurst exponent revisited. *Computational Statistics & Data Analysis, 51*, 4510-4525.

Mills, T. C. (2011). *The Foundations of Modern Time Series Analysis*. Basingstoke, UK: Palgrave Macmillan.

Newton, I. (1687). *Philosophiae naturalis principia mathematica*. London: jussi Societatus Regiae ac typis Josephi Streater.

Nuñez, A. M., Lacasa, L., Gomez, J. P., & Luque, B. (2012). Visibility Algorithms: A Short Review. In Y. Zhang (Ed.), *New Frontiers in Graph Theory* (pp. 119-152). Rijeka, Croatia: InTech.

OECD. (2000). *Measuring the role of tourism in OECD economies*. Paris: OECD.

Olmedo, E., & Mateos, R. (2015). Quantitative characterization of chaordic tourist destination. *Tourism Management, 47*, 115-126.

Phillips, P. C. B., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika, 75*, 335-346.

Poincaré, H. (1883). Sur certaines solutions particulières du problème des trois corps. *Comptes Rendus de l'Académie des Sciences, Paris, 97*(251-252).

Procaccia, I. (1988). Complex or just complicated? *Nature 333*, 498-499.

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics, 84*(1), 371-380.

Rosenstein, M. T., Collins, J. J., & De Luca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D, 65*, 117-134.

Sainaghi, R. (2006). From contents to processes: Versus a dynamic destination management model (DDMM). *Tourism Management, 27*(5), 1053-1063.

Sainaghi, R. (2012). Tourist expenditures: the state of the art. *Anatolia, 23*(2), 217-233.

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., Held, H., van Nes, E. H., Rietkerk, M., & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature, 461*(7260), 53-59.

Schielicke, L., & Nevir, P. (2013). Comprehensive analysis of tornado statistics in comparison to earthquakes: intensity and temporal behaviour. *Nonlinear Processes in Geophysics, 20*(1), 47-57.

Schreiber, T. (1999). Interdisciplinary application of nonlinear time series methods. *Physics Reports, 308*, 1-64.

Small, M. (2005). *Applied nonlinear time series analysis: applications in physics, physiology and finance*. Singapore: World Scientific.

Solomon, S., & Shir, B. (2003). Complexity; a science at 30. *Europhysics News, 34*(2), 54-57.

Sornette, D. (2002). Predictability of catastrophic events: Material rupture, earthquakes, turbulence, financial crashes, and human birth. *Proceedings of the National Academy of Sciences of the United States of America, 99(suppl 1)*, 2522-2529.

Sornette, D. (2003). *Why Stock Markets Crash*. Princeton: Princeton University Press.

Sornette, D., & Osorio, I. (2010). Prediction. In I. Osorio, M. G. Frei, H. Zaveri & S. Arthurs (Eds.), *Epilepsy: The Intersection of Neurosciences, Biology, Mathematics, Engineering, and Physics* (pp. 203-237). Boca Raton, FL: CRC Press.

Sornette, D., & Ouillon, G. (2012). Dragon-kings: mechanisms, statistical methods and empirical evidence. *The European Physical Journal-Special Topics, 205*(1), 1-26.

Sprott, J. C. (2003). *Chaos and Time-Series Analysis*. Oxford: Oxford University Press.

Sriboonchitta, S., Chaitip, P., Balogh, P., Kovacs, S., & Chaiboonsri, C. (2011). On Tests for Long Memory Process Behavior of International Tourism Market: Thailand and India. , 5, . *APSTRACT: Applied Studies in Agribusiness and Commerce, 5*(3-4), 90-100.

Strozzi, F., Zaldívar, J. M., Poljansek, K., Bono, F., & Gutiérrez, E. (2009). *From complex networks to time series analysis and viceversa: Application to metabolic networks* (European Commission Joint Research Centre Scientific Technical Report EUR 23947, JRC 52892). Luxembourg: Office for Official Publications of the European Communities. Retrieved July, 2012, from http://publications.jrc.ec.europa.eu/repository/handle/111111111/1018.

Taleb, N. N. (2007). *The Black Swan: The Impact of the Highly Improbable*. New York, NY: Random House.

von Bertalanffy, L. (1968). *General System Theory: Foundations, Development, Applications*. New York: George Braziller.

Voß, J. P., & Bornemann, B. (2011). The politics of reflexive governance: challenges for designing adaptive management and transition management. *Ecology and Society, 16*(2), art.9.

Waldrop, M. (1992). *Complexity: The Emerging Science and the Edge of Order and Chaos*. London: Simon and Schuster.

Wolf, A. (1986). Quantifying chaos with Lyapunov exponents. In A. V. Holden (Ed.), *Chaos* (pp. 273-290). Princeton: Princeton University Press.

Wolf, A., Swift, J. B., Swinney, H. L., & Vastano, J. A. (1985). Determining Lyapunov exponents from a time series. *Physica D, 16*, 285-317.

Wolfram, S. (2002). *A New Kind of Science*. Champaign, IL: Wolfram Media.

Yang, Y., & Yang, H. J. (2008). Complex network-based time series analysis. *Physica A, 387*(5-6), 1381-1386.

Yule, G. U. (1921). On the time-correlation problem, with especial reference to the variate-difference correlation method. *Journal of the Royal Statistical Society, 84*(4), 497-537.

Yule, G. U. (1927). On the method of investigating periodicities in disturbed series, with special reference to Wölfer's sunspot numbers. *Philosophical Transactions of the Royal Society of London, Series A, 226*, 267-298.

Zivot, E., & Andrews, D. W. K. (1992). Further Evidence on the Great Crash, the Oil-Price Shock and the Unit-Root Hypothesis. *Journal of Business and Economic Statistics, 10*(3), 251-270.