COMPLEX TOURISM SYSTEMS: A QUANTITATIVE APPROACH

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Summary

A growing number of researchers concur that tourism destinations are complex dynamic systems; knowing their structural and dynamic characteristics is certainly needed to reach an effective governance that in turn can allow to obtain sustainable growth and destination competitiveness. Different methods rooted in the complexity science and, broadly, in the idea that a systemic holistic view is more suitable than traditional reductionist approaches, can be used to develop such a knowledge thus allowing tourism studies to benefit from a more appropriate approach. The aim of this chapter is to briefly present and discuss the most common and used techniques (namely: agent-based modeling, non-linear analysis of time series and network analysis), their main aims and tools. Further, it aims at providing information on the requirements that these techniques in terms of data collection and software applications. In doing this, examples from recent literature are described, and implications for a 'good governance' practice are suggested. Finally, the main conclusion from these studies are mentioned and a number of suggestions for future research are provided.

Keywords

Complexity science, tourism destination governance, agent-based modeling, nonlinear time series analysis, network analysis

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2.1 INTRODUCTION

Tourism systems, and tourism destinations in particular, can be defined in many ways and using different approaches (Pearce, 2014); however, it is widely recognized that they can be considered as being complex dynamic systems composed of different entities (companies, associations, etc.) and resources interacting in nontrivial and complicated ways for satisfying needs and wishes of its *users* (Baggio, Scott & Cooper, 2010b).

From a management point of view, tourism destinations may be considered as being strategic business units (Bieger, 1998), thus representing the main unit of analysis (Framke, 2002) and the main target for the implementation of tourism policies (Pearce, 2014). The analysis of structural and dynamic characteristics of tourism destinations enables to understand broad issues which affect tourism and to better take into account the relationships between its different components (Page & Connell, 2006).

Destinations are essentially socioeconomic networks, comprising an ensemble of dynamically interacting stakeholders, jointly producing the experience for the travelers to consume (Baggio et al. 2010b; Del Chiappa & Presenza, 2013); therefore, the harmonization and coordination of these stakeholders is a fundamental element for their governance (Bregoli & Del Chiappa, 2013). The effectiveness of governance highly impacts on the development of tourism destinations (Moscardo, 2011), and ensures a balanced and continuing sustainable growth, and is fundamental for the destination competitiveness.

Managing and governing a complex system is notoriously a daunting task that requires a sound knowledge of the structural and dynamic characteristics of the system. This knowledge can be obtained by using a number of different methods based on the idea that a systemic holistic view is more suitable than traditional reductionist approaches; this perspective is rooted in the research tradition of what is today known as *complexity science*.

Many proposals have been put forward for the investigation of complex systems and some have been successfully applied to tourism destinations. The objective of this chapter is to briefly present and discuss the most common and used techniques (agent-based modeling, nonlinear analysis of time series and network analysis). In doing this, examples from recent literature will be provided, and implications for a “good governance” practice will be suggested.

2.2 COMPLEX TOURISM SYSTEMS

A complex system is an entity composed of a set of elements interacting with each other and with the external environment in dynamic nonlinear ways. The most common and universally recognized characteristics of complex systems are as follows (Brodu, 2009):

- the number (and types) of elements and the number of relationships between them are nontrivial (i.e., not too small but not necessarily huge);
- the relationships between the different parts of the system and with its environment are nonlinear;
- the system has a memory or includes feedback and adapts itself by changing its configuration according to its history or feedback;
- the system can be influenced by, or can adapt itself to, its environment (the system is open) in unexpected and nontrivial ways; and
- the system is highly sensitive to initial conditions.

The system evolves continuously redefining its configuration and functions; it may exhibit an intricate mix of ordered and disordered behaviors and show emergent phenomena which are generally surprising and, at times, extreme. Depending on certain conditions the system may also exhibit a chaotic behavior (Bertuglia & Vaio, 2005).

The analysis of complex systems needs different approaches from those traditionally used. When a system is sufficiently simple, it can be analyzed by decomposing it; its parts are examined individually and the outcomes are recomposed in order to derive the characteristics of the whole. The same method (known as reductionist) can be theoretically adopted even when a huge number of elements are present provided the relationships are linear. However, when a system is complex, or in time frames in which the system undergoes abrupt and critical transitions, a reductionist approach is unable to give meaningful results (Baggio, 2013). As a consequence, we do not have a definite 'metric' able to measure the phenomena we want to study. It is possible, however, to understand the properties of collective phenomena because in most situations they do not depend on the exact microscopic details of the processes involved. Rather, for many questions it is sufficient to consider only the most important features of single elements, and sometimes only higher level features such as symmetries, dimensionality, or conservation laws play a relevant role for the global behavior. In order to generate quantitative statements, and to relate the statistical laws to the microscopic properties of the system, these models need to be calibrated with empirical data measured from real systems (Castellano, Fortunato & Loreto, 2009).

We study a system, a tourism destination in our case, because we want to predict its behavior in the future and assess the possibility to intervene in some way in order to drive the system toward a certain configuration (or state). As complex system, a tourism destination would need a high number of variables for its description; in technical words, the system is embedded in a high-dimensional space (the many variables) called phase space. One point in this space represents a certain configuration of the system. If the system evolves, all the different points form a path which represents the dynamical evolution of the system. In its evolution, a system can assume several different configurations, often identified by the values of some parameter (order parameter) that differentiate its behavior. One or more of the variables can be modified (endogenously or exogenously) and the system's reaction may be more or less strongly affected by these modifications. In a complex or chaotic system these changes may result in the system undergoing some kind of abrupt transformation, shown as jumps or discontinuities in the phase space paths. These critical phase transitions are the points where no full knowledge or predictability of the system is possible (Baggio, 2008).

In its dynamic evolution the system may go from a completely ordered and stable phase to one in which the dynamic behavior is so heavily dependent on small variations of the initial conditions that, although deterministically shaped, appears completely irregular: the chaotic phase. The region at the boundary of these phases, known as the *edge of chaos*, is a region of complexity (e.g., Waldrop, 1992). In this region, small variations in the conditions can lead to unpredictable and unrepeatable outcomes. New properties or structures can emerge and it is difficult to determine accurately how a manager can act or to what extent there is a possibility to effectively steer the system. Yet, this is an important phase: one that ensures adequate dynamicity for allowing the growth of the system or for giving it sufficient robustness to resist shocks.

As a living organism, a complex system, a tourism destination in our case, is always a dynamic entity; it reaches a stable static equilibrium only when it is dead (e.g., Ulgiati & Bianciardi, 1997). Predictability and tractability of the system depend on what type of evolution occurs in the time frame considered and on the time scale, or spatial scale, used for the investigation. Ideally we may want to project it on a lower dimensional space with fewer variables. Several techniques exist that allow this projection, but, obviously, the lower the space dimension, the higher the information lost. Whether this is acceptable or not will depend on whether the approximation made is still able to provide a meaningful description of the system (Sornette, 2008). Many diverse methods have been proposed for the analysis of a complex system and the toolbox of the complexity scientist is today quite crowded. Many of them originate from the work of 19th century scientists, but, since they rely on quite extensive calculations, only modern computational facilities have made it possible to use them in practical contexts.

As can be easily guessed, a complex system such as a tourism destination is difficult to be managed and governed. Due to its strong self-organization capabilities, a rigid deterministic, authoritarian style can be ineffective or even disruptive for the system. When direct and linear cause and effect relationships lose full validity, long-term planning is almost impossible. There may be a need for strong rules or policies, but given the inherent unpredictability (or low predictability) the most important element is to develop the capability to change them dynamically, to react in short times to all the changes that may occur in the system and in the external environment, to monitor the effects generated by the decisions made and use these to re-orient the future actions (Farrell & Twining-Ward, 2004). Further, when a tourism destination is considered, it is possible to adopt the idea that systems do not only adapt to their environments, but help creating them (Stacey, 1996).

Despite these difficulties, it is still possible to manage and understand complex systems, at least at some level. Large-scale behaviors might still be foreseeable if it is possible to describe the overall dynamics of the system including the presence of any preferred evolutionary paths. Once these have been identified, it can be possible to determine whether changes in some specific parameter can produce sudden shifts in behavior, or at least establish a probability distribution for their occurrence (Hansell, Craine & Byers, 1997). Short-term predictions allow identification of the main evolutionary paths and small corrections to the system behavior that may be effective in avoiding undesired regimes.

2.3 THE STUDY OF COMPLEX SYSTEMS: A METHODOLOGICAL OVERVIEW

According to Amaral and Ottino (2004), we can group the approaches for studying a complex system in three main classes: statistical physics, nonlinear dynamics, and network theory.

2.3.1 Statistical Physics

Statistical physics is one of the fundamental fields of physics, and employs statistical methods for addressing physical problems that concern systems with a large number of components. It provides a rigorous framework for relating the microscopic properties of individual "particles" to the macroscopic ones of objects and system observed in everyday life. Statistical physics is the strong theoretical framework that *justifies* all the methods discussed here for the study of a complex system. Specifically, one important outcome is the possibility to use discrete models such as individual–based models and agent-based models (ABMs) (e.g., Baggio, 2011a). The fundamental assumption is that a phenomenon can be modeled numerically in terms of some appropriate algorithm, usually implemented as a computer program, rather than with analytical expressions.

2.3.2 Nonlinear Dynamics

The main feature of complex systems is the nonlinearity of the interactions among the components. The equations describing its behavior can be solved only in very rare cases. Poincaré's (1883) work on the impossibility to fully describe analytically a gravitational system containing more than three bodies is considered the starting point of a study tradition in nonlinear dynamics. Since then, a number of mathematical techniques have been developed to approximate the solutions of the differential equations used to describe such systems. However, only the availability of modern powerful computers has made it possible to find solutions since, in almost all cases, they are obtained by numerical approximations. Much of the mathematics of chaos theory, for example, involves the repeated iteration of simple formulas, which would be impractical to do otherwise (e.g., Gharajedaghi, 2006).

2.3.3 Network Science

A complex system can be described as a network of interacting elements. Understanding the structure and the dynamics of the relationships and the interactions among the elements in a complex system is a key step to comprehend its structure and dynamic behavior. The collective properties of dynamic systems composed of a large number of interconnected parts are strongly influenced by the topology of the connecting network.

A network is made of nodes or vertices, which can be used to represent the system's elements, and links or edges, which usually correspond to the interactions or relationships between the elements. In this context, networks represent the structure of complex systems, but a network can also be used to represent the dynamics or the functions of a complex system (e.g., when interpreting nodes as states and links as transitions). Thus, a network analysis can be applied to the structure and the function of a complex entity. Understanding the relationship between structure and function is one of the major open questions in any discipline, which can, often, be examined by looking at how changes in the structure (topology) of a network affects its state (Baggio et al. 2010b; Baggio, Scott & Cooper, 2013; da Fontoura et al., 2011; Dominici & Levanti, 2011; Newman, 2010).

2.4 MAIN ISSUES IN THE APPLICATION OF COMPLEXITY SCIENCE

Two issues are relevant when approaching the study of a complex system. The first concerns the choice of methods to be used, the second regards the collection of the data needed for the analysis.
As far as the first issue is concerned, it should be noted that when studying complex system the traditional dichotomy between qualitative and quantitative methods, each with its own advantages and disadvantages (e.g., Veal, 2006), is meaningless and can even be dangerous. No matter how sophisticated and effective the techniques used can be; they have little value when applied to a complex system without coupling them with sound physical interpretations. Adopting the language

of social science, this means that a thorough knowledge of the object of analysis is crucial to obtain meaningful outcomes from both a theoretical and a practical point of view. A pure qualitative investigation risks missing or misinterpreting important factors, because the quantitative analysis often provides rather unexpected outcomes. This is even more relevant when employing numerical simulation techniques. If correctly used, simulations are a powerful tool, but the basic assumptions must represent as faithfully as possible the reality and a good comprehension of what will be simulated is crucial.

A reliable model, especially when dealing with a complex system, needs continuous interactions between researchers and empirical issues (Silvert, 2001). For those interested or involved in managing a destination, the combination of both traditional qualitative evaluations and quantitative measurements can give more strength to the decisions made and better inform the actions and policies needed (e.g., Baggio et al. 2010a; Pearce, 2014). Finally, a good integration of quantitative and qualitative methods can help in a substantial way in finding different, new and more effective ways to better understand systems and phenomena under study (Gummesson, 2007; Olsen, 2004).
The second issue faced when analyzing complex systems is related to the quality and the quantity of data needed. Obviously, data quality is important, as ignoring even small variations can hide effects that may develop rapidly to important consequences, and approximate evaluations risk inhibiting a full recognition of the nonlinear effects that characterize complex dynamic systems (Batini & Scannapieco, 2006). More than that, however, the quantity of observations can be a crucial issue. Indeed, as it will be better explained in the next sections, some techniques (e.g., those using time series) are ‘data hungry’. They ask for a large number of data points, typically not widely available in the tourism arena (e.g., Baggio & Sainaghi, 2011). Other methods (e.g., network analysis) call for a possibly complete set of data, representing fully the system examined. As a matter of fact, due to the strong nonlinearity and non-normality of the quantities involved, traditional sampling methods are mostly meaningless and the likelihood to overlook or disregard important factors is quite high (e.g., Kossinets, 2006).

2.5 THE ANALYSIS OF COMPLEX TOURISM SYSTEMS

This section is dedicated to the main methods used for analyzing and assessing complex or chaotic characteristics in a tourism system.

2.5.1 Nonlinear Analysis of Time Series

The object of study in nonlinear dynamics is a time series that contains a certain number of quantities related to some behavior of the system under investigation. In tourism studies, logging of arrivals, overnight stays, or other similar quantities are usually used for depicting the history of a destination, predicting its future development, and interpreting its evolution (e.g., Butler, 1980).
Here, a time series is seen as the representation of the system’s behavior and is used to assess a number of traits about the nature and the extent of the complexity or chaoticity of the system.
Most of the methods give reliable and meaningful results only with relatively *long* series (typically more than some thousand values); unfortunately datasets of this size are not very common in tourism studies. The frequency with which data are collected is another relevant aspect; if it is too low, an interesting dynamic pattern may be lost, while if it is too high, the number of values risks

increasing the computational time needed without need. Only the experience will guide researchers and practitioners toward the “ideal” solution; “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, p. 211). Despite this, an accurate use of the techniques available has shown to provide a wealth of interesting insights into the structural and dynamic patterns of complex and chaotic systems (e.g., Baggio & Sainaghi, 2011).

When dealing with a time series, trend and seasonality components may corrupt the outcomes of the measurements by adding strong effects to the recording of system’s internal dynamics (e.g., Clegg, 2006); in order to remove these effects the series needs to be filtered. However, many classical techniques make some type of “linear” assumptions, which may be not fully appropriate in the case of a complex system, it is better to use some method which uses directly the data without any “external” intervention (such as defining the length of a season). An example of this method is the Hodrick–Prescott filter (Hodrick & Prescott, 1997), a nonparametric, nonlinear algorithm which acts as a tunable bandpass filter controlled by a parameter λ. The effect is the identification of long-term trend components without affecting too much short-term fluctuations. High values for λ give a smooth 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 values: 14,400, 260,100, and 6250,000 for monthly, weekly, and daily data, respectively (e.g., Baggio & Klobas, 2011). Once filtered, the series can be examined to assess whether it originates from a linear or a nonlinear or chaotic process. A common procedure is the Brock, Dechert, and Scheinkman (BDS) test that checks whether a given signal is deterministic (chaotic) or stochastic (Brock, Dechert, Scheinkman & LeBaron, 1996).

A chaotic system is characterized by a great sensitivity to initial conditions; in other words, it has a long memory. This attribute can be assessed by adopting a method due to Harold Edwin Hurst (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 ranges between 0 and 1. If $H = 0.5$, the time series is similar to a random walk; when $H < 0.5$, the time series is antipersistent (i.e., if values increase, it is more probable that they 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 (e.g., Clegg, 2006). The Hurst exponent can also been used as a measure of complexity: the lower its value, the higher the complexity of the system (Giuliani, Colafranceschi, Webber, & Zbilut, 2001).

An attractor in the phase space is, as sketched above, a trajectory of stability for a complex system. The tendency of a system to follow one of these paths can clearly provide interesting information about its dynamics, 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 way 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 [Lyapunov characteristic exponent (LCE)] gives the most important information on the system's motion. 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. In the case of a real system, for which we have a time series representing it, it is possible to calculate LCE by using some numerical methods (e.g., Wolf, Swift, Swinney & Vastano, 1985). When using these methods, it is important to have a null model in order to help the interpretation of the results (here we do not have a clear hypothesis to test via a *p*-value). In chaos theory, one well-known system of such kind is the one described by Lorenz (1963). A series obtained from some solution of his equations is a good null model; since the Lorenz equations are in the three-dimensional space one of the components needs to be used.

As said, all these methods are used by means of a computer application. A useful list of programs is the following:

- 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
- 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

All the outcomes of the analyses described here need a sound qualitative interpretation in order to provide useful insights. These methods, although not frequently used in tourism studies, have anyway provided some interesting results from both a theoretical and a practical point of view. Basically, they assess the extent to which a destination system (or even a single stakeholder) is dynamically stable, thus allowing a better choice of the actions that could be adopted without contrasting with the self-organization tendencies of the system. In turn, this guarantees a higher probability to be effective (e.g., Baggio & Sainaghi, 2011).

2.5.2 Agent-Based Modeling

ABMs are useful tools for the simulation of a complex system. Applications exist in many fields of physical, chemical, biological, and social sciences; propagation of fire, predator–prey models diffusion of diseases, demographic phenomena or the evolution of natural, and artificial organizations can be represented with ABMs (e.g., Baggio & Baggio, 2013).

In ABMs, agents are programmed in order to obey predetermined rules, reacting to certain environmental conditions, interact between themselves, and be able to learn and adapt (Gilbert &

Terna, 2000). The interactions are asynchronous and the global behavior emerges as a cumulative result of these local interactions. A researcher using computer simulated ABMs to represent real systems uses a model-building process that can be outlined as follows (Galán et al. 2009):

- conceptualize the system defining the research question and identifying the crucial variables along with their interrelations;
- find a set of formal specifications that is able to fully characterize the conceptual model;
- code and implement by using an appropriate development environment.

The resulting model is iterative, every agent receives input from the environment, processes it, and acts generating a new environmental input until a pre-determined condition is met (e.g., time limit, all agents in a given condition, etc.).

For the development of ABMs, a number of software applications exist that use relatively simple scripting languages and provide all the facilities needed to run the model and to record the outcomes; NetLogo (ccl.northwestern.edu/netlogo) is one of these. However, an ABM can be implemented with any programming language.
Validating, verifying, and evaluating ABMs is a crucial task, since simulation behaviors are difficult to grasp at first. For this purpose, several criteria have been proposed. The first one is an assessment of its reliability by allowing for different separate implementations and a subsequent comparison of the results. Taber and Timpone (1996) propose three steps for the validation of a numerical simulation model that can be rendered as answers to the following questions:

- Do the results of a simulation correspond to those of the real world (when data are available)?
- Does the process by which agents and the environment interact correspond to the one that happens in the real world (when they are known)?
- Is the model coded correctly so that it is possible to state that the outcomes are a result solely of the model assumptions (i.e., is the computer program free from evident errors)?

In the tourism field, AMBs have been used for different purposes. On one hand, they have been implemented for studying certain processes or examining certain phenomena such as the analysis of the effects of asymmetric information digital market on buyers and sellers' satisfaction and earnings is an example (Baggio & Baggio, 2013). On the other hand, ABM systems have been created to analyze and predict tourism related phenomena in tourism destinations (e.g., Baggio, 2011a; Johnson & Sieber, 2010).

2.5.3 Network Analysis

Tourism destinations can be considered as socioeconomic networks, with groups of interacting players that are related one to another. Literature has provided an extensive set of mathematical tools for analyzing networks and the graphs they represent. Realizing that a social or economic group can be represented by detailing the stakeholders of the group and their mutual relationships, sociologists have used some of these methods to explore their patterns of relations (Freeman, 2004).

Today, the network science toolbox can rely on several metrics (e.g., da Fontoura Costa et al. 2007; Newman, 2010) obtained by combining those coming from the social network analysis tradition with those developed in more recent mathematical studies. The main measurements that can be used to fully characterize topology and behaviors of a complex network are as follows:

- *degree*: the number of links each node has, and degree distribution, the statistical distribution of links and *degree distribution:* the statistical distribution of the number (and sometimes the type) of the linkages among the network elements;
- *assortativity*: the correlation between the degrees of neighbor nodes;
- *average path length*: the mean distance (number of links) between any two nodes and *diameter*, the maximal shortest path connecting any two nodes;
- *closeness*: the mean weighted distance (i.e., the shortest path) between a node and all other nodes reachable from it;
- *betweenness*: the extent to which a node falls between others on the shortest paths connecting them;
- *clustering coefficient*: the concentration of connections of a node's neighbors: it provides a measure of the heterogeneity of the local density of links;
- *eigenvector*: calculated by using the matrix representation of a network and its principal eigenvector, and based on the idea that a relationship to a more interconnected node contributes to the own centrality to a greater extent than a relationship to a less well interconnected node. One variation of this measure is the well-known *PageRank*;
- *efficiency* (at a local or global level): which can be interpreted as a measure of the capability of the system to exchange information over the network;
- *modularity*: the quality of a partition of the network into modules or communities. High values of modularity are found when the connections between the nodes within modules are denser than those between nodes belonging to different modules (Fortunato, 2010).

At a local (nodal) level the metrics described assume, often, the meaning of importance attributed to the single actors (they are also called centrality measures). Actors can be important if they have many connections (friends) or can quickly reach all other actors in the network (closeness) or are a bridge or information broker between different parts of the network (betweenness), or because their local neighborhoods are well connected (clustering coefficient). Moreover the actor's importance can be greater if the connections are set, even indirectly, toward the other most important elements of the network (eigenvector, PageRank). Several software programs allow calculating the main metrics. Some of them (such as NodeXL, Pajek, Gephi, Ucinet, etc.) can be used for general purposes, while some others have been developed for specific tasks, or are libraries to be used by some programming language (e.g., Matlab, R, or Python).

Network analyses in tourism have highlighted a series of interesting outcomes. The first application concerns the topological characterization and the identification of the structural peculiarities of a tourism destination (Baggio et al. 2010b; Bendle & Patterson, 2008; Del Chiappa & Presenza, 2013; Grama & Baggio, 2014; Presenza & Cipollina, 2010; Scott, Cooper & Baggio, 2008). An effective assessment of the characteristics of the network would require to adopt this structural perspective with the relational one so that how the inter-organizational relationships influence the way different nodes can interact and collaborate with each other can be analyzed as well (Del Chiappa &Presenza,

2013). These empirical studies unveiled complex structures with power-law degree distributions, very low density of connections, low clusterization, and negative degree–degree correlations (i.e., highly connected nodes tend to link low-degree elements). These latter features have been interpreted as symptom of the well-known tendency of tourism stakeholders to avoid forms of collaboration or cooperation. The related metrics (clustering and assortativity coefficients) have thus been proposed as quantitative measurements for these characteristics (Baggio, 2007; da Fontoura Costa & Baggio, 2009). This is an important result, because the identification of strategic weaknesses in the cohesiveness of the destination can be addressed by policy and management approaches (Erkuş-Őztürk & Eraydın, 2010).

A modularity analysis has uncovered that some form of aggregations exist in a destination, even if not very well defined or highly significant. However, this community structure goes beyond preset differentiations (by geography or type) of the agents. In other words, companies of the same type (e.g., hotels), or in the same geographical area, tend to connect with some other company which runs a different business or are located in different localities (Baggio, 2011b).

Network analysis methods have been applied also to the virtual network of the websites belonging to destination's stakeholders, with results that are similar to those obtained by studying the real destination network (Baggio, 2006, 2007; Baggio, Scott & Wang, 2007; Piazzi, Baggio, Neidhardt, & Werthner, 2012). This has allowed to gauge the level of utilization of advanced communication technologies among the actors in a destination and measure the extent to which they exploit (or waste) resources universally deemed to be crucial for today's survival in a highly competitive globalized market. Moreover, it has been possible to show the structural integration between the virtual and the real components in a destination. This gives more strength to the idea that a digital ecosystem needs to be fully considered when dealing with tourism activities at a destination (Baggio & Del Chiappa, 2014b).

The substantial similarity of the main topological characteristics, coupled with considerations on the mechanisms with which corporate websites are interlinked, has then suggested the important conjecture that the World Wide Web can provide an efficient and effective way to gather significant samples of networked socioeconomic systems to be used for analyses and simulations (Baggio et al. 2010b).

One more interesting outcome is the possibility to identify the most relevant members in a destination: those who are reputed to give the most important contribution to the tourism activities (Cooper, Scott & Baggio, 2009; Presenza & Cipollina, 2010). Also some important features such as the creativity and innovation potential of the destination or the productive performance of single stakeholders have been related to the network configuration through some of its quantitative peculiarities (Baggio, 2014; Sainaghi & Baggio, 2014). An advantage of a network representation of a complex system is that it is possible to perform numerical simulations. Different configurations can be conceived and several dynamic processes simulated in order to better understand how these configurations influence the behavior of the whole destination system.

Information and knowledge flows in a destination network are relevant determinants of the *health* of the system. Productivity, innovation and growth are strongly influenced by them, and the way in which the spread occurs affects the speed by which individual actors perform (Argote & Ingram, 2000). A common technique to study the problem is based on an analogy with the diffusion of a disease (Hethcote, 2000), which can be implemented using a network as substrate. It has been shown, in fact, that the structure of the network is highly influential in determining the unfolding of the process (López-Pintado, 2008). These methods have been used in tourism to show the effects of possible modifications in the network structure on the extent and the speed of information diffusion or knowledge sharing (Aubke, Wöber, Scott, & Baggio, 2014; Baggio & Cooper, 2010). Based on this strand of research and on the one on digital ecosystem, Baggio & Del Chiappa (2014a) assessed the opinion and consensus dynamics in tourism destinations and proved that a structurally strong cohesion between the real and the virtual components of a destination do exist. It could be argued that current research on diffusion models is still limited; future efforts would be useful to deepen the knowledge in this area (Baggio, 2011c).

2.6 CONCLUSION

This chapter showed how the analysis and management of tourism destinations can benefit from adopting principles and methods rooted in the interdisciplinary approach of *complexity science*. To do this, some of the most common and used techniques were presented, describing, for each of them, aims, tools, and software that can be used to apply them along with the requirements for data collection. Specifically, three different families of methods were considered: agent-based modeling, nonlinear analysis of time series, and network analysis; these are summarized, along with their main purpose in Table 2.1.

TABLE 2.1 Methods for the Analysis of Complex Dynamic Systems.

Method	Data used	Main purpose
Agent-based models	Actors (single entities) Rules that define local interactions between agents	Simulation of large scale behaviors Production of scenarios
Nonlinear analysis of time series	Time series of systems' observable characteristics	Diagnosis of complex and/or chaotic dynamics
Network analysis	Graph of actors and relationships	Structural characteristics of the system Basis for dynamic processes

This contribution also underlined that mixing qualitative and quantitative methods and simultaneously considering the real and virtual components of tourism destinations would be beneficial in supporting researchers and practitioners in their attempt to obtain a better picture of the structure, the evolution, the outcomes, and the governance of the system as a whole.

Finally, the need for an additional refinement of the described methods, both from a theoretical and practical point of view, was highlighted, thus calling for further research and empirical investigations in order to validate them. As stated by San Miguel et al. (2012: 268), however, the challenge is strong and includes:

> "data gathering by large-scale experiment, participatory sensing and social computation, and managing huge distributed dynamics and heterogeneous databases; moving from data to

dynamical models, going beyond correlations to cause-effect relationships, understanding the relationship between simple and comprehensive models with appropriate choices of variables, ensemble modeling and data assimilation, and modeling systems of systems of systems with many levels between micro and macro; and formulating new approaches to prediction, forecasting, and risk, especially in systems that can reflect on and change their behavior in response to predictions, and systems whose apparently predictable behavior is disrupted by apparently unpredictable rare or extreme events."

This also suggests that these new promising approaches can be effectively used to more deeply investigate the dynamics and evolution of tourism destinations and the dynamic processes, such as consensus building and knowledge creation and diffusion that occur on them.

REFERENCES

Amaral, L. A. N.; Ottino, J. M. Complex Networks—Augmenting the Framework for the Study of Complex Systems. *Eur. Phys. J. B.* **2004**, *38*, 147–162.

Argote, L.; Ingram, P. Knowledge Transfer: A Basis for Competitive Advantage in Firms. *Organ. Behav. Hum. Decis. Process.* **2000**, *82*(1), 150–169.

Aubke, F.; Wöber, K.; Scott, N.; Baggio R. Knowledge Sharing in Revenue Management Teams: Antecedents and Consequences of Group Cohesion. *Int. J. Hospital. Manage.* **2014**, *41*, 149–157.

Baggio, J. A. Agent-based Modeling and Simulations. In *Quantitative Methods in Tourism: A Handbook*; Baggio, R., Klobas, J., Eds.; Channel View: Bristol, UK, 2011a; pp 199–219.

Baggio, R. Complex Systems, Information Technologies and Tourism: A Network Point of View. *Inf. Technol. Tourism.* **2006**, *8*(1), 15–29.

Baggio, R. The Web Graph of a Tourism System. *Physica A.* **2007**, *379*(2), 727–734.

Baggio, R. Symptoms of Complexity in a Tourism System. *Tourism Anal.* **2008**, *13*(1), 1–20.

Baggio, R. Collaboration and Cooperation in a Tourism Destination: A Network Science Approach. *Curr. Issues Tourism*. **2011b**, *14*(2), 183–189.

Baggio, R. The Mechanism for Spreading Online Reputation. *Acad. Turistica.* **2011c**, *3*(2), 7–15.

Baggio, R. Oriental and Occidental Approaches to Complex Tourism Systems. *Tourism Plann. Dev.* **2013**, *10*(2), 217–227.

Baggio, R. Creativity and the Structure of Tourism Destination Networks. *Int. J. Tourism Sci.* **2014**, *14*(1), 137–154.

Baggio, R.; Baggio, J. A. Modeling Information Asymmetries in Tourism. In *Tourism Marketing: On Both Sides of the Counter*; Kozak, M., Lebe, S. S., Andreu, L, Gnoth, J.; Fyall, A., Eds.; Cambridge Scholars Publishing: Newcastle upon Tyne, UK, 2013; pp 156–174.

Baggio, R.; Cooper, C. Knowledge Transfer in a Tourism Destination: The Effects of a Network Structure. *Serv. Ind. J.* **2010**, *30*(10), 1–15.

Baggio, R.; Del Chiappa, G. Opinion and Consensus Dynamics in Tourism Digital Ecosystems. In *Information and Communication Technologies in Tourism 2014 (Proceedings of the International Conference in Dublin, Ireland, January 21–24, 2014);* Xiang, Z., Tussyadiah, I., Eds.; Springer: Berlin-Heidelberg, 2014a; pp 327–338.

Baggio, R.; Del Chiappa, G. Real and Virtual Relationships in Tourism Digital Ecosystems. *Inf. Technol. Tourism*. **2014b**, *14*(1), 3–19.

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

Baggio, R.; Sainaghi, R. Complex and Chaotic Tourism Systems: Toward a Quantitative Approach. *Int. J. Contemp. Hospital. Manage.* **2011**, *23*(6), 840–861.
Baggio, R., Scott, N.; Cooper, C. Improving Tourism Destination Governance: A complexity Science Approach. *Tourism Rev.* **2010a**, *65*(4), 51–60.
Baggio, R.; Scott, N.; Cooper, C. Network science—A Review Focused on Tourism. *Ann. Tourism Res.* **2010b**, *37*(3), 802–827.
Baggio, R.; Scott, N.; Cooper, C. Using Network Analysis to Improve Tourist Destination Management. In *Trends in European Tourism Planning and Organisation Systems*; Costa, C.; Panyik, E.; Buhalis, D., Eds.; Channel View: Clevedon, UK, 2013; pp 278–288:.
Baggio, R.; Scott, N.; Wang, Z. What Network Analysis of the WWW Can Tell us About the Organisation of Tourism Destinations. *Proceedings of the CAUTHE 2007, Sydney, Australia, 11–14 February*, 2007.
Batini, C.; Scannapieco, M. *Data Quality: Concepts, Methods and Techniques*; Springer: Berlin, 2006.
Bendle, L. J.; Patterson, I. Network Density, Centrality, and Communication in a Serious Leisure Social World. *Annals of Leisure Research* **2008**, *11*(1–2), 1–19.
Bertuglia, C. S.; Vaio, F. *Nonlinearity, Chaos, and Complexity: The Dynamics of Natural and Social Systems*; Oxford University Press: Oxford, 2005.
Bieger, T. Reengineering Destination Marketing Organisations–The Case of Switzerland. *Revue de Tourisme* **1998**,*53*(3), 4–17.
Bregoli, I., Del Chiappa, G. Coordinating Relationships among Destination Stakeholders: evidence from Edinburgh (UK), *Tourism Anal.* **2013**, *18*(2), 145–155.
Brock, W. A.; Dechert, W. D.; Scheinkman, J. A.; LeBaron, B. A Test for Independence Based on the Correlation Dimension. *Econ. Rev.* **1996**, *15*(3), 197–235.
Brodu, N. A Synthesis and a Practical Approach to Complex Systems. *Complexity* **2009**, *15*(1), 36–60.
Butler, R. W. The Concept of a Tourist Area Cycle of Evolution: Implications for Management of Resources. *Can. Geographer* **1980**, *24*(1), 5–12.
Castellano, C.; Fortunato, S.; Loreto, V. Statistical Physics of Social Dynamics. *Rev. Mod. Phys.* **2009**, *81*(2), 591–646.
Clegg, R. G. A Practical Guide to Measuring The Hurst parameter. *Int. J. Simulation* **2006**, *7*(2), 3–14.
Cooper, C.; Scott, N.; Baggio, R. Network Position and Perceptions of Destination Stakeholder Importance. *Anatolia* **2009**, *20*(1), 33–45.
da Fontoura Costa, L.; Baggio, R. The Web of Connections between Tourism Companies: Structure and Dynamics. *Phys. A* **2009**, *388*, 4286–4296.
da Fontoura Costa, L.; Oliveira, O. N.; Travieso, G.; Rodrigues, F. A.; Villas Boas, P. R.; Antiqueira, L.; Viana, M. P.; Correa Rocha, L. E. Analyzing and Modeling Real-World Phenomena with Complex Networks: A Survey of Applications. *Adv. Phys.* **2011**, *60*(3), 329–412.
da Fontoura Costa, L.; Rodrigues, A.; Travieso, G.; Villas Boas, P. R. Characterization of Complex Networks: A Survey of Measurements. *Adv. Phys.* **2007**, *56*(1), 167–242.
Del Chiappa, G.; Presenza, A. The Use of Network Analysis To Assess Relationships Among Stakeholders Within A Tourism Destination: An Empirical Investigation On Costa Smeralda-Gallura, Italy. *Tourism Anal.* **2013**, *18*(1), 1–13.
Dominici, G.; Levanti, G. The Complex System Theory for the Analysis of Inter-Firm Networks: A Literature Overview and Theoretic Framework. *Int. Bus. Res.* **2011**, *4*(2), 31–37.
Erkuş-Őztürk, H.; Eraydın, A. Environmental Governance for Sustainable Tourism Development: Collaborative Networks and Organisation Building in the Antalya Tourism Region. *Tourism Manage.* **2010**, *31*, 113–124.
Farrell, B. H.; Twining-Ward, L. Reconceptualizing Tourism. *Ann. Tourism Res.* **2004**, *31*(2), 274–295.
Fortunato, S. Community Detection in Graphs. *Phys. Rep.* **2010**, *486*(3-5), 75–174.

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

Freeman, L. C. *The Development of Social Network Analysis: A Study in the Sociology of Science*; Vancouver Empirical Press: Vancouver, 2004.

Galán, J. M.; Izquierdo, L. R.; Izquierdo, S. S.; Santos, J. I.; del Olmo, R.; López-Paredes, A.; Edmonds, B. Errors and Artefacts in Agent-Based Modelling. *J. Artificial Soc. Soc. Simulation* **2009***, 12*(1), 1.

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

Gilbert, N.; Terna, P. How to Build and Use Agent-Based Models in Social Science. *Mind Soc.* **2000***, 1*(1), 52–72.

Giuliani, A.; Colafranceschi, M.; Webber, C. L. J.; Zbilut, J. P. A Complexity Score Derived from Principal Components Analysis of Nonlinear Order Measures. *Phys. A* **2001***, 301*, 567–588.

Grama, C.-N.; Baggio, R. A Network Analysis of Sibiu County, Romania. *Ann. Tourism Res.* **2014***, 47*(1), 89–93.

Gummesson, E. Case Study Research and Network Theory: Birds of a Feather. *Qual. Res. Organ. Manage.* **2007***, 2*(3), 226–248.

Hansell, R. I. C.; Craine, I. T.; Byers, R. E. Predicting Change in Non-linear Systems. *Environ. Monit. Assess.* **1997***, 46*, 175–190.

Hethcote, H. W. The Mathematics of Infectious Diseases *SIAM Rev.* **2000***, 42*(4), 599–653.

Hodrick, R. J.; Prescott, E. C. Postwar U.S. Business Cycles: An Empirical Investigation. *J. Money Credit Bank.* **1997***, 29*(1), 1–16.

Hurst, H. E. Long-Term Storage of Reservoirs: An Experimental Study. *Trans. Am. Soc. Civil Eng.* **1951***, 116*, 770–799.

Johnson, P. A.; Sieber, R. E. An Individual-Based Model of Tourism Dynamics. *Tourism Anal.* **2010***, 15*(5), 517–530.

Kossinets, G. Effects of Missing Data in Social Networks. *Soc. Networks* **2006***,28*(3), 247–268.

López-Pintado, D. Diffusion in Complex Social Networks. *Games Econ. Behav.* **2008***, 62*(2), 573–590.

Lorenz, E. N. Deterministic Nonperiodic Flow. *J. Atmos. Sci.* **1963***, 20*, 130–141.

Moscardo, G. The Role of Knowledge in Good Governance for Tourism. In *Tourist destination governance: Practice, theory and issues* Laws, E., Richins, H., Agrusa, J., Scott, N. Eds., CABI: Wallingford, UK, 2011, pp 67–80.

Newman, M. E. J. *Networks - An introduction*; Oxford University Press: Oxford 2010.

Olsen, W. Triangulation in Social Research, Qualitative and Quantitative Methods Can Really be Mixed. In *Developments in Sociology: An Annual Review* Holborn, M. Ed., Causeway Press: Ormskirk, UK, pp 103–121, 2004.

Page, S. J.; Connell, J. *Tourism: A Modern Synthesis* (2nd ed.); Thomson; London, 2006.

Pearce, D. G. Toward an Integrative Conceptual Framework of Destinations. *J. Travel Res*. **2014**, *53*(2), 141–153.

Piazzi, R.; Baggio, R.; Neidhardt, J.; Werthner, H. Destinations and the Web: A Network Analysis View. *Inf. Technol. Tourism,* **2012**, *13*(3), 215–228.

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

Presenza, A.; Cipollina M. Analysing Tourism Stakeholders Networks. *Tourism Rev*. **2010,** *65*(4), 17–30.

Sainaghi, R.; Baggio, R. Structural Social Capital and Hotel Performance: Is There a Link? *Int. J. Hospital. Manage.* **2014**, *37*, 99–110.

San Miguel, M.; Johnson, J. H.; Kertesz, J.; Kaski, K.; Díaz-Guilera, A.; MacKay, R. S.; Loreto, V.; Érdi, P.; Helbing, D. Challenges in Complex Systems Science. *Eur. Phys. J. Spec. Top.* **2012**, *214*, 245–271.

Scott, N.; Cooper, C.; Baggio, R. Destination Networks—Four Australian Cases. *Ann. Tourism Res.* **2008**, *35*(1), 169–188.

Silvert, W. Modeling as a Discipline. *Int. J. Gen. Sys.* **2001**, *30*(3), 261–282.

Sornette, D. Interdisciplinarity in Socio-Economics, Mathematical Analysis and Predictability of Complex Systems. *Socio-Econ. Rev.* **2008**, *6*(4), 734–745.

Sprott, J. C. *Chaos and Time-Series Analysis*. Oxford University Press: Oxford, 2003; p. 211.

Stacey, R. D. *Complexity and Creativity in Organizations*. Berrett-Koehler: San Francisco, 1996.

Taber, C. S.; Timpone, R. J. *Computational Modeling*; Sage: Thousand Oaks, CA, 1996.

Ulgiati, S.; Bianciardi, C. Describing States and Dynamics in far from Equilibrium Systems. Needed a Metric within a System State space. *Ecol. Modell.* **1997**, *96*(1–3), 75–89.

Veal, A. J. *Research Methods for Leisure and Tourism: A Practical Guide* (3rd ed.); Financial Times—Prentice Hall/Pearson Education: Harlow, UK, 2006.

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

Wolf, A.; Swift, J. B.; Swinney, H. L.; Vastano, J. A. Determining Lyapunov Exponents from a Time Series. *Physica D.* **1985**, *16*, 285–317.