Mapping time series into networks as a tool to assess the complex dynamics of tourism systems

Rodolfo Baggio

Master in Economics and Tourism and
Dondena Center for Research on Social
Dynamics, Bocconi University

rodolfo.baggio@unibocconi.it

Ruggero Sainaghi

Dipartimento di economia, studi
giuridici e aziendali,
IULM University

ruggero.sainaghi@iulm.it

October 2015, accepted in: Tourism Management

Abstract

This paper contributes to filling two gaps: i) the presence of a limited amount of studies focused on tourism demand turning points, ii) the prevalent recourse to linear models in demand analysis, disregarding the complex structure of tourism destinations. The paper uses the Horizontal Visibility Graph Algorithm, a technique able to transform a time series of observations into a network whose topology preserves some fundamental characteristics of the system examined. The empirical work focuses on Livigno, an Italian alpine destination.

Findings reveal four turning points in the last 50 years; these changes are built around shifts in the origin market segments. The network's degree distribution confirms the complex structure of the destination and reconfirms the importance of non-linear models and methods for the analysis of tourism demand.

Keywords

Tourism destinations, complex systems, time series, tourism demand, horizontal visibility graph algorithm, network analysis.

Highlights

- The paper focuses on turning points and complex structure of tourism demand
- Overnights time series are transformed into networks and examined
- The analysis confirms the complex structure of the destination context
- Findings reveal four turning points in the case study analyzed
- The relevance of non-linear models for the analysis of tourism demand is highlighted

1. Introduction

Demand plays a crucial role in the life of any firm and industry (Bain, 1942) and tourism is no exception to this rule, as is testified by the growing interest in tourism demand studies (Nicolau & Más, 2005). Over time, this research movement has generated an impressive number of contributions (Song & Li, 2008). Modeling tourism demand to analyze the effects of various determinants, and accurate forecasting of future tourism demand are the two major focuses of these studies (Li, Song & Witt, 2005).

Concerning the first stream, the published reviews, especially since the 1990s, have traced some determinants of tourism demands such as: tourists' incomes, destination prices compared with those in the origin country, prices in competing destinations (i.e., substitute prices) and exchange rates (Crouch, 1994, 1995, 1996; Lim, 1997; 1999). Econometric models have primarily contributed to developing this field. Song and Li (2008) find that 71 of 121 reviewed papers employ econometric models. Similarly, Li, Song and Witt (2005) affirm that an econometric approach has a crucial role in tourism demand studies. From a methodological point of view, the most used techniques are linear models in which regression techniques (typically Ordinary Least Square, or OLS) are pivotal. Since 2000, some studies have used new methods, principally based on artificial intelligence models such as neural networks (Kon & Turner, 2005), the rough set approach (Au & Law, 2000, 2002; Law & Au, 2000), the fuzzy time-series method (Wang, 2004). In any case, linear models are predominant (Frechtling, 2001).

The second research stream (forecasting), comprises a huge work primarily oriented to producing the most accurate demand predictions possible, in order to sustain and orient tourism policy at different territorial levels (Peng, Song & Crouch, 2014). Researchers have proposed different methods, considering key variables such as: data frequency, origin and destination pairs, forecasting horizons, number of competing models included in the forecasting exercise and variables to be forecasted (demand level or growth) (Song & Li, 2008). Recent empirical studies have confirmed that there is no exclusive winner in a tourism demand forecasting competition (Chen, Bloomfield, & Cubbage, 2008; Smeral, 2007). Therefore some researchers have attempted to combine the demand forecasts generated by different models in order to improve accuracy (Wong et al., 2007), as the general literature suggests (Armstrong, 2001; Oh & Morzuch, 2005). Forecasting models see a dominance of the integrated autoregressive moving-average models (ARIMAs) proposed by Box and Jenkins (1970), along with a number of variations, such as SARIMA, which considers seasonal patterns (Cho, 2001), or MARIMA, a multivariate model (Goh & Law, 2002).

In synthesis, researches on tourism demand determinants, and forecasting activities tackle two central themes. The first approach attempts to identify some key causes able to influence the number of attracted tourists or the amount of tourist expenditures, while the second stream generates forecasts concerning a more or less near future. Between these two research streams there is a dialogue, where results achieved by the first stream (determinants of tourism demand) are seen to be able to improve the accuracy and reliability of forecasting models (Song & Witt, 2000). These important results, however, leave open two main gaps, that drive the present study. A first point concerns the object that demand research proposes to explore. In a period characterized by high tourism volatility and quick changes in trends, a small number of papers focus on 'turning points', i.e. proposing methods able to identify discontinuities in demand time series (Coshall, 2000). This has a high practical value because tourism-related firms are keen to know not only the overall trends of tourism demand, but also the timing of the directional change in tourism growth. In this perspective, there is a need for new ways to identify turning points in past time series and to create a monitoring system for the present, able to signal symptoms of change.

A second gap refers to methodologies used and, more importantly, to the underlying concept of tourism system or destination. As previously stated, the majority of tourism studies have used linear (or linearized) models, that introduce (usually implicitly) a mechanistic or Newtonian perspective of both tourism systems and destinations, anchored on equilibrium and stability (Farrell & Twining-Ward, 2004; Faulkner & Valerio, 1995). The linear reductionist approach analyzes a system by breaking it down into its constituent parts and searching for linear relationships between single variables (Stevenson, Airey, & Miller, 2009). This approach disregards the increasing number of studies revealing and describing the complex traits and dynamics of tourist systems (Baggio, 2008; McKercher, 1999; Russell & Faulkner, 1999; Zahra & Ryan, 2007). The complexity of a destination is strongly related to its constituent elements, a wide number of 'co-producing' firms (Flagestadt & Hope, 2001; Haugland et al., 2011; Sainaghi, 2006), and to the non-linearity of the relationships between these entities that create complex dynamic behaviors with a possibility to exhibit chaotic features (Baggio & Sainaghi, 2011). For this reason, there is a need to employ methods that are more consistent with the nature of the object of study and the complexity of a tourism system.

This paper has therefore two goals: i) to develop a methodology able to identify turning points in the evolutionary history of a tourism system (destination); ii) to propose non-linear measures, able to consider the complex relationships typical of complex or chaotic systems.

The rest of the paper is organized as follows. The next section contains a brief introduction to the main concepts of complexity and chaos theories. The methods and the data for the empirical study are examined in section 3. Finally a discussion of the outcomes and the implications along with the limitations and possible future developments are presented. The contribution proposes an application to an alpine destination: Livigno, Italy.

2. Literature review

In the last decades tourism has dramatically increased its dynamicity (von Bergner & Lohmann, 2014). New flexible structures (Pehlivanoğlu, 2011), fast changing customer behaviors (Woodside, Hsu, & Marshall, 2011) and the development of transportation technologies (Duval, 2013) have put a heavy pressure on the sector. In addition, the advent of the Internet, and the consequent information technology revolution, has profoundly modified the very nature of the relationships between the actors operating in the field (Alford & Clarke, 2009; Werthner & Klein, 1999). These changes have reinforced the complex nature of tourism systems and destinations, that can be briefly summarized by observing the presence of: i) non-linear relationships, ii) self-organization behaviors, iii) emergence of modular and hierarchical structures, iv) robustness or fragility regarding some events. Destinations can be seen as complex networks of components, where nodes are organizations and people, and links represent different types of business (such as institutional, commercial, ownership) or 'personal' relationships (i.e. family, friendship, trust) (Sainaghi & Baggio, 2014). In this context it is very difficult to fully describe the nature and strength of ties (Burt, 1992) and relationships, owing to their non-linear characteristics (Faulkner & Russell, 2001).

During its life, then, a complex system gives birth to several intermediate structures that appear spontaneously without any apparent external influence (Bertuglia & Vaio, 2005; Lewin, 1999). This self-organization has the objective of optimizing the available resources and making the system better suited to face external or internal burdens. Even when examined on different temporal or spatial scales the system appears to have similar configurations (modularity and self-similarity) (Baggio, 2011). These complex adaptive systems continually interact with the external environment, adjusting both their internal structure and their behaviors. The visible effects can be seen in the system's ability to sometimes withstand large shocks without dramatically modifying itself or its evolutionary path, or in its complete disruption after a seemingly irrelevant event (Faulkner & Vikulov, 2001).

The application of complexity science methods, well known in disciplines such as physics (Ellis, 2005; Prigogine & Hiebert, 2008), mathematics (Mainzer, 2005), sociology (Holling, 2001) and economics (Perona, 2007), has already provided a good set of insights into the structural and dynamical characteristics of a tourism destination. The approach has been adopted in several studies investigating different aspects, such as the analysis of destination development (Cole, 2009; Faulkner, 2002; Warnken, Russell, & Faulkner, 2003; Zahra & Ryan, 2007), the management and the effects of crises and disasters (Crandall, Parnell, & Spillan, 2010; Faulkner & Vikulov, 2001; Laws & Prideaux, 2005; Prideaux, Laws, & Faulkner, 2003; Ritchie, 2004; Scott & Laws, 2005), the forecast of future demand (Faulkner & Russell, 2001; Faulkner & Valerio, 1995), the development of entrepreneurship (Russell & Faulkner, 1999, 2004), the structure of the networks between tourism companies (Tinsley & Lynch, 2001) or the management of hospitality businesses (Edgar & Nisbet, 1996). Tourism destination complexity has been explored also by applying network analysis methods (Baggio et al., 2010b; Beaumont & Dredge, 2010; Timur & Getz, 2008), agent-based simulations (Johnson & Sieber, 2010; Pizzitutti, Mena, & Walsh, 2014) and non-linear time series analysis techniques (Baggio, 2008; Baggio & Sainaghi, 2011).

Given its inherently complex nature, it is very difficult to have an analytical representation of a tourism destination and its components (Lansing, 2003). What is possible is to record a number of observable quantities that can give a representation of the system's behavior and to derive, from these, some hints into its deep structural and dynamical characteristics (Kurtz & Snowden, 2003). There are some exceptions, such as some studies rooted in psychology that explore complex adaptive systems in groups (i.e. Guastello, 2010; Navarro & Arrieta, 2010; Ramos-Villagrasa, Navarro, & García-Izquierdo, 2012). However, these contributions usually focus on relatively small groups composed of individuals – respectively, 225 undergraduates, 48 employees, 23 basketball teams –, while, in the case of tourism destinations, there are hundreds of firms and organizations. For this reason, in the case of tourism destinations, it is important using a *proxy* related to the movements of tourists and to their activities at destination. The number of tourist arrivals, the nights or the money spent at destination are familiar observables and normally used for planning and forecasting purposes (Athiyaman & Robertson, 1992). Moreover, such time series are a measurable representation of the dynamics of a system (Kantz & Schreiber, 1997). In tourism this idea, for example, underlies some attempts to explain the history and development of a destination, such as the well-known model of destination life cycle and its many variations (Butler, 1980, 2005a, 2005b). A number of different conceptual approaches have been used to study the features of dynamic systems based on observational time series. Popular methods employed in a variety of applications include: Lyapunov exponents, Hurst exponent, fractal dimensions, symbolic discretization, and measures of complexity such as entropies or quantities derived from them (Kantz & Schreiber, 1997; Sprott, 2003). Essentially, all these techniques measure certain dynamically invariant properties of the system under study based on temporally discretized realizations of the system's evolutionary trajectories. However, their application requires sophisticated procedures that are not always completely and rigorously defined, but frequently rely on the researcher's experience and knowledge. Despite the existence of reasonably 'usable' software tools, their usage and the interpretation of the results are tasks which can be problematic for many, especially practitioners (Baggio, 2008; Baggio & Sainaghi, 2011). Moreover, the most relevant problem is that all these methods require, for their good functioning, large amounts of observations that are not very common in the tourism field.

A recent methodological proposal has interesting characteristics for the task of evaluating the state of a system and understanding its *complexity* features (Campanharo et al., 2011). The idea is to transform a time series of observations into a network and use the well-established methods and tools of network analysis for the study (Strozzi et al., 2009). It is possible to consider a time series just as a set of numeric values and, by using some appropriate transformation, derive a different mathematical object: a network graph. The technique works when it is known which properties of the original set are conserved, which are transformed, or what can be inferred about one of the representations by examining the other, preserving the notion that time series are a universal method of extracting information from dynamic systems. Besides its theoretical appeal and its intrinsic interest, a number of *practical* insights can be derived by using this method, as already reported in a number of works on natural, social and economic systems examining stock market indices, exchange rates, macroeconomic indices, human behaviors, occurrence of hurricanes, or dissipation rates in turbulent systems (Chao & Jin-Li, 2012; Elsner, Jagger, & Fogarty, 2009; Tang, Wang, & Liu, 2013; Wang, Li, & Wang, 2012). In particular, one of the proposed methods has remarkable characteristics of clarity, coupled with computational simplicity, and can be usefully applied in the context of tourism. The approach uses a set of algorithms named *visibility graph algorithms* (Lacasa et al., 2008). By using these techniques the structure of a time series is inherited in the associated graph, so that periodic, random, and fractal series map into networks with different topologies (random exponential or scale-free) (Nuñez et al., 2012).

2.1 The horizontal visibility graph algorithm

Visibility graph algorithms are a group of geometric transformations that provide various methods for mapping a time series of N values into a graph of N nodes (Nuñez et al., 2012). One of these is called Horizontal Visibility Graph (HVG). The algorithm works as follows. Consider a time series of observations ($x_1 \ldots x_n$) represented as vertical bars (Figure 1a). Each and every bar is linked to all those that can be connected with a horizontal segment without intersecting any other intermediate bar (Figure 1b). Formally, two data points *i* and *j* have horizontal *visibility* if every intermediate value x_k satisfies the condition: $x_k < \inf [x_i; x_j]$; k: i<k< j. A network is then built where nodes are the data points and links (undirected) are the horizontal segments (i.e. two nodes are connected if are 'in view', whence the name of visibility graph).

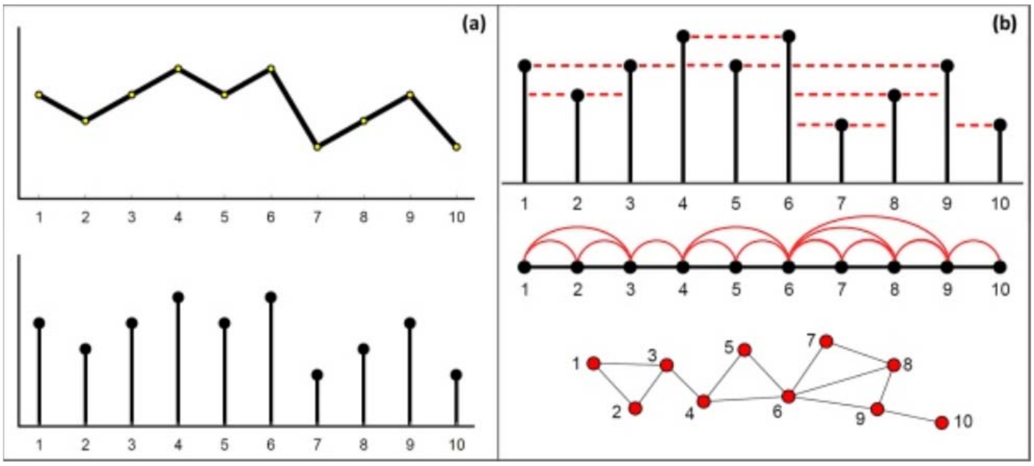

Figure 1. A time series (a) and the HVG procedure for obtaining a network (b)

Some scholars (Luque et al., 2009; Lacasa & Toral, 2010) achieve an interesting result by analytically calculating the shape of the degree distribution making it possible to distinguish between a stochastic (correlated or uncorrelated) and a chaotic time series. In other words, their method makes it possible to determine whether the system under study has chaotic, deterministic or stochastic dynamics, an important issue for the understanding of the system's characteristics and the predictability of its future behaviors. The relevance of this problem relies on the fact that both stochastic and chaotic processes share many features, and the distinction between them is

often elusive (Cencini et al., 2000).
The results obtained (Luque et al., 2009; Lacasa & Toral, 2010) show that, when an exponential degree distribution is found (i.e. when the number of nodes having degree k, N(k) follows a relationship of the form: $N(k)e^{-\lambda k}$), there is a threshold that separates systems having a chaotic behavior from those whose dynamics is a correlated stochastic process. The parameter $\lambda_C = \ln(2/3) = 0.405$ is the value that enables distinguishing between the two behaviors. Correlated stochastic series map into an horizontal visibility graph with an exponential degree distribution with a slope that slowly tends to its asymptotic value λ_C for very weak correlations, that is to say, also, that infinitely large correlations will be associated to a diverging value of λ. Chaotic series, instead, do the same but converge to the limiting value in the opposite direction (i.e. for $< \lambda_C$). In other words we can use this result as an indicator for the dynamic characteristics of a system that will be chaotic for $<< \lambda_C$, will show an edge of chaos behavior in the region around λ_C, while being stable and predictable for $>> \lambda_C$.
The technique, thus, naturally takes into account nonlinearities in the phenomenon under study. Moreover, as will become clear with the investigation conducted in this work, it highlights the transitions (turning points) possibly present in a simple and effective way.
It must be mentioned here that the technique, as shown by Ravetti et al. (2014), may fail in some cases, namely in those for which it is impossible to define an unique linear scaling zone in the degree distribution when drawn on a semi-log plot, that is: when the shape of the distribution is not clearly exponential. In these cases a more sophisticated procedure is needed to assess the dynamic characteristics of the system. For the cases examined here, however, this does not happen. All the series can be clearly identified, and an analysis conducted by using the methods proposed by Ravetti et al. (2014) confirms this statement.

3. Materials and methods

The case chosen is the tourism destination of Livigno, Italy. Livigno is a mountain destination located in the Northern Italian Alps, close to the Swiss border, at about 240 kilometers from Milan, and 280 kilometers from Munich (Germany). The town (approximately 6,000 inhabitants) is a duty free area situated at an altitude of 1,816 meters. Usually, rich snowfalls ensure long snow seasons from the end of November to the beginning of May. Livigno totals roughly one million annual overnight visitors per year showing a strong seasonality with two peaks in winter (December-March) and summer (July-August).
Among the many possibilities, the number of nights spent in a destination by tourists is an interesting quantity for our purposes. As a matter of fact, overnight stays play an important role as a determinant of destination demand influenced by the perceived characteristics of the destination and, rather obviously, strongly related to tourist spending (Sainaghi, 2012). A thorough investigation into the general dynamics of their time evolution is therefore important to better understand the whole phenomenon (Barros & Machado, 2010). Four time series of overnight stays were used. Three cover the period 2004-2013 and contain daily, weekly and

monthly data (Day, Week and Month in what follows). The fourth has monthly data for the period 1963-2013 (Figure 2, All in what follows). For the latter, data refer to domestic and international tourists. International data were also divided by countries of origin (source for all data: Livigno tourism board).

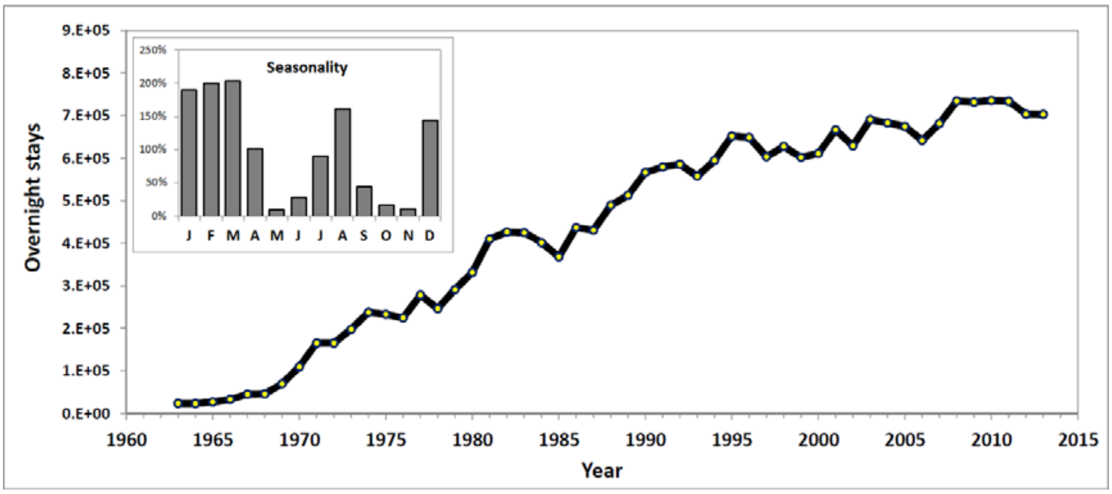

Figure 2. Overnight stays for Livigno in the period 1963-2013.
Inset shows seasonality index averaged over the last five years

In total we have the number of observations shown in Table 1.

Table 1. Number of observations for the time series examined

Series	All	Day	Week	Month
No. of observations	612	3379	489	111

The time series were then transformed into networks using the HVG algorithm. Once the networks corresponding to the different time series were obtained, we analyzed their structural characteristics by using standard network analytic methods (Baggio et al., 2010b; da Fontoura Costa et al., 2007; Newman, 2010; Scott, Baggio, & Cooper, 2011), assessing their degree distributions in particular. In order to better see the differences we compared the outcomes of the Livigno series analyses to those obtained for a random series (Rnd), a random Brownian motion (fBm) which is a white noise, representing uncorrelated stochastic dynamics (the series was generated with Hurst exponent H=0.5), and two series obtained from well-known chaotic systems: a logistic map (Lgst) and the Lorenz equations (Lrnz) (Parker & Chua, 1989). For each of these, series of the four different lengths (see Table 1) were created. The process was repeated ten times, thus taking into account the randomness of the generation, and all results were averaged.
The same analysis was performed also by using the series containing the overnight stays of the tourists coming from the main origin markets for the destination: France, the Netherlands,

Germany, Denmark, Belgium, Sweden and Switzerland, with the aim of identifying the main behavior of these origin markets.

Lastly, we ran a modularity analysis. This is a common practice in network studies and aims at uncovering groups of nodes that have denser connections between them than with nodes outside the group. These communities are a common feature of many real systems and are important for the comprehension of their composition and evolution. Many techniques have been proposed for this task (Fortunato, 2010); they mainly differ in their resolution power (i.e. capability to distinguish fine structures). Here we used the one proposed by Clauset, Newman and Moore (2004). This has the advantage of being quite fast and computationally simple and able to provide a coarse grained solution, which is the one we are interested in. The analysis identifies the different groups, and the 'quality' of the identification is given by a modularity index defined as:

$$Q = \sum_i (e_{ii} - a_i)^2$$

where e_{ii} is the fraction of edges in the network between any two nodes in the module i, and a_i the total fraction of links originating from it and connecting nodes belonging to different ones. Q is a normalized quantity, i.e. it assumes values 0 to 1, where 0 means absence of modules, 1 a perfect division into completely separated groups.

For a network derived from a time series representing economic or business data, the interpretation of the different communities is straightforward: nodes belonging to the same community represent periods with the same economic dynamics or belonging to the same business cycle (Schumpeter, 1934). In our case nodes in the same community have the same dynamics in the tourism development process. The modularity analysis makes it possible to reveal these different periods and identify various phases.

4. Results and discussion

Following our research questions, this section contains three parts: the first focuses on the identification of the turning points, the second explores the characteristics of the system studied, while a third one discusses some policy implications.

4.1 Turning points

The first enquiry concerns the four time series based on overnight stays. The networks obtained are shown in Figure 3. A visual inspection shows a substantial similarity of the four pictures, all exhibiting a sort of modular structure made of a limited number of subnetworks. As will become clear in the following analysis, we can identify five groups with four transition points. These features are more evident in the first network (All).

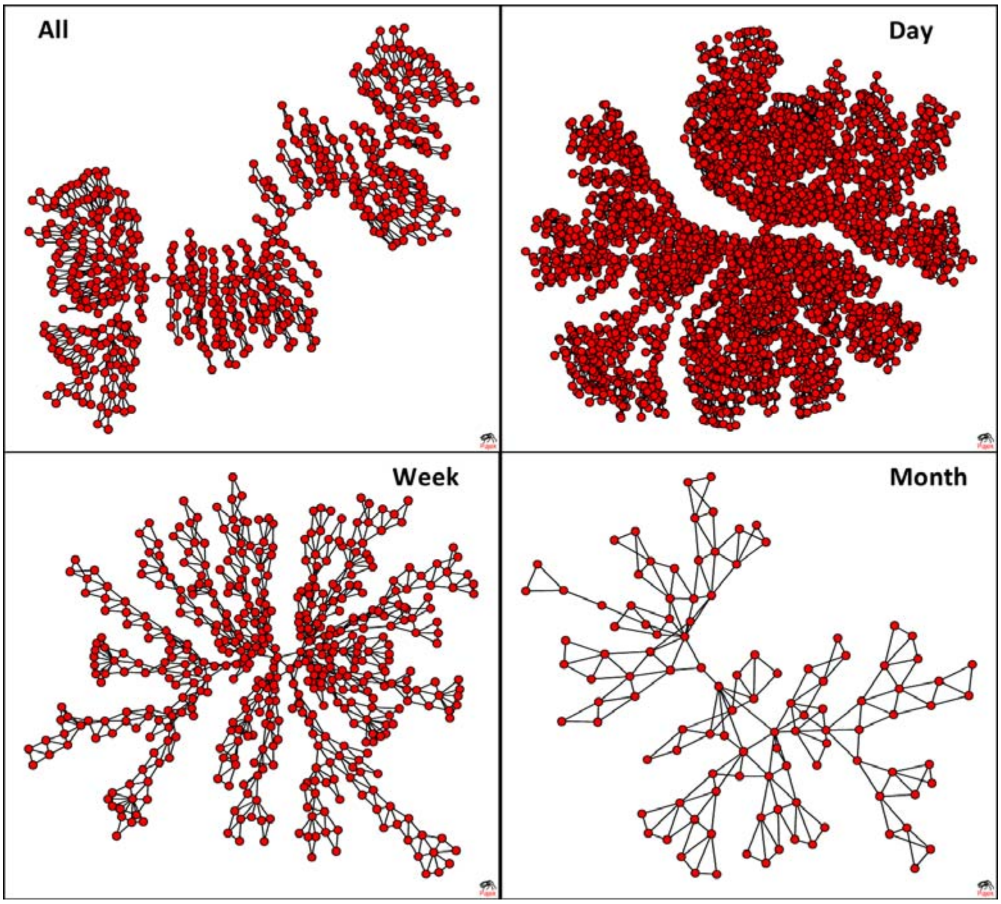

Figure 3. The HVG networks

In order to verify this structure, a stochastic modularity analysis can be performed which identifies groups of densely connected nodes. As mentioned above, these modules, when well resolved, correspond to periods with similar dynamics. The analysis provides a good subdivision (modularity index Q = 0.879, which indicates a good separation between the different modules identified). When we determine the separation points in the main network (Figure 4a), we find that they correspond to some major changes in the communities as shown in Figure 4b, where the horizontal segments indicate the belonging of a node to a community (nodes in the same community share the same segment and module changes are identified with segments at different levels).

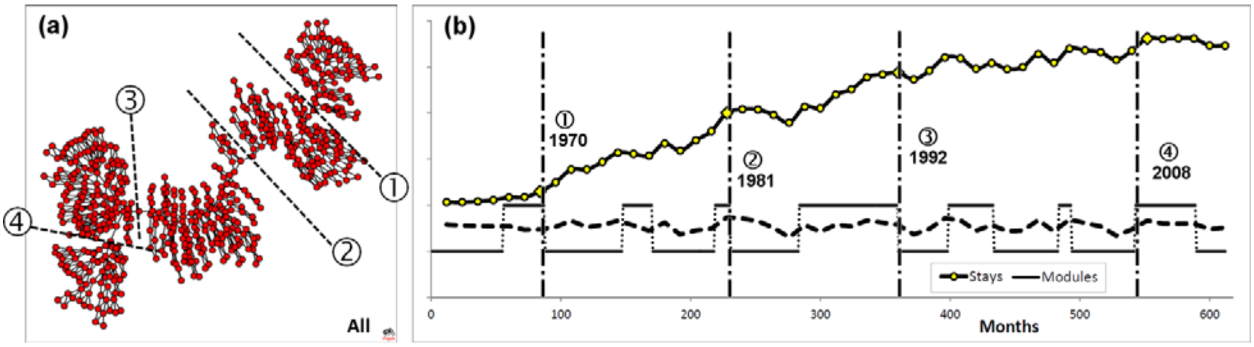

Figure 4. Modularity analysis of the All network(a) and comparison with the overnight stays time series (b).

This leads us to identify four major changes in the dynamic history of the destination corresponding to the years 1970, 1981, 1992, 2008.
The interpretation of these *breaks* can be helped by looking at the behavior of the overnight stays' time series split into two components: one relating to domestic tourists (DOM), the second one due to international visitors (INT). As can be seen in Figure 5, three of the four points (1970, 1981 and 2008) correspond to years where there is a variation in the predominance of one of the two series. The remaining transition, in 1992, corresponds to the year in which Italy exited the European Monetary System and devalued its currency, generating a peak in domestic visitors. Hence all four points correspond to clear changes in the basic dynamics of the system represented by the different influences of domestic and international overnights.

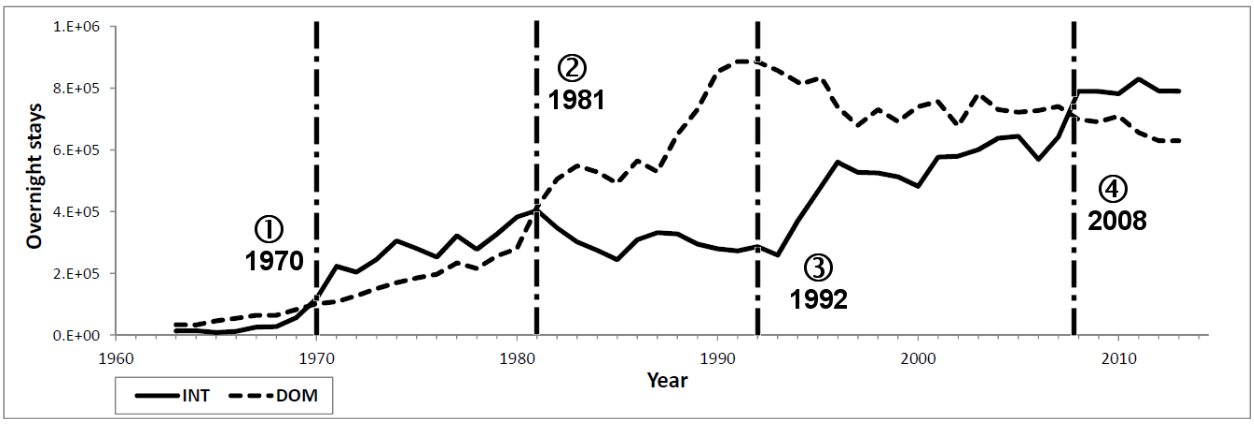

Figure 1. Domestic and international tourists' stays. The turning points are shown by vertical dotted lines

In order to better understand this outcome, and to better assess the importance of international tourism, an examination of the main components was performed. In the main series we identify the trends due to the major origin countries. These were classified according to their numeric importance (i.e. contribution to total stays in the period examined), but also looking at their influence on the trend of international stays. To do this we resorted to a Granger causality test

(Granger, 1969). This is a commonly used test to assess the directional characteristics of an interaction between time series. By testing the different contributions on the total series it is possible to use the F statistic calculated by the test to rank the strengths of the relationships (the higher F the more significant the relationship). The results are shown in Table 2. Here we first assess the prevalence of the international component on the overall series; we then identify the most important international markets.

Table 2. Main overnight stays series components, numeric contribution and Granger F statistic values for the main series components

Component	%of Total stays	F-value
International (INT)	44%	226.02
Domestic (DOM)	56%	110.78

INT Component	%of INT stays	F-value
France (FR)	4%	400.75
Germany (DE)	33%	219.03
Denmark (DK)	5%	143.54
Belgium (BE)	9%	96.23
Sweden (SE)	2%	83.31
Switzerland (CH)	6%	83.26
The Netherlands (NL)	2%	82.85

The Granger test results thus confirms the idea of a stronger influence of international tourist flows on the general dynamical evolution of the destination, and among these, those that contribute more, in general, influence more.

4.2 Chaos and complexity

Let us now turn to the topology of the networks obtained. In analyzing the structural characteristics of a network, the statistical distribution of the nodal connections (the degree distribution) is a commonly used way to assess the main properties of the system under study (Baggio et al., 2010b). Typically, exponential or power-law distributions are associated with systems that exhibit complex or even chaotic dynamics. The long tails of these distributions, in fact, are representative of self-organization and self-similarity features that characterize these systems.

As can be seen from Figure 6, the distributions, and hence the structural properties, look quite similar. They follow an exponential curve (Figure 6a). The same applies to the three series used as null models for comparison (random: Rnd; fractional Brownian motion: fBm; logistic map: Lgst; and Lorenz: Lrnz). Their degree distributions are shown in Figure 6b and compared with the All series.

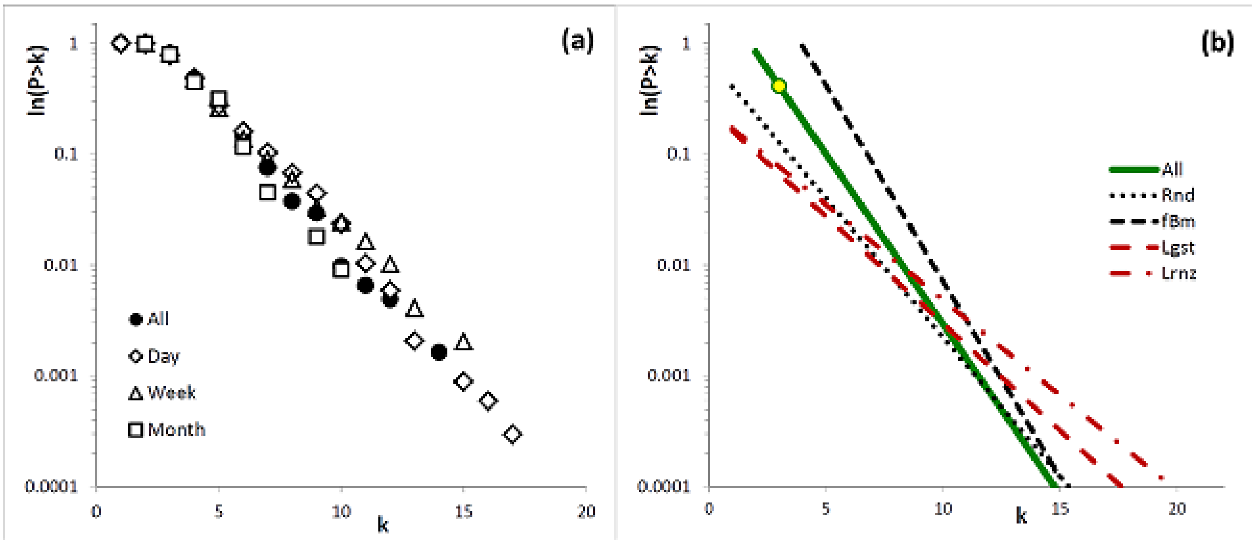

Figure 6. Degree distributions for the Livigno time series graphs (a) and the null models (b). For better visibility and comparison (b) contains only the shape of the All degree distribution

The similarity in the HVG networks derived from the Livigno series (Figure 6a) is rather obvious given the origin of the data, but testifies that, even in the presence of different 'sampling' the algorithm provides consistent results (differences in scales are due to the different sizes of the networks). In other words, this means that the technique is relatively insensitive to the number of observations used, and to the length of the period considered, thus allowing its usage even with a relatively limited amount of data.

The null models, instead, show (Figure 6b) different characteristics (slope) in their degree distributions, mainly concerning the logistic map and the Lorenz system (Lgst and Lrnz). As Lacasa and Toral (2010) have revealed, in fact, their slope, with their lower exponent, are a symptom of a chaotic dynamic, while higher values for the exponent of the degree distribution signal a stable and predictable system where these characteristics are enhanced with the increase of the exponent. Figure 7 and Table 3 report the exponents of the degree distributions with their 95% confidence intervals. The exponents reported here for the null models are averaged over the different realizations and lengths. This is justified by the fact that the differences in the exponents calculated lie within their confidence intervals.

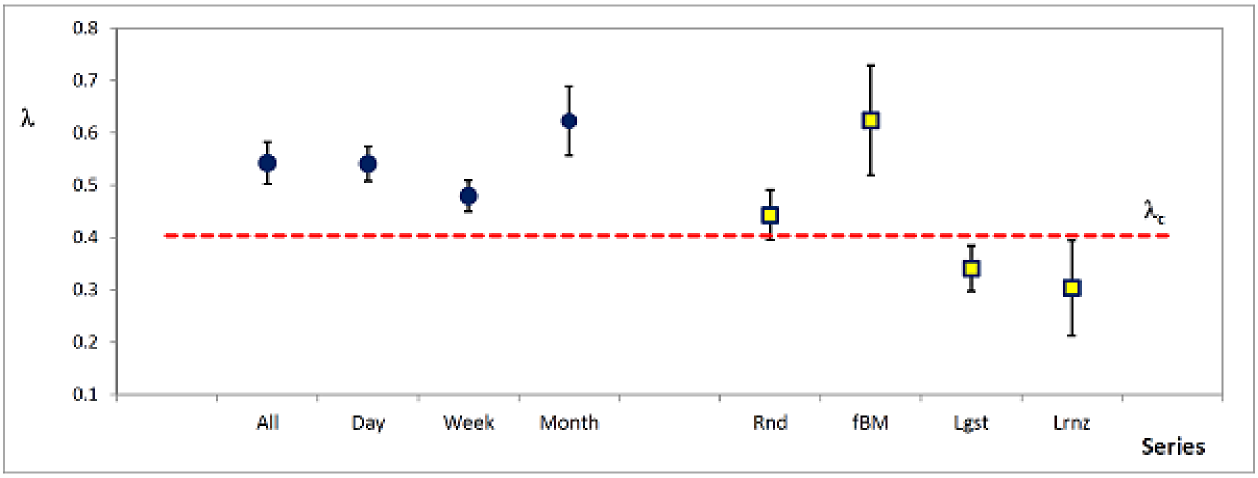

Figure 7. The degree distribution exponents for the HVG graphs examined. Vertical bars are 95% confidence intervals, horizontal dotted line is the limiting value λ_C

Table 3. Degree distribution exponents for the HVG graphs examined with their 95% confidence interval

Series	λ	95%CI
All	0.542	0.040
Day	0.541	0.033
Week	0.479	0.030
Month	0.623	0.066
Rnd	0.443	0.048
fBm	0.624	0.105
Lgst	0.341	0.043
Lrnz	0.304	0.091

The first three series (All, Day, Week) show fairly consistent values, while the monthly (Month) series is slightly different and shows a much larger variability. We can ascribe this result to the smaller number of data points in the monthly series and argue that a reasonable size to obtain meaningful results is in the range of a few hundred points. This could correspond to collecting five to ten years of weekly data or twenty to thirty years of monthly data, which should be obtainable by most destinations without much difficulty.

The second important result is that in our case the system cannot be considered a chaotic one, but the values obtained put it in a region characterized a relatively weak correlated stochastic process. In other words the system is close to the *edge of chaos* in a complexity window as has been already recognized as a typical state for tourism destinations. As shown previously in the literature review, a tourism destination is a complex system, which, if not well governed, could

transit to a chaotic phase.
Finally we use the same HVG transformation of the different component series and calculate the degree distribution exponents, obtaining the results shown in Figure 8 where, as before, the null models are reported for comparison and the limiting λ_C value is shown.

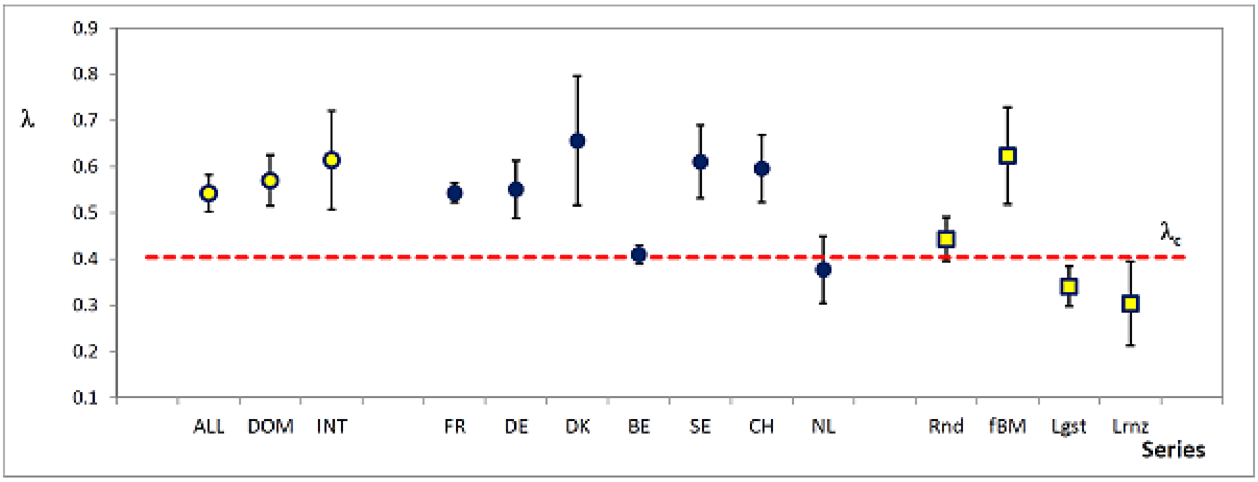

Figure 8. The degree distribution exponents for the components HVG graphs compared to the null models. Vertical bars are 95% confidence intervals, the horizontal dotted line is the limiting value λ_C

Most of the components (FR, DE, DK, SE and CH) have the same dynamical characteristics of the main series. BE and NL have a different behavior. They are random or slightly chaotic phenomena, and are thus the less predictable among the different components.
We can finally summarize our results as follows:

- the HVG technique provides meaningful results and is relatively insensitive to the length of the series used. An optimal length for giving good outcomes is of a few hundred points;
- the analysis of the HVG networks examined gives outcomes consistent with the idea of a complex system, with limited predictability;
- the modularity analysis highlights well identifiable behaviors and the changes in the overall system dynamics;
- the different components of the main series have a consistent behavior, with small differences in some of the components.

4.3 Policy implications for destination managers

The horizontal visibility graph (HVG) methodology provides three main policy implications for destination managers: i) a profound rethinking of the destination concept, paying particular attention to its structure and dynamic; ii) an improvement of destination performance measurement system, based on the introduction of non-linear indicators that favor a complex perspective; iii) an enrichment of the destination planning process, by providing a sound basis for the development of an adaptive approach to governance and the experimentation of a niche-innovation perspective. Below each point is analyzed, bringing some evidence related to the Livigno case.

Empirical findings confirm the complex nature of tourism destination, with its distinctive traits described before (see paragraph 2). Destination managers and, more generally, destination marketing and management destinations (DMOs) are called to govern the system, managing some processes at a territorial level. To manage this system, destination managers need to have a clear idea about the concept of destination. Livigno, as seen, has some traits typical of complex systems; it is not a chaotic one, but is close to the edge of chaos. Destination managers must have a clear idea about the relevance of non-linear relationships, the presence of self-organization behaviors, the emergence of modular and hierarchical structures, the robustness or fragility of the destination with respect to possible events. In contrast, the destination is often perceived, experienced and managed as a single object that results from the simple aggregation of several pieces (i.e. organizations, firms, attractions, service, etc.).

The destination complex nature requires a rethinking of its performance measurement system. Alongside traditional metrics, often focused on a past and short-term perspective (Sainaghi, 2010), the Livigno experience shows the relevance of indicators able to monitor and identify turning points, to evaluate the system robustness or fragility, or the encroachment into the threshold of chaos. This analysis is relevant both for the whole system and for the main attracted segments (origin markets), as shown previously. Currently, destination managers evaluate the territorial performance primarily using linear indicators and almost ignoring the complex nature of what they manage. Implicitly this approach assumes a continuity in the system behavior and an high predictability, often contradicted by reality.

Complexity introduces some interesting insights also with reference to destination planning. Given the structure of the local system, a destination manager cannot fully control its development paths. As such, a complexity science perspective inspires the pursuit of adaptive, incremental approaches to tourism area development, able to deal with uncertainties and changing circumstances, alongside the more traditional large-scale blue-print plans and end-state projects (Hartman, 2015). The self-organizing nature limits the ability of single agents to change the system. In fact, the entrepreneurial behaviors of individuals, firms and institutions modify continuously the destination, creating what Mintzberg (1985) called “emerging strategy”. Adaptation is, therefore, likely to include (multiple) public and private actors and to involve governance issues related to policy frameworks, decision-making and power, or to top-down versus bottom-up approaches. Furthermore, empirical evidence suggests developing a niche approach, in order to consider the chaotic or robustness structure of single markets. If, for example, some relevant markets show a progressive slipping towards the threshold of chaos, an intervention based on traditional marketing approaches may be completely ineffective.

5. Concluding remarks

The present paper contributes to filling two gaps: i) the presence of a limited number of studies focused on demand turning points, ii) the prevalent recourse to linear models in demand analysis disregarding the complex structure of tourism destinations. In this final section we draw some conclusions concerning these two points, for both academics and practitioners. Lastly, this study suggests some implications regarding the horizontal visibility graph (HVG) methodology.

First of all, the empirical analysis has revealed the presence of four turning points in the last 50 years in the Livigno context. The main changes are built around shifts in the attracted segments, with particular emphasis on domestic and international clients. The methodology used easily makes it possible to identify different destination phases, especially if the time series is populated by a significant number of points (see section 4.2). The identification of turning points opens interesting implications for both academic research and practitioners. From a theoretical point of view, it is possible to rethink some frameworks built around phases or turning points, such as the well-known model of destination life cycle (Butler, 1980), or other models focused on destination phases, such as those concerning strategies, governance, processes (Beritelli, 2011; d'Angella, De Carlo, & Sainaghi, 2010; Pearce, 2014; Sainaghi, 2006). The implications for destination managers and more generally for companies operating in a networked environment appear to be important. The identification of phases and turning points, in fact, helps both territories and businesses to increase the consciousness of their strategies and permits to align managerial levers to changes. An example can clarify this point. In the Livigno case, one of the four turning points was located in 1992, when the national currency was heavily devalued against other European currencies and in particular against the German mark. In a similar context, the ability to orient communication and marketing actions to markets that enjoy the most favorable exchange rates can improve destination performance.

The second gap examined concerns the complex structure of a destination network (Dredge, 2006; Haugland et al. 2011) and suggests the relevance of non-linear models for the analysis of tourism demand. Our findings are of particular interest because they describe an articulated situation. The destination analyzed, in fact, is surely a complex network. This result, confirmed by previous studies of tourism networks (e.g. Baggio & Sainaghi, 2011), has important implications for research. On the one hand, if the system is not in a chaotic configuration, linear models can be usefully applied, at least to a certain extent. This renders the intuitive idea of inertia in the dynamic behavior of a (at least partially) stable system. On the other hand, however, if the network is close to the edge of chaos, even small size changes can drive the destination towards bifurcation points, creating completely new situations where linear models are surely unable to fully explain present configurations or predict future ones. In fact, linear frameworks show good (or very good) forecasting abilities if the system remains stable, but, when the destination goes beyond the edge of chaos, these linear models experience serious issues. This situation is reinforced when specific destination segments (e.g. single markets) are taken into account, because there may be a growing probability of finding some market segments exhibiting chaotic behaviors.

Implications are, therefore, very interesting for both theory and practice. With reference to academic studies, the empirical findings suggest the importance of using non-linear methods in demand research. Studies examined in the literature survey show that a considerable number of models are essentially linear in nature, while non-linear frameworks are few. Implications are relevant also for practitioners. If destinations are close to the edge of chaos and if some segments show chaotic behaviors, then it is very important to use models and indicators that may be closer to the non-linear nature of the system. It is important that destination managers, as well as top managers of local firms, develop conceptual maps and governance approaches aligned to themes such as discontinuity and chaos. As noted in previous studies, the edge of chaos is characterized by high instability and unpredictability, where some apparently marginal events (butterfly effect) can trigger the system to a chaotic region, or can generate bifurcations in the system evolutionary path. In this context, a managerial adaptive creativity is a precious resource.

Finally, the analysis suggests some conclusions on the method employed. The horizontal visibility graph (HVG) algorithm used for the analysis of a complex tourism destination system is able, with limited requirements regarding the data to be collected, and with a relatively simple computational effort, to provide interesting insights into the main characteristics of the system under study. The HVG method shows results very similar to those generated by very complex methods – such as the Lyapunov exponents, Hurst exponent, fractal dimensions, symbolic discretization (Kantz & Schreiber, 1997; Sprott, 2003) – but avoiding the operational complexity typical of these tools.

The techniques also furnish a rough method to identify different regimes. A good qualitative expertise of the destination and its history makes it possible to provide meaningful explanations for these transitions. With a sound quantitative basis, they may increase the knowledge of the dynamic characteristics of the destination, a fundamental prerequisite for any governance action. The methods used here have small shortcomings, for example, a good qualitative understanding of the system studied is needed for a correct interpretation of the results.

5.1 Limitations and further research

This study presents two main limitations (which can guide new research efforts): i) the use of a single case study can limit the generalizability of the outcomes, ii) the structure of the data affects the number and the structure of phases and turning points uncovered. Concerning the first issue (single case study), it could be interesting to analyze new and different tourism systems in order to verify whether the present findings (the system is complex, close to the edge of chaos, some markets show chaotic behaviors) are confirmed. Additional outcomes can contribute to solving questions such as: are tourism destinations usually close to the edge of chaos? Do turning points show similar frequency and duration? Are the causes that create turning points similar? Is it possible, when comparing different destinations, to classify the main triggering events?

As far as the second point is concerned, the main findings of this paper are clearly shaped by the time series used, and in particular by the consideration of the domestic and international data. Both phases and turning points are, as seen, mainly influenced by the evolution of national and international markets. It could be interesting to employ different time series for the same destination and verify whether both phases and turning points remain the same or whether different outcomes can be found. Moreover, it would be interesting to see whether the complex and chaotic traits are confirmed when other types of data series are used, and to deepen this type of analysis by using more sophisticated techniques (see e.g. Ravetti et al., 2014).

Neither limitations reduce the value of the empirical findings, but it disclose interesting stimuli for researchers, showing how relevant and promising an approach based on the study of the complex and chaotic structure of tourism destinations may be.

Acknowledgments

The authors gratefully acknowledge the valuable and constructive comments of an anonymous reviewer that have greatly helped to improve the quality of this paper.

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